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DISSERTATION

REGIONAL EVAPOTRANSPIRATION AND PAN EVAPORATION:
COMPLEMENTARY INTERACTIONS AND LONG-TERM TRENDS ACROSS THE
CONTERMINOUS UNITED STATES

Submitted by

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In partial fulfillment of the requirements
for the Degree of Doctor of Philosophy

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Fall 2004

UMI Number: 3160093

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WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER
OUR SUPERVISION BY MIKE HOBBS ENTITLED REGIONAL
EVAPOTRANSPIRATION AND PAN EVAPORATION: COMPLEMENTARY
INTERACTIONS AND LONG-TERM TRENDS ACROSS THE CONTERMINOUS
UNITED STATES BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS
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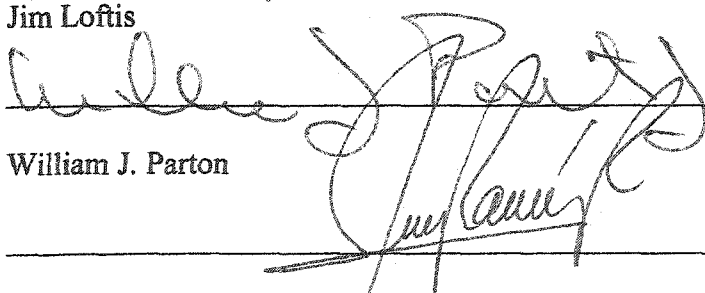
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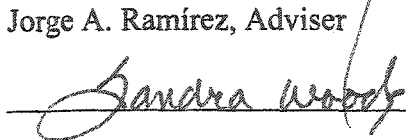


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ABSTRACT OF DISSERTATION

REGIONAL EVAPOTRANSPIRATION AND PAN EVAPORATION: COMPLEMENTARY INTERACTIONS AND LONG-TERM TRENDS ACROSS THE CONTERMINOUS UNITED STATES

Long-term observations of pan evaporation and water budget-derived evapotranspiration across the conterminous United States provide the first observational evidence supporting the hypothesis of a complementary relationship in regional evapotranspiration, in terms both of the evaporation rates themselves and of long-term trends in their component dynamics. The conjectured relationship has now become an observational fact. To establish a baseline for the study of climate change and/or variability, a complementary relationship model estimates spatially distributed actual evapotranspiration across the conterminous US on a monthly basis over a recent 42-year period. This is used to examine two advective calibration approaches, and trends in actual evapotranspiration and its components as to their direction, magnitude, statistical significance, and spatial distributions.

In observations of trends in ET_a and in its two component trends—the radiative energy and regional advective dynamics—it is shown that, contrary to previous conclusions that have been predicated on questionable and restrictive assumptions over near-continental scales, trends in the components must be examined concurrently within the context of the complementary relationship to explain trends in regional ET_a . It is further shown that only by examining spatially concurrent observations at smaller spatial

scales can good conclusions be drawn about the “strength” of the complementary relationship, specifically, and *ET* trends in general.

The two most problematic data sets used in the analysis are improved: solar radiation, which suffers from the effects of local topography; and pan evaporation, which bears the effects of anthropogenic heterogeneities inherent in a variously sourced data set.

A procedure is developed to mitigate the confounding influence of rugged terrain on the analysis of the short-wave radiative balance, producing a long-term, high-resolution, topographically corrected net radiation data set. Twelve years of missing diffuse radiation data are replicated based on their historical relationships to coincident, contemporaneous direct normal and global radiation. A monthly topographic correction factor is derived to account for the incidence of direct solar radiation on arbitrarily oriented ground surfaces at any latitude throughout the diurnal and annual cycles. The factor is applied to spatially interpolated surfaces of monthly direct solar radiation which, when added to surfaces of diffuse radiation, provide the total incident solar radiation input to an existing energy budget. This yields the net surface radiation that may then applied in evapotranspiration models.

Pan evaporation observations are gathered from two data sources for 228 pans across the conterminous US toward an examination of long-term trends in annual and warm-season totals. The data are characterized by their incompleteness and, more importantly, non-homogeneity that, unless accounted for, can introduce spurious biases into analyses of long-term trends. However, what scant metadata are available are elliptical. The need to retain climatically driven trends after homogenization requires a technique that resolves understandings of both the physical dynamics and the statistical properties of the

data by combining objective rigor with subjective judgment. Using the *t*-test to indicate statistically significant abrupt shifts in each pan's time-series, 172 pans are adjusted at a total of 326 abrupt data-shifts, adjusting 43% of the annual data and 55% of the warm-season data. Comparing trend results from pre- and post-adjustment data across all pans, some differences are noted in the details, but they are not together significant enough to change the conclusions of the trend analysis.

Pan evaporation has decreased at 64% of the year-round pans in the conterminous US over the past half-century. The so-called "Pan Evaporation Paradox" is shown to be no more than a manifestation of the natural complementarity between actual and potential evapotranspiration. An examination of trends in the radiative energy and regional advective components of basin-derived actual evapotranspiration shows that both components must be considered together to explain the relationship between actual and potential evapotranspiration.

Actual evapotranspiration is modeled using a regional, seasonal Advection-Aridity approach to create a spatially distributed, monthly time-series for a 42-year period at a 5-km resolution over the conterminous US. Formulations of both dynamics in the evaporative process are improved with respect to the applicability of the model across large topographic and climatic variations. The radiative input is the aforementioned topographically corrected data set. The advective input is improved by analysis of two regional calibrations of the wind function: first such that modeled actual evapotranspiration matches basin-derived evapotranspiration at 655 basins across the conterminous US; second such that potential evapotranspiration matches point observations of pan evaporation across the southern tier of states. Each calibration

invokes different assumptions and limitations on its applicability in the temporal and spatial domains. The parameter sets of the derived wind functions are similar in value, but the first is noisier while the second bears less significant functional relationships to wind speed.

The modeled annual evapotranspiration data are verified against observed water budget-derived actual evapotranspiration. The basin-derived calibration of the wind function performs the best, while the pan evaporation-based calibration under-estimates evapotranspiration. In purely statistical terms, the basin-derived calibration is preferred, but the performances of both calibrations bear functional relationships to the precipitation, basin-derived evapotranspiration, and wind speed in the areas of application. In terms of long-term trends over the modeling period WY 1953-1994, for the conterminous US as a whole, a 4.2% decrease in modeled annual actual evapotranspiration is observed for the basin-derived calibration, a trend significant at the 69% confidence level according to the Mann-Kendall test. Over the southern tier of states, a 3.1% decrease in modeled annual actual evapotranspiration is observed for the basin-derived calibration (significant at 62%), and a 2.1% decrease in modeled annual actual evapotranspiration for the pan evaporation-derived calibration, (significant at 47%).

Reducing the spatial scale of trend-analyses—from the continental US through the nested component 18 Water Resource Regions and the further-nested 334 Accounting Units to the 655 relatively undisturbed basins across the continental US—allows for clearer identification of areas with significant trends, and the breakdown into component

dynamics shows that trends in actual evapotranspiration can be determined to originate in either energy or water fluxes, or both.

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LIST OF SYMBOLS

A	scalar representing a in $f(U_2)$
$\mathbf{A}$	arbitrary vector
$ \mathbf{A} $	magnitude of vector $\mathbf{A}$
A_{SW}	global short-wave albedo
A_{LW}	long-wave albedo
B	scalar representing b in $f(U_2)$
$\mathbf{B}$	arbitrary vector
$ \mathbf{B} $	magnitude of vector $\mathbf{B}$
C	net long-wave radiation transfer from the evaporating surface
E	surface emissivity
$\mathbf{E}$	vector representing time-series of ET_a
E_A	drying power of the air
ET	evapotranspiration
ET_a	actual evapotranspiration
ET_a^*	basin-derived evapotranspiration
ET_p	potential evapotranspiration
ET_{pan}	pan evaporation
ET_{pan}^{WS}	warm-season pan evaporation
ET_w	wet environment evaporation
G	ground heat flux
$\mathbf{G}$	gradient vector

H	sensible heat flux
JD	Julian day
$LW\uparrow$	upward long-wave radiation
$LW\downarrow$	downward long-wave radiation
N	sample size
R	streamflow
R_D	direct normal incident solar radiation
R_{Di}	R_D for hour i
R_G	global incident radiation
R_H	diffuse incident solar radiation
R_N	net global radiation
R_d	gas constant for dry air
P	precipitation
P_a	atmospheric pressure
Q_N	net available energy
S	sum of the series of <i>signum</i> functions of each x_i against all successive x_i 's
S	vector parallel to the line of sight to the sun
S_{WX}	covariance matrix of the two indicated time-series (e.g., W and X)
S_{XX}	variance matrix of the indicated time-series (e.g., X)
T	air temperature in K
T_c	Student's t test-statistic
$T_{1-\alpha/2, v}$	$1-\alpha/2$ quantile of the Student's t -distribution with v degrees of freedom
$U_{1-\alpha/2}$	$1-\alpha/2$ quantile of the standard normal distribution

U_r	wind speed at height r meters
U_2	wind speed at height 2 meters
V_{dif}	vapor pressure deficit
W	heat storage of evaporating layer
$\mathbf{W}$	vector representing the time-series of energy flux in ET_a
$\mathbf{X}$	vector representing a component time-series of advective flux in ET_a
$\mathbf{Y}$	vector representing a component time-series of advective flux in ET_a
Z	solar zenith angle
$Z(.)$	Mann-Kendall test statistic for the parenthetical variable
a_v	ratio of eddy diffusivity to eddy viscosity under neutral conditions
a	intercept of calibrated $f(U_2)$
b	slope of calibrated $f(U_2)$
$\{a,b\}$	parameter set describing $f(U_2)$
$\{a,b\}_i^{\text{PAN}}$	$\{a,b\}$ for month i for pan indicated
$\{a,b\}^{\text{PAN}}$	annualized $\{a,b\}^{\text{PAN}}$
$\{a,b\}^{\text{BASIN}}$	$\{a,b\}$ for basin indicated
$\cos\theta$	instantaneous topographic correction factor for R_D
$\cos\theta_{\text{MONTH}}$	monthly integrated $\cos\theta$
d_0	displacement height
e_a	actual vapor pressure
e_a^*	saturation vapor pressure
$f(U_2)$	wind function for U_2
$f(U_r)$	wind function for U_r

g	groundwater domain
i	context-dependent time-index
i_{SR}	sunrise hour
i_{SS}	sunset hour
j	context-dependent time-index
k	complementary relationship constant
k_{vK}	von Kármán constant
p	order of an autoregressive process
p_i	hourly proportion values of daily total R_D for 15 th day of month i
q_1	energy available when $ET_a < ET_w$
q_2	energy available when $ET_p > ET_w$
s	surface domain
x_i	i 'th value of data in a generic time-series of x
z_0	roughness length
z_{0m}	roughness length for momentum
z_{0v}	roughness length for water vapor
z_r	height of the wind speed measurement
z_2	height at which e_a is measured
Γ	day angle
Δ	slope of the saturated vapor pressure curve at air temperature
α	aspect of an arbitrarily oriented surface
α_{PT}	Priestley-Taylor coefficient
β	slope of an arbitrarily oriented surface

γ	psychrometric constant
δ	solar declination
ε	water balance closure error or “closure error”
ε_t	random and normally distributed uncorrelated series or “white noise”
θ	incidence angle for an arbitrarily oriented surface
λ	latent heat of vaporization
μ	solar azimuth angle
ν	degrees of freedom
ρ	proportional increase in atmospheric radiation due to clouds
ρ_j	lag- j autocorrelation coefficients
σ_{SB}	Stefan-Boltzmann constant
φ	latitude
φ_j	autoregressive coefficients
ψ	ratio of the gas constant of dry air R_d to that of water vapor R_v
ω_s	sunrise angle for flat surfaces
ω_{sr}	sunrise angle for sloping surface
ω_{ss}	sunset angle for sloping surface

1. Introduction

1.1 General Motivation

Climatic change and variability will have myriad effects on life on Earth, none more immediate than those involving the hydrosphere. Changes in the global hydrologic regime will inevitably foment resource-based conflicts at all scales—between nations bordering a shared resource (e.g., Mexico and the USA regarding the Rio Grande and Colorado River), or between upstream and downstream states in a regional basin (e.g., the states currently part of the Colorado River Compact), within states (e.g., between Colorado mountain communities and the Front Range megalopolis)—and across the gamut of hydrologic characteristics—different demands on the hydrologic regime as to the volume, flow-rate, timing, or quality of water supplied are made by irrigators, urban water managers, ski-area operators, wildlife managers, and recreationists alike. In order to understand the effects of an anthropogenically altered hydrologic cycle, hydrologists and water managers are increasingly turning their attention to climate models, but it is essential first to establish a baseline for such modeling by rigorously examining past change.

In providing the sorely needed trend analyses at the watershed scale most useful to the resolution of issues of water supply and demand in increasingly variable hydroclimatic conditions, it is the invisible fluxes of evaporation from bare ground and transpiration from plants—indivisible enough as to be known under the conflated term “evapotranspiration” (ET_a)—that remain amongst the most sensitive to climatic variations while presenting the greatest modeling challenge. Unique amongst the

components of the hydrologic cycle, ET_a is detectable only by its passing, of what it leaves behind. At the basin scale, ET_a is observed generally as the spatially lumped residual when observed runoff is subtracted from precipitation. Often, observations of the evaporative process on a point-scale are limited to those of the theoretical maximum, or potential, ET rate (ET_p) and are made using evaporation pans wherein, again, ET is taken as a deficit in water levels in the pan.

1.1.1 Traditional Paradigm of Evapotranspiration Estimation

The dearth of direct analysis of ET_a —i.e., analyses based on its physical dynamics as opposed to analyses based on ET_a calculated as a residual of other flux-estimations—has resulted from the difficulties inherent in calculating ET_a and the complications of scale. Consequently, of trend analyses of actual (as opposed to potential) ET , there are almost none. In the context of the practical application of the estimation of evapotranspiration, the successful modeling of the physics of energy and mass transfer at the land surface-atmosphere interface at small temporal and spatial scales [Katul and Parlange, 1992; Parlange and Katul, 1992a; Parlange and Katul, 1992b] is of limited use to water managers, who require an understanding and applicable models of these processes at larger, basin-wide or regional scales. As a result, their ability to estimate regional evapotranspiration at such scales has often been constrained to the traditional paradigm, whereby ET_p is considered independent of ET_a as feedbacks and interactions across the land surface-atmosphere interface are ignored. In using this paradigm, ET_a is generally modeled either as a simple, often empirical function of ET_p derived from pan evaporation (ET_{pan}) observed at nearby weather stations, or by ground-based models that tend to rely

on gross assumptions regarding processes in the soil, vegetative, and atmospheric systems.

Vegetation is generally assumed to act as a “passive wick” in the transfer of moisture from tension storages to the atmosphere, an assumption that ignores the effects of irradiance, leaf temperature, carbon dioxide concentration and humidity of the ambient air [Dickinson *et al.*, 1993]. This latter control has been observed to act in a feedback loop that contradicts the passive wick assumption, but instead decreases transpiration rates even as ET_p increases. A reduction in soil moisture leads to decreasing moisture fluxes to the atmosphere, driving up the vapor pressure deficit (V_{dif}); in these conditions, plant stomata close—i.e., stomatal resistance increases—in order to create the potential gradient necessary to sustain a given flux.

With regard to the atmospheric assumptions of the soil-plant-atmosphere system, ET_p is traditionally assumed to be independent of ET_a and is used to reflect evaporation demand. It is often calculated by approximate solutions such as the Penman equation (1.7). However, it is well known that the passage of air masses over land surfaces modifies them according to the proportion of net radiative energy taken up by ET_a and transferred back to the atmosphere as latent heat. Decreases in ET_a due to reductions in water availability lead to temperature increases and humidity decreases of the overpassing air, which lead to an increase in the drying power of the air through an increase of V_{dif} .

These difficulties—the gross assumptions as to the nature of moisture dynamics in each of the components of the land surface-atmosphere interface, of the interactions between them, and the modeling complexities involved in explicitly linking the

components and the inadequacy of traditional paradigm models—point to the need for models of regional ET_a that consider the evaporative system as an integrated whole, that bypass the poorly understood dynamics within each component, and that incur minimal data requirements as to the nature of the land surface. The examination of trends in ET_a in a more direct fashion requires a model that is physically based, well-calibrated, accurate, and that predicts ET_a on a regional basis such that it can be applied across un-metered basins and at a range of spatial scales. Complementary relationship models are such models.

1.1.2 Complementary Relationship Models

Although an independent, theoretical proof of *Bouchet's* [1963] complementary relationship hypothesis has not yet been established, that the hypothesis of a complementary relationship between actual and potential rates of ET allows for predictions of ET_a on a regional scale that can be of functional use to water managers and of scientific merit has been shown indirectly by numerous studies [*Morton*, 1965, 1975, 1976, 1978, 1979, 1983; *Brutsaert and Stricker*, 1979], with more recent studies [*Claessens et al.*, 1995; *Claessens*, 1996; *Hobbins et al.*, 1999, 2001a, 2001b] testing the application of the hypothesis in scores of basins across a wide range of climatic regimes. This study provides the first direct observational evidence in support of the complementary relationship hypothesis, thereby changing what has heretofore remained conjecture into an observational fact.

To hydrologists, one of the primary advantages of models of the complementary relationship is that they rely solely on routine climatological observations and allow the

estimation of ET over regional-scale land surfaces without *a priori* knowledge of the nature of the land surface, beyond that it satisfies the assumption of homogeneity at scale lengths conducive to establishment of a well-mixed boundary layer. As they implicitly account for the soil moisture-dependence of ET_p , their data requirements are significantly lighter than other soil-dependent models. ET_a can be estimated using only data that describe the conditions of the over-passing air, thereby bypassing the complex and poorly understood soil-plant processes and obviating the need for locally optimized coefficients and surface parameterizations of soil moisture or stomatal resistance. When properly formulated, they can accurately predict ET_a over regional extents, as indicated by the near-zero mean annual error for the regional, seasonal Advection-Aridity model reported in *Hobbins et al.* [2001b].

Hobbins et al. [2001c] state that for hydrologists working in large-scale homogenous areas, these complementary relationship models should be preferred over traditional evapotranspiration models that use land-based parameterizations, as the input data are distributed and reflect surface conditions regardless of the origins of the water and degree of anthropogenic disturbance.

Such models have been shown to predict ET_a on a regional scale and at a variety of temporal scales—from multiples of days [*Brutsaert and Stricker*, 1979] to months [*Morton*, 1983; *Claessens et al.*, 1995; *Hobbins et al.*, 2001a]—with a useful degree of accuracy in areas of homogeneous relief. However, *Claessens et al.* [1995] and *Hobbins et al.* [1999, 2001a, 2001b] have shown that the applicability of these models in mountainous areas has been limited by certain data and methodological problems. Briefly, these relate to the following: 1) the assumption of well-mixed boundary layers

over homogeneous land surfaces on a regional scale (*Bouchet* [1963] specifically mentions scale lengths on the order of hundreds of meters) will not hold in regions of rugged terrain where the influence of heterogeneities may far outweigh the integrative effect of turbulent mixing; and 2) the spatial interpolation of input variables across topographic discontinuities may lead to the spatial variability of these inputs being poorly reflected in input surfaces and result in inaccurate estimates of ET_a . These issues point to the need to improve the applicability of the complementary relationship in terrain that is challenging to the model due to its topographical heterogeneity. With respect to input variables to the models, these improvements must be made to both the advective and the radiative input fields, and with respect to the verification of the model, a precipitation input developed specifically for heterogeneous terrain is favored.

While this study renders the complementary relationship hypothesis into observational fact, the utility of the complementary relationship hypothesis as a modeling tool and its tunability towards specific or extreme regional physiographic and climatic characteristics depends on the resolution of the problems listed above.

1.1.3 Scales of Analysis

With regard to ET , the effects of an anthropogenically altered atmosphere and hydrosphere on basin hydrology are manifold and operate at all spatial scales. Globally, warming as a result of the greenhouse effect may be predicted by General Circulation Models (GCMs), which, by modeling the effects of greenhouse gases, can examine the effects of increases in the concentration of greenhouse gases (from fossil fuel burning or land use changes) on global temperature and the global hydrologic cycle. The primary

effects at this scale are those of the rising mean temperature resulting in a more energetic hydrologic cycle.

On a regional scale, effects on the hydrologic cycle may run from modifications to weather patterns—e.g., deviation of storm tracks—to the effects of land-use changes—e.g., increased latent heat flux and humidity from large-scale irrigation. These effects may be manifested in the short term—e.g., in anthropogenic migrations of agriculture—and in the long term—e.g., as natural migrations of vegetative species in response to changes in moisture availability that result from changes in precipitation and temperature.

At the basin scale, the effects of an anthropogenically altered climate include the direct effects of temperature on *ET* (which may be readily modeled by use of regional *ET* models) and the local variations in the dynamics of the hydrologic cycle. The latter may include changes in storages, the seasonality of precipitation, and in vegetation type and cover. Hydrological practice has historically been conducted at the regional- and basin-scales.

The likely effects of climate change and variability on hydrology act are felt at the still-smaller scale of variations in the stomatal conductance of individual leaves. Progressing down through these scales to an increasingly complex and subtle understanding of these processes exposes a paradigm separation between ecological and hydrological outlooks in their considerations of spatial scale. Bridging this divide will necessitate a more advanced understanding of the processes than is generally assumed in the applied modeling of hydrologic processes.

Hydrologists, therefore, seek a model that can produce estimates at a bridging scale—a model that must perforce be spatially distributed and able to render estimates over

climatologically diverse regions at a spatial resolution that is constrained by the viability of assumptions regarding homogeneity of topography and moisture availability at the upper end and at the lower end by computational burdens, the availability of data, and the physics themselves.

The spatial resolution chosen for this study was approximately 5 km. In utility, this resolution is below that used in most site-specific agricultural applications (i.e., the field scale) and of micro-meteorological considerations. Henceforth, this resolution shall be referred to as the regional scale, unless otherwise indicated.

1.1.4 Thesis Statement and Outline of Dissertation

Given the previous discussion and the state of the science of *ET*-estimation, the thesis statement of this study takes the form of a basic science question and its resolution, and a consequent discussion of its applicability, as follows:

That at a regional scale, ET_a and ET_p are mutually complementary; that this is supported by independent observations of ET_a^ and properly adjusted ET_{pan} and via trend analyses of the radiative and advective component dynamics of the evaporative process; that in the context of the complementary relationship, ET_a , and therefore trends in ET_a , are estimated better than by traditional paradigms over a wide variety of terrains and climatic regimes; that a model of the complementary relationship whose component dynamics are then formulated with reference to topographically corrected solar radiation, in the case of the*

radiative input, and properly calibrated with reference to homogeneous observations of ET_{pan} , in the case of the advective dynamic, can then be a useful tool for estimating spatially distributed regional ET_a .

Broadly, this dissertation addresses this thesis statement in four chapters in the form of papers bookended at the start by this general introductory chapter and at the end by a summary chapter. As such, there may appear to be some repetition of text, especially with regard to methodologies and data sets as they appear across the different chapters. This will be kept to a minimum within the constraints that each chapter stands alone as a submission-ready or published paper. The numbering of equations, tables, figures, and sections follows a dissertation format and the references for all chapters are listed at the end.

So far, having discussed the difficulties of ET -estimation, the introduction has provided a general motivating context for all the work that follows. The rest of this chapter takes the form of a literature review. This review proceeds by tracing the development of the complementary relationship hypothesis from first principles, and raising some specific issues about its performance relating to its central assumption. Then, its recent applications are summarized, especially with respect to the Advection-Aridity model, which is shown to be useful in predicting large-scale ET_a across a broad spectrum of climatic regimes (and which will then be used in Chapters 4 and 5). Finally, the recent relevant research on trends in ET_a , especially as it pertains to the complementary relationship, is summarized.

Chapter 2—the first paper—addresses an issue that has until now bedeviled estimates of distributed ET_a in rugged terrain: that is, the estimation of the energy budget. The chapter presents the development of a time-series of the energy input (the net available energy for evaporation, Q_N) to the evaporative process that is long-term (42 years at a monthly time-step), large-scale (across the conterminous US), high resolution (5-km pixel size), and that, more importantly, reflects the varying and confusing effects of local slope and aspect through time and space on the input variables. This chapter also demonstrates the infilling of missing variables.

Chapter 3 provides, for the first time, observational evidence of the complementary relationship between ET_a and ET_p . As a result, the complementary hypothesis is no longer a conjecture but an observational fact. Chapter 3 then deals with the development of a long-term time-series of ET_{pan} through 50 years across the conterminous US. This entails the collation of raw data from various sources and at various time-steps and the resolution of the crucial issue of data-homogeneity. As this data set is used to examine trends in ET_{pan} , a non-standard procedure for detecting and resolving anthropogenic heterogeneities in each time-series is developed and applied.

Chapter 4 delves deeper into the examination of observed trends in both ET_{pan} and basin-derived ET_a^* that is further briefly summarized in Chapter 5, examining advection as it pertains to the complementary relationship in ET_a , and the component trends (Q_N and the advective flux, E_A); this last component decomposed even further—into V_{dif} and wind speed (U_2). The chapter then moves onto modeling ET_a , offering and comparing two parameterizations of this component: one based on basin-derived ET_a^* derived from basin-scale water budgets, the other on the pan estimates that were homogenized in

Chapter 3. This last task introduces a calibration that is based on direct physical observations of an evaporative process rather than one that merely absorbs the water balance residual. Two $f(U_2)$ -calibrations in the Advection-Aridity model of ET_a based on the complementary relationship are compared—one that is basin-based, the other that is pan-based—for use in the estimation of long-term trends. This development of climatically robust ET_a data sets that are both long-term and large-scale permits the examination of secular trends in regional ET_a on a spatially distributed basis. Further, the component- and ET_a -trend results generated in this study are compared to the work of others, and these trends and trends in modeled ET_a are examined over a variety of scales.

Chapter 5 steps back from the in-depth study of Chapter 4 and summarizes much of the previous work in a shorter, sharper fashion, and offering quantitative analyses of the trends discussed in Chapter 4. This chapter is formatted in a paper published in the journal *Geophysical Research Letters*. The chapter addresses the issue of the “Pan Evaporation Paradox” that has been raised by many researchers, who note that globally decreasing trends in ET_{pan} were observed contrary to expectations under a global warming trend. Here, the paradox is observed and resolved using spatially coincident observations, and the first reported observations are provided that show that complementary relationship models integrate those effects better than do traditional paradigms and therefore support the resolution of the paradox in favor of the complementary relationship hypothesis. In order to (a) confirm the existence of the complementary relationship reflected in the trends in ET_a and its component fluxes, and (b) verify the performance of the complementary relationship model described in Chapter 4 in estimating long-term trends in ET_a , one must turn instead to independent

observations of ET_a^* . To this end, trends in annual ET_a^* , Q_N , and E_A are examined at 655 hydrologically undisturbed basins across the conterminous US. In performing this examination at these smaller spatial scales, closer to the minimum scale at which such complementarity is hypothesized to operate (in the original hypothesis, *Bouchet* [1963] suggests scale lengths on the order of hundreds of meters), it is shown that, in estimating ET_a at the regional scale, drawing the familiar conclusion that ET_a can be calculated as a function of soil moisture below a maximum rate defined by an ET_p -estimate that is itself independent of ET_a is physically indefensible. It is further shown that, contrary to the conclusions drawn by recent workers in this field, it is only by examining trends in both components of ET_a^* and ET_{pan} —the energy flux and the advective flux—that observed trends may be resolved, and that this resolution is an expression of the complementary relationship.

1.2 Literature Review

1.2.1 The Complementary Relationship

The hypothesis of the complementary relationship in regional evapotranspiration, first proposed by *Bouchet* [1963], considers ET_p a function of feedback processes between the land surface, through limitations of water availability at the land surface, and the atmosphere, through the evaporative power of the overlying atmosphere. In the context of modeling ET_a , this hypothesis avoids the difficulties inherent in coupling the microscale (surface) and macroscale (free atmosphere) phenomena in the soil-plant-atmosphere

system, allowing ET_a to be estimated using only data that describe the conditions of the over-passing air and that are already measured for ET_p .

A brief development of the complementary relationship starts with the instantaneous energy budget of the evaporating surface, which is shown in Figure 1.1 and expressed as follows:

$$\frac{\partial W}{\partial t} = (R_D + R_H)(1 - A_{sw}) + LW \downarrow (1 - A_{LW}) - LW \uparrow - \lambda ET_a - H - G \quad (1.1)$$

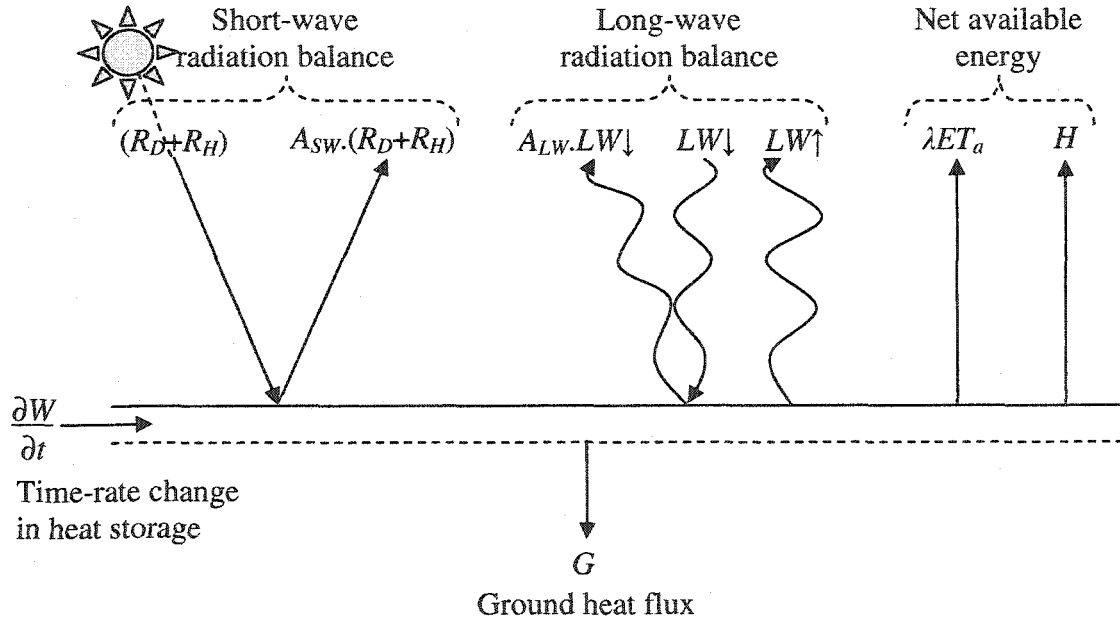


Figure 1.1: Schematic representation of the instantaneous energy budget at an evaporating surface.

where $\partial W/\partial t$ represents the time-rate of change in heat storage of the evaporating layer, R_D is the direct normal incident solar radiation, R_H is the diffuse incident solar radiation, A_{sw} is the global short-wave albedo, $LW \downarrow$ is the long-wave radiation from the atmosphere to the surface, A_{LW} is the long-wave albedo, $LW \uparrow$ is the long-wave radiation emitted by

the evaporating surface, λET_a is the latent heat flux, H is the sensible heat transfer from the surface to the atmosphere, and G is the ground heat flux, or that part of the surface energy budget that is transferred from the surface to the ground below. All negative or subtracted quantities are fluxes away from the surface.

In this study, monthly ET_a estimates are accumulated over an integer-multiple of years. This permits assumptions that ground heat fluxes into the ground are balanced by fluxes out and that there is no net change in heat storage in the evaporating layer, and thereby allows G and $\partial W/\partial t$ to be eliminated from the budget. Thus, in making long-term estimates of ET_a , Equation (1.1) devolves to the following expressions for the net energy available at the evaporating surface (Q_N):

$$Q_N = \lambda ET_a + H \quad (1.2a)$$

$$Q_N = (R_D + R_H)(1 - A_{SW}) + LW \downarrow (1 - A_{LW}) - LW \uparrow - G - \frac{\partial W}{dt} \quad (1.2b)$$

As shown in Equation (1.2a), Q_N is partitioned into the sensible heat flux H and the latent heat flux λET_a .

The complementary relationship hypothesis holds that, over areas of a regional scale (scale lengths of the order of 1-10 km, or areas of 10-100 ha) far enough away from any sharp environmental discontinuities, a well-mixed atmospheric boundary layer develops that leads to a complementary feedback mechanism between ET_a and ET_p rates [Bouchet, 1963].

Under these conditions, when ET_a equals ET_p the rate is referred to as the wet environment evaporation (ET_w). Under conditions where, independently of energy availability (e.g., if the supply of water for evaporation is limited), ET_a falls below ET_w ,

an amount of energy q_1 , that would otherwise be taken up by the evaporative process, becomes available at the surface.

$$\lambda ET_w - \lambda ET_a = q_1. \quad (1.3)$$

Bouchet [1963] assumed that q_1 does not affect the short-wave radiation balance and only weakly affects the long-wave radiation balance through the temperature and humidity of near-surface air, and thus has negligible effects on Q_N at a regional scale. The raised temperature and humidity gradients in the over-passing air due to q_1 lead directly to an increase in ET_p of q_2 , or:

$$\lambda ET_p = \lambda ET_w + q_2. \quad (1.4)$$

Given the well-mixed boundary layer previously specified, the increase in ET_p is assumed to be equal in magnitude to the decrease in ET_a , i.e., q_1 is assumed to be equal to q_2 :

$$q_1 = q_2 \quad (1.5)$$

A combination of Equations (1.3), (1.4), and (1.5) leads to the familiar expression for the complementary relationship between ET_a and ET_p at a regional scale:

$$ET_a + ET_p = 2ET_w \quad (1.6)$$

Briefly, then, the hypothesis of a complementary relationship between actual and potential ET states that, for uniform surfaces of a regional scale under conditions of constant energy input, when ET_a is limited by moisture availability at the evaporating surface, then ET_p is increased by the same amount. The hypothesis assumes a well mixed atmospheric boundary layer and that only temperature, humidity, and turbulence in the equilibrium sub-layer are affected: the net radiation at the evaporating surface is not

affected. The hypothesis leads to the three measures of ET following and shown schematically in Figure 1.2:

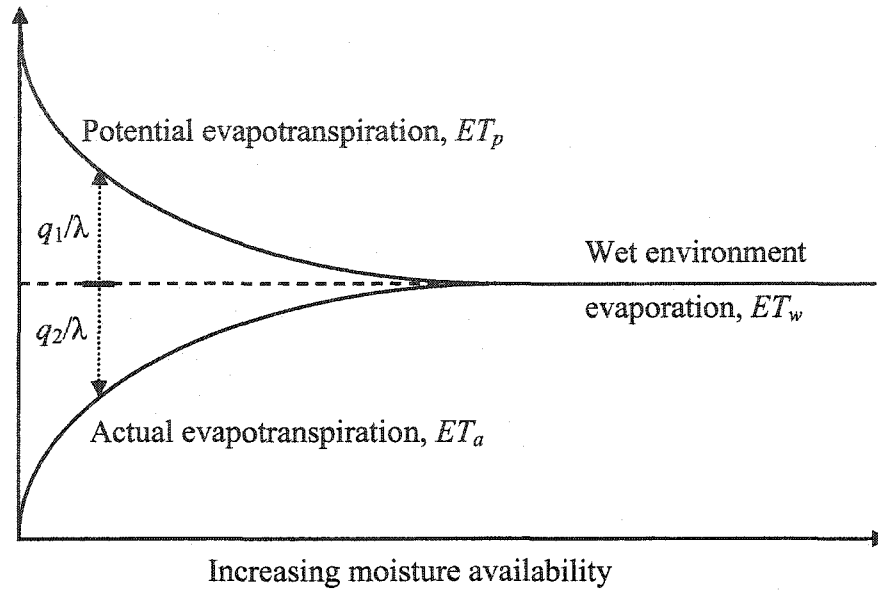


Figure 1.2: Schematic representation of the complementary relationship in regional evapotranspiration (assuming constant energy availability).

- (i) ET_a , Actual Evapotranspiration: occurs in all conditions of moisture availability (equal to ET_p under unlimited moisture conditions and then referred to as ET_w);
- (ii) ET_p , Potential Evapotranspiration: the theoretical rate if any excess in surface energy budget resulting from moisture limitations could be used to evaporate further moisture (equal to ET_a under unlimited moisture conditions and then referred to as ET_w);
- (iii) ET_w , Wet Environment Evaporation: the rate under conditions where the only limitation is the availability of energy.

The reader is encouraged to seek out other papers for further detail on the complementary relationship hypothesis [Bouchet, 1963] and testing [Hobbins *et al.*, 1999,

2001a, 2001b; Morton, 1965, 1975, 1976, 1978, 1979, 1983; Brutsaert and Stricker, 1979].

The complementary relationship raises two important and related issues regarding evaporation from pans (ET_{pan}). First, it is important to note that the complementary relationship hypothesis implies that a free-water surface at a point in a homogenous region will evaporate at the potential rate—that is to say, that under these conditions, ET_{pan} and ET_p are theoretically identical. Second, the complementary relationship resolves the so-called “Pan Evaporation Paradox” wherein globally decreasing ET_{pan} has been observed concurrently with seemingly paradoxical increases in temperature [Roderick and Farquhar, 2002] or increases in observed precipitation and cloudiness and in GCM-derived ET_a [Brutsaert and Parlange, 1998]. This so-called “Pan Evaporation Paradox” is discussed later and resolved based on the complementary relationship (see Chapter 4).

1.2.2 Complementary Relationship Performance

The most appropriate study with which to compare the work reported herein is that of Sugita *et al.* [2001], who estimated regional ET_a at a daily time-step using a complementary relationship model with a convective boundary layer (CBL) component and examined the effects of relaxing the primary assumption of the hypothesis: that all energy available for evaporation at the surface that is not taken up as such drives the air temperature up and humidity down, or put simply, that, in Equation (1.6), the factor multiplying ET_w , commonly denoted by k does not take the value 2.

Working in a sandy desert area in northwest China, they integrated a CBL model proposed by *Lhomme* [1997]—first created for instantaneous, continuous output—over a daily time-step. The CBL was used to simulate the vapor pressure deficit at a saturated surface and thereby calculate ET_w , and then with the actual vapor pressure deficit to calculate ET_p . In doing so, they avoided local calibration of parameters and also the somewhat thorny question of the value of the Priestley-Taylor coefficient α_{PT} (which has been suggested not to equal 1.26 [*Morton*, 1983; *Hobbins et al.*, 2001b], as was first reported by *Priestley and Taylor* [1972]).

Modeled estimates were compared to ET_a directly determined from applying the eddy correlation technique to an energy balance at the evaporating surface that was measured by extensive instrumentation in and above the soil column. Although the surface energy budget was found to close for periods greater than 10 days, this technique was estimated to yield mean errors in ET_a of the order of only 10-25 W/m². Climatological data for the modeling were drawn from direct observations and, in the case of daily mean temperature and humidity, from NCEP reanalysis data.

Despite the differences between the *Sugita et al.* [2001] study and the work already reported in *Hobbins* [2000] and *Hobbins et al.* [1999, 2001a, 2001b, and 2001c] and reported herein—different locations; time-steps; E_A formulation; ground-truthing techniques (surface energy budget vs. long-term, large-scale water budgets)—their results and conclusions are still instructive, still support the findings of *Hobbins* [2000] and *Hobbins et al.* [1999, 2001a, 2001b, and 2001c] as to the applicability of the complementary relationship, and further, provoke interesting avenues of research. In applying the model that bears the most similarity to that described herein (i.e., the

Priestley-Taylor equation for ET_w (Equation 1.12) and the Penman equation for ET_p (Equation 1.7) with $k = 2$), they found that $k = 2$ over-estimates ET_a , increasingly so with increasing aridity, implying that using $k < 2$ yields more accurate estimates, lending support to the initial findings of *Hobbins et al.* [2001c]: that $k = 1.9462$ works in mountainous and/or arid regions of the conterminous US. They ascribe the over-estimation to the mis-calibrated value of $\alpha = 1.26$ in the formulation of ET_w , which again supports the doubts cast on the adequacy of this value first raised by *Morton* [1983] and further questioned in *Hobbins et al.* [2001b], both of which studies found, paradoxically in the context of an over-estimation of ET_a , that a higher land-surface value of $\alpha = 1.3177$ is more appropriate.

The CBL model, with $k = 2$, generated ET_a estimates that were significantly less biased towards the over-estimation with increasing aridity found in the simpler model, but with similar scatter. Having back-calculated k for a variety of conditions: surface roughness; aridity; mean daily temperature; net available energy for evaporation Q_N ; and psychrometric constant γ , they found an obvious seasonality of errors in ET_a when $k = 2$, or, therefore, in the value of k itself.

In an attempt to remove the bias towards over-estimation of ET_a with increasing aridity, *Sugita et al.* [2001] introduce a “Relaxed Complementary Relationship” model, similar to the CBL-model mentioned above, but without pre-determining $k = 2$; instead, the model iterates for a value of k starting from $k = 2$. In applying this model, they generated estimates of ET_a that, when compared to their surface energy budget-derived direct determinations, yielded a significant performance improvement over the CBL model with $k = 2$: almost no bias, a very similar scatter, and very little seasonality in the

errors. While they mention further improvements to the CBL-with-iteration component that could limit the scatter even further, their results indicate the power of their Relaxed Complementary Relationship approach, thereby adding weight to the argument against constraining k to 2.

Sugita et al. [2001] conclude that their Relaxed Complementary Relationship-CBL model yields promising results, but that the CBL component should be further examined to reduce the noise induced (i.e., the scatter) in the results by the iteration process. They acknowledge that this model represents a step away from one of the primary advantages of previous complementary relationship models: their simplicity. They go on to conclude that the complementary relationship breaks down in regions of significant advection, and imply that they intend to test the model over larger areas and for longer time-periods (i.e., monthly). *Sugita et al.* [2001] state that, “In light of the above result, depending on the surface features and environmental conditions and also on a specific purpose of estimating $[ET_a]$ and required accuracy, one may need to modify the complementary relationship to produce more accurate estimation of evaporation.”

1.2.3 The Regional-Seasonal Advection-Aridity Model

All the research reported herein was predicated on the production of ET_a surfaces using the regionally, seasonally calibrated Advection-Aridity model, or a variation thereof. In this section, therefore, the components of the complementary relationship— ET_p and ET_w —are summarized for the Advection-Aridity model (for a more detailed treatment, see *Hobbins et al.* [2001b] and *Brutsaert and Stricker* [1979]). In this model, ET_p is calculated by combining information from the energy budget and water vapor

transfer in the Penman equation (1.7), and ET_w is calculated based on derivations of the concept of equilibrium evapotranspiration under conditions of minimal advection, first proposed by *Priestley and Taylor* [1972], and shown in Equation (3.6). ET_a is then calculated as a residual of Equation (1.6).

The familiar expression of the Penman equation for ET_p is:

$$\lambda ET_p = \frac{\Delta}{\Delta + \gamma} Q_N + \lambda \frac{\gamma}{\Delta + \gamma} E_A \quad (1.7)$$

where λ represents the latent heat of vaporization, Δ is the slope of the saturated vapor pressure curve at air temperature, and γ is the psychrometric constant. The second term of this combination approach represents the effects of large-scale advection in the mass transfer of water vapor, and takes the form of a scaled factor of an aerodynamic vapor transfer term E_A . Also known as the “drying power of the air,” E_A is a product of the vapor pressure deficit (V_{dif} or $e_a^* - e_a$) and a “wind function” of the speed of the advected air $f(U_r)$, and takes the form:

$$E_A = f(U_r)(e_a^* - e_a) \quad (1.8)$$

where U_r represents the wind speed observed at r meters above the evaporating surface, e_a^* and e_a are the saturation vapor pressure and the actual vapor pressure of the air at r meters above the surface, respectively.

The wind function $f(U_r)$ is either theoretically or empirically derived. *Brutsaert and Stricker* [1979] suggested the following theoretical expression for the wind function under neutral—i.e., a stable atmospheric boundary layer—conditions:

$$f(U_r) = \frac{\psi a_v k_{vK}^2 U_r}{R_d T \ln[(z_2 - d_0)/z_{0v}] \ln[(z_r - d_0)/z_{0m}]} \quad (1.9)$$

where ψ is the ratio of the gas constant of dry air R_d to that of water vapor, a_v is the ratio of eddy diffusivity to eddy viscosity under neutral conditions, k_{vK} is the von Kármán constant, z_{0m} and z_{0v} are the roughness lengths for momentum and water vapor, respectively, T is the air temperature in K, z_2 is the height at which e_a is measured, d_0 is the displacement height, and z_r is the height of the wind speed measurement.

While much work has been done in the agricultural arena to calibrate or reformulate the proposed wind function for use in the combination or Penman equation (e.g., *Allen* [1986], *Van Bavel* [1966], *Wright* [1982]), these formulations operate on a limited spatial and temporal scale, do not account for feedbacks of a regional nature, and require local parameterizations of resistance and canopy roughness. Thus, they are not applicable in predicting regional ET_a . Also, in the context of modeling monthly regional ET_a with the complementary relationship, the effects of atmospheric instability and the onerous data requirements rule out theoretical formulations such as Equation (1.9). *Penman* [1948] originally suggested the following empirical linear approximation for $f(U_r)$:

$$f(U_r) \approx f(U_2) = 0.26(1 + 0.54U_2) \quad (1.10)$$

which, for wind speeds at 2 m elevation in m/sec and vapor pressures in hPa, yields E_A in mm/day. This formulation of $f(U_r)$ was first proposed for use in the Advection-Aridity model operating at a temporal scale of a few days [*Brutsaert and Stricker*, 1979]. As demonstrated in *Hobbins et al.* [2001a], use of Equation (1.10) at a monthly time-step in the Advection-Aridity model increasingly under-estimates ET_a with increasing mean annual wind speed, especially for wind speeds above 4 m/sec, and significantly under-estimates ET_a for regions across the conterminous US, by a mean of 7.92% of mean annual precipitation. In general, the accuracy of the Advection-Aridity model has been

shown to depend strongly on its advective input, with ET_a -estimation errors increasing with wind speed, highlighting the need for proper selection of the wind function $f(U_r)$ [Hobbins, 2000; Hobbins *et al.*, 1999, 2001a, 2001b].

In reparameterizing and recalibrating the Advection-Aridity model on a regional, seasonal basis across the conterminous US, Hobbins *et al.* [2001b] suggest an empirical linear approximation for $f(U_r)$, of the form:

$$f(U_r) \approx f(U_2)_{i,WRR} = a_{i,WRR} + b_{i,WRR} U_2 \quad (1.11)$$

where U_2 is the mean monthly wind speed at 2 meters above the ground, a and b are respectively the intercept and slope of the linear approximation, and the subscripts i and WRR represent the month and water resource region (WRR) of application.

In calculating ET_w , the Advection-Aridity model uses the Priestley and Taylor [1972] partial equilibrium evaporation equation:

$$\lambda ET_w = \alpha_{PT} \frac{\Delta}{\Delta + \gamma} Q_N \quad (1.12)$$

where the value of α_{PT} , the Priestley-Taylor coefficient for many different land-cover types and climatic conditions has been examined by many authors, [Davies and Allen, 1973; Stewart and Rouse 1976, 1977; McNaughton and Black, 1973; DeBruin and Keijman, 1979; Morton, 1983]. Results by this author [Hobbins *et al.*, 2001b] indicate that a value of $\alpha_{PT} = 1.3177$ removes a consistent bias towards under-estimation of ET_a at a monthly time-scale across a set of 139 basins in the conterminous US. This value of $\alpha_{PT} = 1.3177$ was then used in this study.

Combining the expressions for the wind function $f(U_r)$ (1.11), the drying power of the air E_A (1.8), ET_p (1.7), and ET_w (1.12) into the expression of the complementary relationship (1.6), and rearranging yields the following expression for ET_a (1.13):

$$\lambda ET_a = (k\alpha_{PT} - 1) \frac{\Delta}{\Delta + \gamma} Q_N - \lambda \frac{\gamma}{\Delta + \gamma} (a_{i,WRR} + b_{i,WRR} U_2) (e_a^* - e_a) \quad (1.13)$$

where, it is important to note, the first term on the right represents the influence of the energy budget, and the second term the local wetness.

In reparameterizing the wind function on a regional and seasonal basis and recalibrating the Priestley-Taylor coefficient α_{PT} , *Hobbins et al.* [2001b] improved the performance in large-scale, long-term water budgets to an under-estimation of ET_a to 0.39% of basin-wide mean annual precipitation.

1.2.4 Advection-Aridity Model Performance

The model's performance is measured by the difference between modeled ET_a and water budget-derived independent estimates of actual evapotranspiration (ET_a^*) expressed as a percentage of mean annual precipitation. This measure represents the error invoked in closing a large-scale, long-term water balance using the modeled ET_a and is known as the "closure error" ϵ , and is calculated for each basin.

The performance of the model as it is originally formulated by *Brutsaert and Stricker* [1979] is affected by basin climatology, generally under-estimating ET_a (7.9% of mean annual precipitation) in all but extreme arid climates at high elevations. Errors in closing the long-term, large-scale water balances increase in variability with increasing aridity but converge towards zero with increasing humidity. Thus, the predictive power of the model increases moving towards regions of climate control of evapotranspiration rates, and decreases towards regions of increasing soil control. Further, the model's performance was found to be strongly affected by the wind speed input, with error

strongly correlated to wind speed. This demonstrates the sensitivity of this model to the formulation of the original wind function $f(U_2)$ described in Equation (1.10). A re-parameterization of this wind function (Equation 1.11) specific to regional (i.e., WRRs) spatial scales and monthly temporal scales yielded both accurate ET_p estimates and unbiased closure errors, with parameter values within reasonable physical bounds. Removal of the bias towards under-estimation of ET_a entailed optimizing the Priestley-Taylor coefficient α_{PT} in the ET_w formulation subject to the constraint of a zero mean closure error for a calibration subset of basins. This procedure yielded a value of $\alpha_{PT} = 1.3177$, very close to the value ($\alpha_{PT} = 1.32$) predicted by *Morton* [1983] in his re-assessment of results reported by *Priestley and Taylor* [1972]. Use of this α_{PT} -value with the regional, seasonal wind function further reduced—in absolute terms—the mean water balance closure error of a validation subset to -1.15% , and of the complete set of 139 basins to -0.39% , representing a significant improvement over a mean of $+13.45\%$ for the validation subset and $+12.67\%$ for the complete set for the original *Brutsaert and Stricker* [1979] model using Equation (1.10).

On a mean annual basis, the relationships observed between modeled ET_p and ET_a^* were very similar to those predicted by the complementary relationship hypothesis. In the western part of the study area, regions were identified where modeled ET_a exceeds precipitation on an average annual basis, corresponding to the areas of lowest precipitation: this over-estimation of ET_a can be attributed to either the model itself, or to the inappropriateness of the meteorological forcing data fields, either through low data quality or inadequacies involved in their spatial interpolation.

The near-zero mean annual water balance closure errors for the improved seasonal, regional Advection-Aridity model here indicate the utility of complementary relationship models in general, and the Advection-Aridity model in particular, for providing independent estimates of ET_a . For homogenous areas at regional scales, these complementary relationship models should be preferred over traditional paradigm models using land-based parameterizations, as they implicitly account for the soil moisture dependence of ET_p , their data requirements are significantly lighter, and they require no local calibration of parameters.

1.2.5 Recent Research on Trends in Evapotranspiration

While many studies have concentrated on the directly observable components of the hydrological cycle; namely precipitation [*Karl and Knight*, 1998] and streamflow [*Wahl*, 1992; *Chiew and McMahon*, 1996; *Lins*, 1997; *Lins and Slack*, 1999], few complete the hydrologic cycle by examining the elusive ET_a . Even those studies that take a more holistic hydrological approach—whether it be an examination of indices of climate change [*Karl et al.*, 1996] or long-term hydroclimatological trends [*Lettenmaier et al.*, 1994] over the conterminous US, or of the effects of climate change on the hydrologic cycle of a smaller, regional-scale basin [*Westmacott and Burn*, 1997]—do not examine trends in ET_a . When ET_a has been studied, it has generally been in the context of ET_p at a point [*Lockwood*, 1994]—and that often derived from observations at evaporation pans [*Eitzinger et al.*, personal communication, 2001; *Roderick and Farquhar*, 2002]—and not ET_a at a regional scale. While such studies are of interest in the context of trends in the standard agrometeorological variables, wherein ET_a is taken to be a function of ET_p

determined by coefficients that are purported to describe local crop and soil moisture conditions, they neglect the complementarity of ET_a and ET_p that will be shown in Chapters 4 and 5 to be evident at the regional scale. There is therefore a need for analyses of trends in ET_a , whether they are due to climate change and variability or land-use change, on a seasonal temporal basis and regional spatial scale useful in the resolution of water management issues raised by an increasingly variable hydroclimate.

Interest in the seemingly paradoxical behavior of trends in ET_{pan} when compared to other climatological variables and predictions has provoked a heuristic argument by *Brutsaert and Parlange* [1998] in favor of the complementary relationship, but their work lacked empirical evidence to support it. More recently, studies of trends in ET —referring here to work by *Szilagyi* [2001], *Szilagyi et al.* [2001], *Roderick and Farquhar* [2002], and *Ozdogan and Salvucci* [2004]—have either resorted to ET_{pan} as a surrogate measure of ET_a , or to single station observations of ET_a and then gross averaging if continental-scale estimates are desired. While the use of ET_{pan} observations as "perfect estimators" of ET_p [*Szilagyi et al.*, 2001] is supported by the complementary relationship hypothesis—at a point in a homogeneous region, the hypothesis indicates that a free-water surface will evaporate at the potential rate ET_p —in practice it is, as will be shown (Section 4.4.4.2), a problematic correspondence.

1.2.5.1 Brutsaert and Parlange [1998]

Brutsaert and Parlange [1998] state that, globally, ET_{pan} is observed to be decreasing counter to predictions of increased ET_a by GCMs and concurrent with increasing precipitation and cloudiness: evidence of an apparent "pan evaporation paradox." In a

heuristic fashion, they argue that ET_{pan} has not been treated correctly as an indicator of climate change, but that in non-humid, or water-limited, environments, ET_{pan} is not a good predictor of ET_a . According to *Brutsaert and Parlange* [1998], traditionally, in non-water-limited environments a pan coefficient of order one is used to convert ET_{pan} to ET_p but, when water becomes limited, the traditional conception of ET_p as a constant function of ET_{pan} breaks down, and the complementarity between ET_a and ET_{pan} becomes obvious. In arguing thus, they are restating the complementary relationship as an explanation for complementary trends in ET_{pan} and ET_a without redefining ET_p as a rate that is dependent on water availability—a re-definition shown in Section 1.2.1 and upon which the rest of this study is predicated. *Brutsaert and Parlange* [1998] make this argument without referring to any data or observations specifically.

1.2.5.2 Ohmura and Wild [2002]

Looking forward in a recent editorial in the journal *Science*, *Ohmura and Wild* [2002] state that, “ultimately, what is important is the trend in actual evaporation. Pan evaporation matters insofar as it can offer a useful clue to the direction of the change in actual evaporation.” They also raise an important issue that will be addressed as specifically as possible in this dissertation: “...the direction of the evaporation trend is not determined by temperature alone. That a warmer atmosphere does not necessarily produce more evaporation...”

Ohmura and Wild [2002] therefore call for an examination of ET_a in the context of its two components: the radiative and advective: “The diurnal temperature range (DTR) must be separated into two components: one due to the 24-hour periodicity and the other

due to the non-24-hour variation. The former represents the effect of the diurnal cycle in radiation; the latter indicates the strength in advection. This treatment makes it possible to determine to what extent the trend in evaporation is due to changes in radiation fields or in the strength of advection.” It is the latter suggestion that is addressed in this study, and the results (Sections 4.5 and 5.5) not only confirm and refute widely reported conclusions by other workers, but lead to fundamental support for the complementary relationship hypothesis itself.

The decomposition of trends in ET_a has been addressed to some extent, theoretically by *Brutsaert and Parlange* [1998], and in practice by *Roderick and Farquhar* [2002] and *Szilagyi et al.* [2001]. However, the former did not have access to the data sets required for a spatially and temporally distributed analysis, and the latter invoked restricting assumptions of zero-trend in one or other component and consequently reached conclusions that lack general validity. A general description of their work follows.

1.2.5.3 Szilagyi [2001] and Szilagyi et al. [2001]

The first attempts to determine long-term, large-scale trends in ET_a across the conterminous US were published by *Szilagyi* [2001] and *Szilagyi et al.* [2001], who estimated long-term trends in regional ET_a across the conterminous US using the complementary relationship and observations of ET_{pan} for ET_p . Their work shows the potential of complementary relationship models for determining trends in ET_a . However, it raises a number of questions, both with regard to the methodologies and assumptions therein, but also as a result of the conclusions drawn.

In using ET_{pan} as predictors of ET_p —and therefore of ET_a —one is exposed to the vagaries of the ambient conditions that determine ET_{pan} . *Hobbins et al.* [2001b] list four primary reasons why this assumption is problematic: (i) the heterogeneity of the reach upwind of the evaporation pan may confound the presumed complementarity of ET_a and ET_{pan} and many or most pans are situated in urbanized areas or where local climatological conditions are anthropogenically influenced; (ii) changes in land-use upwind of the pan will affect the ET_{pan} record, such that, for example, in observing an average decrease in ET_{pan} at a particular site, one may simply be observing the long-term effects of urbanization around the pan, or a change in land-use (e.g., irrigation or deforestation) and may therefore be inadvertently mis-diagnosing simple effects of such local changes as long-term climatological trends on a regional scale; (iii) there is often significant spatial disjoint between evaporation pans (such as those producing the data reported by *Peterson et al.* [1995]) and the stations where the meteorological data are gathered; and (iv) there are clear spatial and seasonal biases in the national ET_{pan} record. These factors limit the accuracy of trend analyses of an ET_a data set derived from ET_{pan} data that has not been carefully examined (see Chapter 3).

Szilagyi et al. [2001] noted a 6% increase in warm-season (MJJASO) ET_a over the period 1948-1996, in conjunction with an 11% increase in precipitation. They cursorily examined the causes of such trends with regard to some climatological input variables—temperature, V_{dif} —and generated ET_a^* estimates for six basins together covering about 50% of the land area of the conterminous US, whereupon they observed increasing ET_a^* over the same period, but only to the tune of 3%. From this comparison, they conclude that predictions of ET_a -trends modeled by the complementary relationship over-estimate

observed trends in ET_a^* ; a conclusion that must be regarded with some skepticism in the light of two factors: (i) their choice of basins, wherein regions at the climatic extremes are not represented—none are in the arid southwest or the hyper-humid northwest; and (ii) their assumption that there is no long-term trend in Q_N , and that therefore, changes must come from changes in E_A , which is to say changes in either V_{dif} or U_2 , or both. The reasons for making such a far-reaching assumption are not clear and *Szilagyi et al.* [2001] do not examine its effects on their conclusions. If, as the paper states, there has been an increase in cloudiness over the same time-period, then this *must* affect the energy available at the ground surface for evaporation and therefore decrease—in the case of increasing cloudiness—all evaporative measures: ET_w , ET_p , and ET_a . Indeed, they go on to conclude that, while there has been a significant increase in predicted ET_a (to coincide with the observed increase in precipitation), there has been no increase in V_{dif} . Thus there must be either a decrease in U_2 or in cloudiness. However, the available data are never examined to support or refute this claim.

While *Szilagyi et al.* [2001] represents a good starting paper, the methodologies and less-restrictive assumptions in the work described in this dissertation will be shown to represent significant improvements, particularly with regard to the completeness of all climatologic and hydrologic input datasets and the use of spatially distributed modeling to allow the examination of regional sensitivities to climate change and variability at a variety of scales.

1.2.5.4 Roderick and Farquhar [2002]

Roderick and Farquhar [2002] observe the “Pan Evaporation Paradox” by noting that the global mean temperature has increased by $0.15^{\circ}\text{C}/\text{decade}$ over the last 50 years and that the expected increase in evaporation from terrestrial open water bodies due to drier air at the surface and evident in an increase in ET_{pan} does not occur. In fact, they observe decreasing ET_{pan} . They propose and examine two explanations to resolve the paradox: (1) the complementary relationship between actual and potential ET rates, and (2) a decrease in irradiance at the earth’s surface, due, in part, to an increase in the concentration of aerosols. In this paradigm, pollution is supposed to lead to a decrease in the vigor of the hydrologic cycle.

In their analysis of the complementary relationship, *Roderick and Farquhar* [2002] summarize it as follows: in water-limited environments, an increase in regional ET_a will cool and moisten the air, driving ET_{pan} down in the region. While observations of ET_a^* in water-limited environments in the US and former USSR are shown to be increasing, they state that the complementary relationship explanation is unsatisfactory for the following two reasons: (i) that ET_{pan} in non-water limiting environments is also decreasing, that is, ET_{pan} and ET_a are decreasing, and (ii) that V_{dif} across the conterminous US has remained stationary over the last 50 years.

In response to their first proposed reason for negating the effects of the complementary relationship, it must be noted that the complementary relationship dynamic holds everywhere; it is only in water-limited environments that it is obvious. In climate-limited environments, $ET_a = ET_w = a.ET_{pan}$ (where a is a pan-constant that allows ET_{pan} to estimate ET_p).

Further, as will be shown in Chapters 4 and 5, their observation of decreasing ET_{pan} and ET_a does not contravene the complementary relationship hypothesis. In such a case, the curves representing ET_w , ET_p , and ET_a simply move downwards in the complementary relationship diagram (Figure 1.2) in response to lower energy availability, due, presumably, to the lower irradiance they observe.

Their second reason for discounting the complementary relationship hinges on their observation that V_{dif} across the US has remained constant over the last 50 years. They support this assertion in the face of increasing temperature by stating that the dew-point has been increasing twice as fast as the average temperature, which they support using an observed change in global mean temperature of $0.15^\circ\text{C}/\text{decade}$. In Section 4.5, their assertion of zero change in V_{dif} across the conterminous US—which is, in fact, based only on an observation by *Szilagyi et al.* [2001] of a non-significant difference in mean annual V_{dif} averaged over 132 stations between the periods 1949–1964 and 1984–1996—is herein challenged by more detailed temporally continuous observations made on a spatially distributed basis.

Turning to their analysis of irradiance, they check the effect of trends in Q_N on trends in ET_{pan} , assuming no trend in V_{dif} and that, therefore, trends in ET_{pan} must come from trends in Q_N alone. They use a version of the Priestley-Taylor equation for evaporation under conditions of minimal advection:

$$0.7\lambda ET_{pan} \approx 1.26 \frac{\Delta}{\Delta + \gamma} Q_N, \quad (1.14)$$

and therefore, in terms of first-order changes in ET_{pan} due to changes in global solar irradiance,

$$\delta ET_{pan} \approx \frac{1.26}{0.7\lambda} \frac{\Delta}{\Delta + \gamma} \delta Q_N = \frac{1.44}{\lambda} \frac{\Delta}{\Delta + \gamma} \delta Q_N, \quad (1.15)$$

where Q_N is net irradiance $\approx 0.8(R_D + R_H)$. In northwestern Russia, they observed a decrease in $(R_D + R_H)$ of 2-4%/decade, or $\delta(R_D + R_H)$ of -315 MJ/m²/year, which is the evaporative equivalent of δET_{pan} of -90 to -155 mm/year (the range results from the range in values of Δ , which is temperature-dependent). At seven pans in the region, they observe a mean decrease in annual ET_{pan} of 110 mm, which is within the range predicted. From this they assume that trends in ET_{pan} are due solely to trends in Q_N , and not to trends in E_A , and that therefore, the complementary relationship is not an important dynamic in determining trends in ET_{pan} , or by extension, in ET_a .

The central tenet of *Roderick and Farquhar* [2002] then becomes that trends in ET_{pan} are a function of trends in Q_N only; not of trends in E_A . This is in marked contrast to *Szilagyi et al.*, [2001] who assume exactly the opposite: that there are no trends in Q_N , and that trends in ET_a are due solely to trends in E_A .

1.2.5.5 Ozdogan and Salvucci [2004]

Most recently, and contemporaneously with the work described in this dissertation, *Ozdogan and Salvucci* [2004] examine the effects of local land-use change on ET_{pan} as measured by a pan located in a semi-arid region undergoing significant irrigation development. They offer a field observation of the complementary relationship at a single point within a single region, and report an analysis of the sensitivity of trends in ET_{pan} to trends in its components. In doing so, they highlight the vulnerability of pans to regional or local changes—an issue that is addressed in more detail in Section 3.

Ozdogan and Salvucci [2004] compare trends in ET_{pan} observed at a point, regional ET_p as estimated by the Advection-Aridity model from local aerological observations, and ET_a^* as estimated by a water balance derived from irrigation supply during a period of no precipitation. They observe the complementary relationship between ET_p and ET_a^* : as ET_a increased (the area under irrigation increased tenfold in a 23-year period), ET_p and warm-season ET_{pan} decreased—the latter from 14 mm/day to 7 mm/day.

From a sensitivity analysis of the effects of Q_N , air temperature, E_A , V_{dif} , and U_2 on trends in modeled ET_p , they conclude that δET_p is not sensitive to δQ_N but is sensitive to δE_A and by further decomposing the trends, that U_2 is more powerful in its effects on ET_p than is V_{dif} . They describe the relatively weak dependence of δET_{pan} on δQ_N and comparatively strong dependence on δU_2 , as resulting from the complex relationships in the surface energy budget driving ET_a (see Equation 1.2), as follows: R_G , which provides the energy incident at the surface and is therefore a positive function of ET_a , is itself a negative function of cloudiness, which is in turn a positive function of ET_a —thus closing a negative feedback loop wherein increased ET_a is repressed by its own effects. Further feedbacks relate the decreasing surface temperature and increased cloudiness resulting from increasing ET_a to upward and downward long-wave radiation, thereby bearing both increasing and decreasing influences on, and effects of, ET_a , as just described.

Ozdogan and Salvucci [2004] suggest four reasons to explain the strong dependence of δU_2 and δET_p . First, they mention the oasis effect, wherein irrigation affects local wind circulation in both magnitude and direction. Second, akin to the findings of *Alpert and Mandel [1986]*, from back-calculated seasonal estimates of z_0 (akin to the roughness lengths for water vapor z_{0v} and momentum z_{0m} in Equation 1.9) increasing throughout the

season to 0.1 times the height of the crop, *Ozdogan and Salvucci* [2004] found that the seasonal growth of irrigated crops results in increased surface roughness over large distances. Third, they examined local shielding of the wind speed instrumentation by trees planted specifically to reduce wind speeds over the crops, but found it to be insignificant. Fourth, they examined whether local wind speed is decreasing due to climatologic factors acting on a regional or supra-regional scale unrelated to local ET_a changes, but found no such trends beyond those observed on the local scale.

Ongoing work by Ozdogan and Salvucci will, when published, report on modeling of their observations with a mesoscale model incorporating instability considerations. Their new results will highlight the extent to which the complementarity of ET rates depends on changes in wind speed and will indicate a high pressure anomaly that significantly slows the prevailing winds over the study area [*Salvucci*, personal communication, 2004].

1.3 Questions Addressed

The research reported in this dissertation is as much motivated by the need to confirm the complementary relationship hypothesis and correct the misapprehensions inherent in the traditional paradigm of ET_a -estimation (as described in Section 1.1) as it is by the work of others, whether by explicitly suggested avenues for research, or by desires to correct specific methodologies, assumptions, assertions, or interpretations. In this section, the main questions the research answers are summarized; some are general and open-ended, some are motivated by previous work by the authors and by others.

More specifically, the work described in this dissertation will address the following questions:

- Are there long-term trends in ET_a and ET_{pan} across the conterminous US? Are they significant? If so, where? How do long-term changes in each of their components change ET_a and ET_{pan} ? Are there spatial patterns to these changes?
- How are ET_{pan} and ET_a observed to interact? Is the complementary hypothesis a mere conjecture or an observational fact?
- Is the much-ballyhooed “Pan Evaporation Paradox”—wherein globally decreasing ET_{pan} appears counter to a global warming trend—observed in spatially coincident and long-term ET_a and ET_{pan} data? In other words, is ET_{pan} decreasing—as often reported—where and while ET_a is increasing? Does the complementary relationship explain these interactions? Does the resolution of this “paradox” in trends in ET_{pan} and ET_a favor the complementary relationship, as proposed by *Brutsaert and Parlange* [1998]?

Before modeling ET_a or examining trends in ET_{pan} , various issues relating to the input data must be resolved. The following questions relate to the heterogeneity inherent in the ET_{pan} data set, to the spatial interpolation of input data, specifically solar radiation in heterogeneous terrain, and to the modeling of ET_a :

- Is the poor performance previously noted [*Hobbins et al.*, 2001b] in models of the complementary relationship in high and/or arid basins a result of the treatment of input variables in areas where the surfaces are interpolated from fewer stations and/or across heterogeneous terrain?
- Does the homogenization of the raw ET_{pan} data drawn from different sources have a significant effect on the behavior of the data set in the context of the

complementary relationship? As the ET_{pan} data are variously sourced, their homogeneity cannot be assumed, raising two questions. First, how best to homogenize these data? Second, to what extent does said homogenization affect the behavior of the data set as a whole, particularly in the context of the complementary relationship?

- What is to be gained by relating the calibration of the wind function in the ET_a model to ET_{pan} rather than, as before, to a residual of the water balance? Which parameterization of the wind function—that relating ET_a to ET_a^* , or that relating ET_p to ET_{pan} —offers the best estimates for ET_a and for trends in ET_a ? Are there regional and/or seasonal differences in the performance of these different options?
- What advantages does the distributed trend analysis described in this dissertation have over the station-based analyses of the past? At which scales are such analyses most useful?

Further, in breaking down these trends into the two driving components of ET_a : the solar radiation flux, as measured by the energy available Q_N , and the regional advective or vapor transfer flux, as reflected by the drying power of the air E_A and its component vapor pressure deficit (V_{dif}), trends will be examined at a variety of scales. In this research, far more pans will be used than in *Roderick and Farquhar* [2002] and far more basins than *Szilagyi et al.* [2001]. Further, in the work described in this dissertation, observations of Q_N and ET_{pan} are spatially coincident, topographically corrected in the case of Q_N , and homogenous in the case of ET_{pan} . Use of these improved data sets should support or refute the findings of *Roderick and Farquhar* [2002] and *Szilagyi et al.* [2001].

The following questions, then, are specifically provoked by the work of other researchers in the field of estimation of trends in ET_a :

- The warm-season ET_{pan} data set allows the comparison of results generated herein to those of *Szilagyi et al.* [2001], and the annual ET_{pan} data to those of *Roderick and Farquhar* [2002]. Is the 6% increase in warm-season ET_a predicted by decreasing trends in ET_{pan} applied through a complementary relationship model observed, or the 3% increase in budget-derived ET_a^* reported by *Szilagyi et al.* [2001]?
- Is the 10-20% trend in Q_N over the past 50 years reported by *Roderick and Farquhar* [2002] observed, or is there no trend, as assumed by *Szilagyi et al.* [2001]?
- Is the conclusion of *Szilagyi et al.* [2001]—that the complementary relationship over-estimates trends in ET_a —supported?
- Is the claim of *Roderick and Farquhar* [2002]—that there has been no trend in V_{diff} across the US in the last 50 years—supported?
- Is the complementary relationship hypothesis insignificant in explaining or driving trends in ET_a , as claimed by *Roderick and Farquhar* [2002]?
- If these claims are not supported, or these assumptions challenged, what are the consequences within the context of the complementary relationship and long-term climatic variability?

2. Developing a Long-term, High-resolution, Continental-scale, Spatially Distributed Time-series of Topographically Corrected Solar Radiation

2.1 Abstract

This chapter describes the development of a long-term, high resolution net radiation data set that accounts for the effects of local topography; such a data set may then be used in direct observations of the effects of long-term change and variability in the solar radiation input to the land surface-atmosphere interface, particularly with reference to the estimation of evaporation. Direct and diffuse solar radiation data are gathered from all reporting stations across the conterminous US for the period 1950-1994 and integrated at a monthly time-step. Twelve years of diffuse radiation data missing from the data sources are replicated based on their historical relationships to coincident and contemporaneous observed direct normal and global radiation. A topographic correction factor is derived to account for the incidence of direct solar radiation on arbitrarily oriented surfaces at any latitude at any moment in any day of the year, and combined with slope and aspect surfaces for the conterminous US derived from a 5-km digital elevation model. As preliminary uses of this data set, mean annual and long-term trend surfaces of net surface radiation over the conterminous US for the period WY 1953-1994 are presented.

2.2 Introduction

In the field of hydrology, there is scarcely a more dire need than for analyses of trends in all components of the hydrologic cycle on the temporal and regional scales useful to water managers charged with the resolution of issues of water supply and

demand in increasingly variable hydroclimatic conditions. The short-wave radiation balance provides the energy driving the hydrologic cycle, and is used to develop the net available energy (Q_N) in the estimation of actual evapotranspiration (ET_a). Inputs of Q_N that are accurate, spatially flexible, and long-term are prerequisites in studies of secular trends in the hydrologic cycle in general and in ET_a in particular.

With regard to the estimation of ET_a , the development of a preliminary 27-year, continental-extent distributed data set of regional ET_a [Hobbins *et al.*, 2001b] has demonstrated the efficacy of models based on Bouchet's [1963] complementary relationship hypothesis and, in particular, their tunability in areas of homogeneous relief [Brutsaert and Stricker, 1979; Morton, 1983; Claessens *et al.*, 1995; Hobbins *et al.*, 2001a, 2001b]. However, more questions have been raised about their accuracy in areas of rugged relief such as those typified by the western US. The heterogeneous topography in such areas stretches the assumptions inherent in modeling the complementary relationship, but, more importantly in the context of this chapter, emphasizes the primary difficulties in generating useful Q_N input data. These are two-fold: (i) the spatial and temporal scarcity of ground-based observations of short-wave radiation balance, and (ii) the intricacies inherent in accurately representing the interaction of solar radiation and local topography.

Observation stations of inputs to the short-wave radiation budget are sparse—whether these inputs are in the form of direct normal radiation (R_D) and diffuse radiation (R_H), or of global incident radiation (R_G). At any one time in the last 50 years, there have only been about 50 stations actively measuring—as opposed to modeling—solar radiation across the conterminous US. Further, the necessity of building long-term data sets raises

the need for conflation of data from different sources. Given the unstable nature of the solar radiation recording network across the conterminous US, the issue of rebuilding an incomplete data set must be resolved by stitching data sets together and filling in gaps.

The influence of varied topography presents its own set of complications, which, unless they are resolved, may lead to the spatial variability of input variables being poorly reflected in input surfaces, particularly so in using R_D data in rugged terrain. These complications arise from the difference between the orientation of the sensors and the surface of interest. R_D is defined as the amount of solar radiation received within a 5.7-degree field of view centered on the sun, and the instruments (pyrheliometers) therefore point directly at the sun throughout its daily trajectory. As this measurement technique is independent of local topography, corrections for the angle between the receiving surface and the normal incidence path to the sun are required. Such a correction must also reflect the temporal variations of the orientation of the terrain with respect to R_D on diurnal and seasonal scales. R_H is defined as the amount of solar radiation received from the sky (excluding the solar disk) on a horizontal surface, and is non-directional and therefore not significantly affected by local topography. R_G is defined as the sum of the beam (i.e., R_D) plus diffuse irradiance on a horizontal surface. As a combination of R_D and R_H , this measurement is not preferred for this study, as the R_D component cannot be teased out for topographic adjustment from R_G without further information. (In this study, measurements of R_G are only used where necessary to estimate missing R_H data.) Due to the nature of the instrumentation (pyranometers), the accuracy of measured of R_G declines at high incidence angles [Iqbal, 1983], further limiting their utility in regions

where high slopes at predominantly eastward or westward aspects prevail, such as in the western US.

Other studies of trends in the hydrologic cycle have concentrated on the directly observable components of the hydrological cycle; namely precipitation [Karl and Knight, 1998] and streamflow [Wahl, 1992; Chiew and McMahon, 1996; Lins, 1997; Lins and Slack, 1999]. Even those studies that take a more holistic hydrological approach—whether it be an examination of indices of climate change [Karl *et al.*, 1996] or long-term hydroclimatological trends [Lettenmaier *et al.*, 1994] over the conterminous US, or of the effects of climate change on the hydrology of a smaller, regional-scale basin [Westmacott and Burn, 1997]—do not examine trends in ET_a , or in its radiative flux, Q_N . When evapotranspiration has been studied, it is in the context of potential evapotranspiration at a point [Lockwood, 1994]—and that often derived from observations at evaporation pans [Eitzinger *et al.*, personal communication, 2001]—and not ET_a at a regional scale. More recent and specifically related studies of trends in ET_a or of Q_N have remained station-based [Szilagyi, 2001]. Szilagyi [2001] offers the closest and most recent comparable study on the effects of trends in the components of ET_a , but they conclude that models based on the complementary relationship over-estimate increases in ET_a , without examining the effect of their assumption of no long-term change in Q_N , which would negate this apparent error. With the data set proposed in this chapter this gap will be closed, allowing trends in all components of the ET_a expression, including Q_N , to be examined. Further, while past reliance on station-based, or small-scale estimates avoids issues relating to errors due to spatial interpolation and rugged topography or the combination of both, it does not allow for study of regions outside of cities, or in rugged

terrain. In generating large-scale, spatially distributed estimates of ET_a and, therefore, of Q_N , this chapter aims to do no less than shed light to these dark spots on the hydrologic map.

Having here motivated this study, the following section summarizes the role of Q_N in the hydrologic cycle, specifically in the energy budget of an evaporating surface, and describes the gathering and infilling of the data sets used. The rest of the chapter describes the development of Q_N from R_G , the breakdown of R_G into R_D and R_H , and the development of a correction factor for R_D that both adjusts for topography and accounts for the various temporal solar cycles mentioned above. Results of this analysis are shown in the form of surfaces of mean annual Q_N and annual trends in R_G over the conterminous US at a spatial resolution of 5-km for the period WY 1953-1994. Then the conclusions of this study, their implications, and the further work suggested to improve the development of the data set are discussed.

2.3 Methodology

This section proceeds from a general examination of the surface energy budget, deriving the energy available at the surface Q_N from the net surface radiation R_N or R_N 's component inputs, R_D and R_H , through a summary of issues of gathering and infilling these input component data and other data required, to a specific analysis of the interaction of temporally varying solar geometry on varied topography.

2.3.1 Energy Budget at an Evaporating Surface

The instantaneous energy budget of the evaporating surface is shown in Figure 2.1 and may be expressed in terms of the energy available at the surface Q_N , as follows:

$$Q_N = \lambda ET_a + H = (R_D + R_H)(1 - A_{SW}) + LW\downarrow(1 - A_{LW}) - LW\uparrow - G - \frac{\partial W}{dt} \quad (2.1)$$

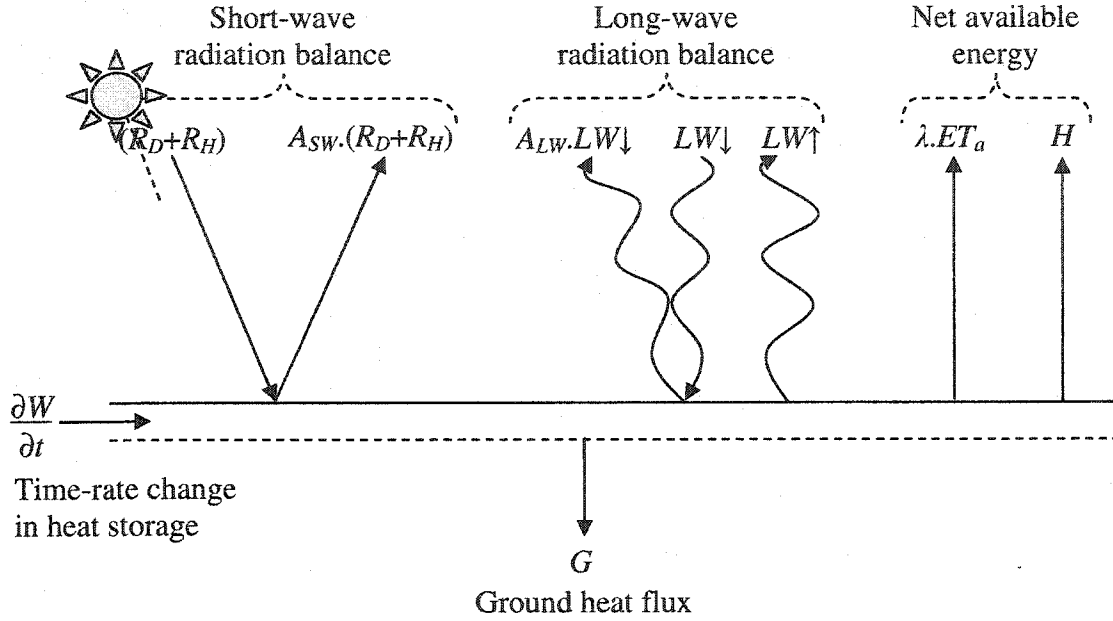


Figure 2.1: Schematic representation of the instantaneous energy budget at an evaporating surface.

where $\partial W/\partial t$ represents the time-rate of change in heat storage of the evaporating layer, R_D is the direct incident solar radiation, R_H is the diffuse solar radiation, A_{SW} is the global short-wave albedo, $LW\downarrow$ is the long-wave radiation from the atmosphere to the surface, A_{LW} is the long-wave albedo, $LW\uparrow$ is the upward long-wave radiation emitted by the surface, λET_a is the latent heat flux, H is the sensible heat flux from the surface to the atmosphere, and G is the ground heat flux. All negative or subtracted quantities are fluxes away from the surface.

In this study, monthly ET_a estimates are accumulated over an integer-multiple of years. This permits assumptions that ground heat fluxes into the ground are balanced by fluxes out and that there is no net change in heat storage in the evaporating layer, and thereby allows G and $\partial W/\partial t$ to be eliminated from the budget. Thus, in making long-term estimates of ET_a , Equation (2.1) devolves to:

$$Q_N = \lambda ET_a + H = (R_D + R_H)(1 - A_{SW}) + LW \downarrow (1 - A_{LW}) - LW \uparrow \quad (2.2)$$

where the terms on the left— Q_N and $(\lambda ET_a + H)$ —represent the energy available for evaporation. To calculate Q_N , both the short-wave and long-wave radiation balances must be calculated (see Figure 2.1), and the radiative input to the short-wave balance corrected for topography. The short-wave balance is calculated as follows:

$$R_N = (1 - A_{SW})R_G = (1 - A_{SW})(R_D + R_H) \quad (2.3)$$

where R_N is net or absorbed global radiation, A_{SW} is global short-wave albedo, and R_G is incident global radiation, the sum of direct and diffuse incident radiation. The long-wave balance is calculated from:

$$C = LW \uparrow - (1 - A_{LW})LW \downarrow = E\sigma_{SB}T^4(0.71 + 0.007e_a P_a/1013)(1 + \rho) - \sigma T^4 \quad (2.4)$$

where C is the net long-wave radiation transfer from the evaporating surface, E is the emissivity, σ_{SB} is the Stefan-Boltzmann constant, T is the air temperature, e_a is the vapor pressure, P_a is the atmospheric pressure, and ρ is the proportional increase in atmospheric radiation due to clouds. The parenthetical term $(0.71 + 0.007e_a P_a/1013)$ in Equation (2.4) models the effects of long-wave albedo (i.e., the $(1 - A_{LW})$ term). It represents a fit of the relationship between e_a (in mb) and the ratio of clear-sky atmospheric radiation to black-body radiation, and was derived for a wide range of e_a (from 4-22 mb) [Sellers, 1965].

Equations (2.1) and (2.4) are then used to calculate Q_N corresponding to the soil-plant surfaces at air temperature:

$$Q_N = R_N - C = (1 - A_{SW})(R_D + R_H) + E\sigma_{SB}T^4(0.71 + 0.007e_a P_a/1013)(1 + \rho) - E\sigma_{SB}T^4 \quad (2.5)$$

2.3.2 Data Sources and Considerations

Production of the time-series of R_N (Equation 2.3) requires data on solar radiation (R_D and R_H), and global short-wave albedo (A_{SW}). As shown in Equation (2.5), then developing the Q_N time-series further requires data on air temperature, humidity and atmospheric pressure (T , e_a , and P_a). The sources for these data are as follows:

- Solar Radiation: R_D and R_H data were extracted and temporally integrated on a monthly basis from three data sources representing sequential time-periods: SOLMET [NCDC, 2001] for 1952-1960 (26 stations in the conterminous US); “Solar and Meteorological Surface Observation Network (SAMSON)” [NOAA, 1993] for 1961-1990 (216 stations, of which 25% were 1st-order observing stations, and the rest of which were 2nd-order stations where solar data radiation were modeled); and “NCDC Surface Airways” [EarthInfo, 1998b; NCDC, 2004c] for 1991-1994 (25 stations). However, R_H data were absent from both the SOLMET and the Surface Airways data sets and therefore had to be infilled, as outlined in Section 2.3.3.
- Albedo: Average monthly surfaces of A_{SW} are AVHRR-derived estimates from the Gutman [1988] data set. This data set contains Advanced Very High Resolution Radiometer (AVHRR) derived albedo estimates, with an initial resolution of about 15 km.

- Temperature: The T data were obtained from the “Summary of the Day” [*EarthInfo*, 1998a; *NCDC*, 2004a] CD-ROM, issued by NCDC.
- Humidity: The e_a data were obtained, initially in the form of dew-point temperature, from the “Surface Airways” [*EarthInfo*, 1998b; *NCDC*, 2004c] CD-ROM, issued by NCDC.
- Elevation: These data were derived from a 30-arc-second DEM (NOAA-NGDC), and used to derive p for use in the derivation of Q_N , and converted to surfaces of slope and aspect for use in the topographic correction of R_D .

2.3.3 Infilling the Missing SOLMET and Surface Airways Data:

In order to replicate the R_H data missing from the SOLMET data set for the years 1952-1960 and that never recorded at the Surface Airways stations for the years 1991-1994, it was assumed that they bore significant physical relationships to the simultaneously recorded R_D and R_G data—neither of which were missing—and that the monthly relationships could be inferred using relationships between the R_H , R_D , and R_G data recorded at the equivalent SAMSON stations during the years 1960-1990. Thus, for each of the 27 SOLMET and 25 Surface Airways stations, the corresponding SAMSON stations were identified, and their R_H , R_D , and R_G data used in linear relationships to relate R_H to R_D alone, R_G alone, and R_D and R_G together. The statistics of the regressed relationships were compared with respect to the coefficient of determination (R^2) of the fit, its significance (p -value), and the normality of the residuals as measured by a Kolmogorov-Smirnov test. Of the three possible relationships— $R_H \sim f(R_D)$, $R_H \sim f(R_G)$, and $R_H \sim f(R_G, R_D)$ —those with the highest R^2 and p -values less than 0.05 were used. The

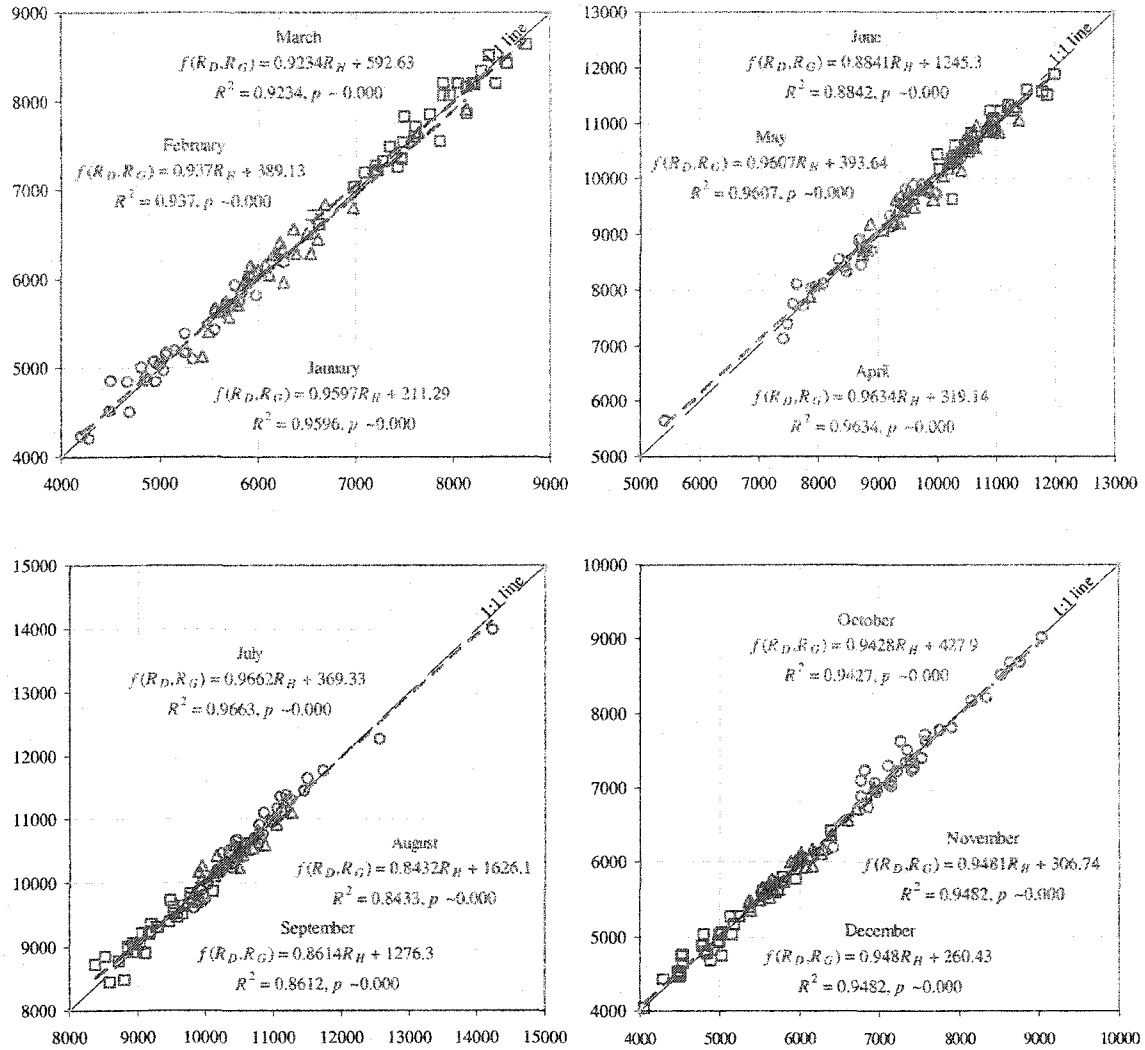


Figure 2.2: Monthly $R_H \sim f(R_D, R_G)$ relationships derived from multiple regression analyses between R_H , R_D , and R_G data observed in 1961-1990 at Miami, FL: (i) January, February, and March; (ii) April, May, and June; (iii) July, August, and September; and (iv) October, November, and December.

R^2 values for the $R_H \sim f(R_G, R_D)$ regression were in all cases the highest, ranging from 0.818 to 0.992, with an average value of 0.9512. As an example of these fitted relationships, Figure 2.2 indicates the observed data used to regress $f(R_D, R_G)$ on observations of R_H over the period 1961-1990 at Miami, FL. These relationships were

developed for all stations missing R_H data and were applied to the SOLMET and Surface Airways R_D and R_G data to re-create the R_H data for the years 1952-1960 and 1991-1994.

2.3.4 Solar Radiation Geometry

It is important to note that the 2-dimensional surface of solar radiation shown in Figure 2.1 represents estimates of solar radiation on a level surface, i.e., a surface with no slope or aspect. The slope of a surface (β) is its steepest slope in the vertical plane, subject to $0 < \beta < \pi/2$, and its aspect (α) is the clockwise angle between the northward direction and the direction of the steepest slope projected onto the horizontal plane. Terrain with a non-zero slope oriented at any aspect—i.e., more rugged terrain—receives significantly different amounts of solar radiation incident on its surface than the level surface shown in Figure 2.1, as the effective area that a given packet of incoming solar radiation covers is changed. Therefore, the value at each grid-cell must be adjusted to take into account its slope and aspect. To do this, R_G must be separated into the two components and a topographic correction factor that is a function of the slope and aspect applied to R_D , as shown in:

$$R_G = R_H + R_D \cdot f(\text{slope, aspect}) \quad (2.6)$$

In correcting the short-wave radiation balance for the effects of variable topography, one must first define the angle between the normal vector to an arbitrarily oriented ground surface and the vector parallel to the line of sight to the sun, as shown in Figure 2.3. In Figure 2.3, the angles are defined as follows: μ on the x-y plane (N-W) is the azimuth angle, that is, the clockwise angle between the northward direction and the direction of the line of sight to the sun projected onto the horizontal plane; α on the x-y

plane (N-W) is the aspect angle; β on plane b-0-d is the slope angle; Z on plane b-0-S is the solar zenith angle, that is, the angle between the normal to a horizontal surface of the planet and the line of sight to the sun; and θ on plane S-0-G is the incidence angle, that is, the angle between the line of sight to the sun and the normal vector to the arbitrarily oriented surface. This last is the angle of interest.

From analytical geometry, the angle between any two vectors **A** and **B** is given by:

$$\cos \Theta = \frac{\mathbf{A} \cdot \mathbf{B}}{|\mathbf{A}| |\mathbf{B}|} \quad (2.7)$$

where the numerator is the inner (or dot) product of the vectors **A** and **B**, and $|\mathbf{A}|$ and $|\mathbf{B}|$ are the magnitude (length) of vectors **A** and **B**, respectively. The inner product of any two n -dimensional vectors is defined as:

$$\mathbf{A} \cdot \mathbf{B} = (a_1, a_2, \dots, a_n) \cdot (b_1, b_2, \dots, b_n) = \sum_{i=1}^n a_i b_i \quad (2.8)$$

and the magnitude as:

$$|\mathbf{A}| = \sqrt{\mathbf{A} \cdot \mathbf{A}} = \sqrt{\sum_{i=1}^n a_i^2} \quad (2.9)$$

In order to determine θ , then, the unit vectors defining the directions of the gradient vector (steepest slope) and the line of sight to the sun must be determined. Let **G** be the gradient vector. Then, from simple geometry (see Figure 2.3) this vector is equal to:

$$\mathbf{G} = |\mathbf{G}|(\mathbf{i} \sin \beta \cos \alpha + \mathbf{j} \sin \beta \sin \alpha + \mathbf{k} \cos \beta) \quad (2.10)$$

Let **S** be the vector parallel to the line of sight to the sun. Then, again from simple geometry (Figure 2.3) this vector is equal to:

$$\mathbf{S} = |\mathbf{S}|(\mathbf{i} \sin Z \cos \mu + \mathbf{j} \sin Z \sin \mu + \mathbf{k} \cos Z) \quad (2.11)$$

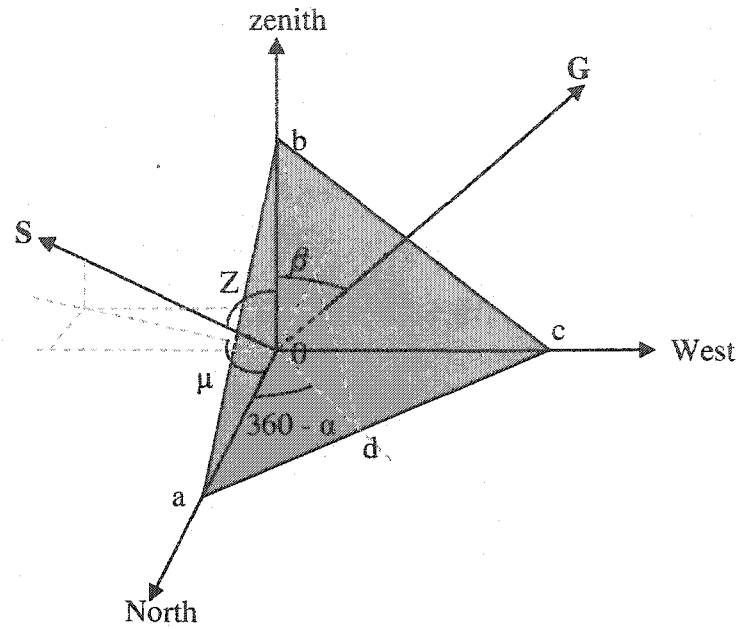


Figure 2.3: Direct solar radiation incident on an arbitrarily inclined surface (abc).

Finally, using (2.10) and (2.11) in (2.7):

$$\cos \theta = \frac{\mathbf{S} \cdot \mathbf{G}}{|\mathbf{S}| |\mathbf{G}|} \quad (2.12)$$

and applying the definitions of inner product and magnitude yields:

$$\cos \theta = \frac{[|\mathbf{S}|(\mathbf{i} \sin Z \cos \mu + \mathbf{j} \sin Z \sin \mu + \mathbf{k} \cos Z)] \cdot [|\mathbf{G}|(\mathbf{i} \sin \beta \cos \alpha + \mathbf{j} \sin \beta \sin \alpha + \mathbf{k} \cos \beta)]}{|\mathbf{S}| |\mathbf{G}|} \quad (2.13)$$

which can be simplified to yield:

$$\cos \theta = \sin Z \cos \mu \sin \beta \cos \alpha + \sin Z \sin \mu \sin \beta \sin \alpha + \cos Z \cos \beta \quad (2.14)$$

Equation (2.14) then defines the incidence angle θ between the vector gradient of any arbitrarily oriented surface and the line of sight to the sun. The cosine of this angle $\cos \theta$ is then the correction factor to be applied to the magnitude of the direct solar radiation to resolve the effects of the topography (i.e., slope and aspect) of the evaporating surface.

More conveniently (i.e., obviating calculations of solar zenith angle Z and solar azimuth angle μ) [Iqbal, 1983], $\cos\theta$ may be calculated from:

$$\begin{aligned}\cos\theta = & (\sin\phi\cos\beta + \cos\phi\sin\beta\cos\alpha)\sin\delta \\ & + (\cos\phi\cos\beta - \sin\phi\sin\beta\cos\alpha)\cos\delta\cos\omega \\ & + \cos\delta\sin\beta\sin\alpha\sin\omega\end{aligned}\quad (2.15)$$

where δ is the solar declination (north positive), ω is the hour angle (0° at noon and morning positive), and ϕ is the latitude (north positive). Input surfaces of slope β and aspect α were derived from a DEM, and a surface of latitude ϕ was generated in the geographical projection domain.

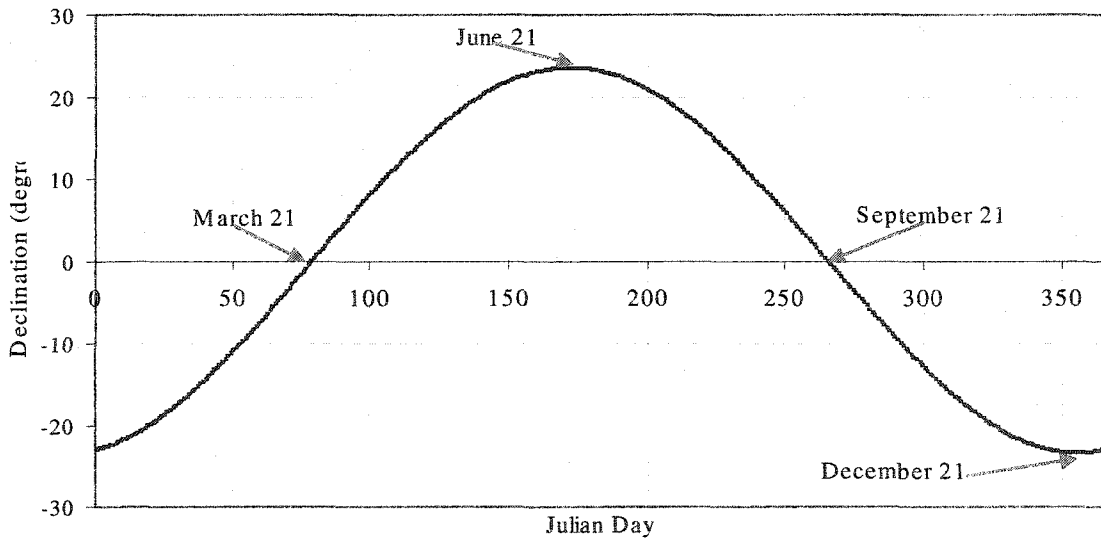


Figure 2.4: Annual cycle of declination of the sun. Origin for time-axis is January 1; north is positive.

The cycle of declination δ throughout the year (Figure 2.4) is calculated (in degrees) from:

$$\delta = \frac{180}{\pi} \left(0.006918 - 0.39912\cos\Gamma + 0.0757\sin\Gamma - 0.006758\cos 2\Gamma \right. \\ \left. + 0.000907\sin 2\Gamma - 0.002697\cos 3\Gamma + 0.00148\sin 3\Gamma \right) \quad (2.16)$$

where Γ is the day angle (in radians), calculated from:

$$\Gamma = 2\pi \frac{JD - 1}{365} \quad (2.17)$$

where JD is the Julian Day (January 1 = 1).

The hour angle ω (in degrees) is 0° at noon, $+15^\circ/\text{hour}$ between sunrise and noon, $-15^\circ/\text{hour}$ between sunrise and sunset. The sunrise angles for flat surfaces are calculated from:

$$\omega_s = \cos^{-1}(-\tan \phi \tan \delta) \quad (2.18)$$

with the sunset angles given by $-\omega_s$. For a surface oriented toward the east (i.e., $0 < \alpha < 180$), the sunrise angle ω_{sr} and sunset angle ω_{ss} are:

$$\omega_{sr} = \min \left[\omega_s, \cos^{-1} \left(\frac{-xy - \sqrt{x^2 - y^2 + 1}}{x^2 + 1} \right) \right] \quad (2.19a)$$

$$\omega_{ss} = -\min \left[\omega_s, \cos^{-1} \left(\frac{-xy + \sqrt{x^2 - y^2 + 1}}{x^2 + 1} \right) \right] \quad (2.19b)$$

while, for a surface oriented toward the west (i.e., $180 < \alpha < 360$), they are:

$$\omega_{sr} = \min \left[\omega_s, \cos^{-1} \left(\frac{-xy + \sqrt{x^2 - y^2 + 1}}{x^2 + 1} \right) \right] \quad (2.19c)$$

$$\omega_{ss} = -\min \left[\omega_s, \cos^{-1} \left(\frac{-xy - \sqrt{x^2 - y^2 + 1}}{x^2 + 1} \right) \right] \quad (2.19d)$$

where:

$$x = \frac{\cos \phi}{\sin \alpha \tan \beta} + \frac{\sin \phi}{\tan \alpha}, \quad y = \tan \delta \left(\frac{\sin \phi}{\sin \alpha \tan \beta} - \frac{\cos \phi}{\tan \alpha} \right). \quad (2.20)$$

From the equations above it is possible to derive the topographic correction factor $\cos\theta$ for the incidence of direct solar radiation on arbitrarily oriented surfaces at any latitude at any moment in any day of the year. However, this correction factor is not constant, as the position of the sun in the sky (vector $\mathbf{S}$) varies with season and time of day. At a monthly time-step, it is necessary to correct monthly radiation totals for use in Equation (2.6). Therefore, monthly magnitude-weighted correction factors that account for the intra-monthly periodicity in $\cos\theta$ must be derived.

Incidence angles θ_i were generated for each daylight hour of the 15th of each month at each grid-cell in the conterminous US. The 15th day was assumed to represent the mean astronomical parameters for the month, with 10 years of data used to generate a mean 15th day. The monthly values of $\cos\theta$ were then derived as a weighted average of the hourly proportion values p_i for the 15th day of each month as shown in:

$$\cos\theta_{\text{MONTH}} = \sum_{i=i_{SR}}^{i_{SS}} \cos\theta_i \cdot p_i \quad (2.21)$$

where $\cos\theta_{\text{MONTH}}$ is the monthly topographic correction factor for direct solar radiation, the index i represents the local daylight hours between i_{SR} and i_{SS} , R_{Di} is the direct solar radiation for hour i , and p_i is the proportion of the daily total of direct solar radiation received in hour i , on day 15 of each month, based on a 10-year average of 15th days. The variation of p_i is shown for a single example station in Figure 2.5. The derivation of the p_i surfaces is described below.

Hourly proportions of direct solar radiation p_i values were calculated for each station as the mean of 10 years of hourly data for day 15 of each month. For the lower-48 states,

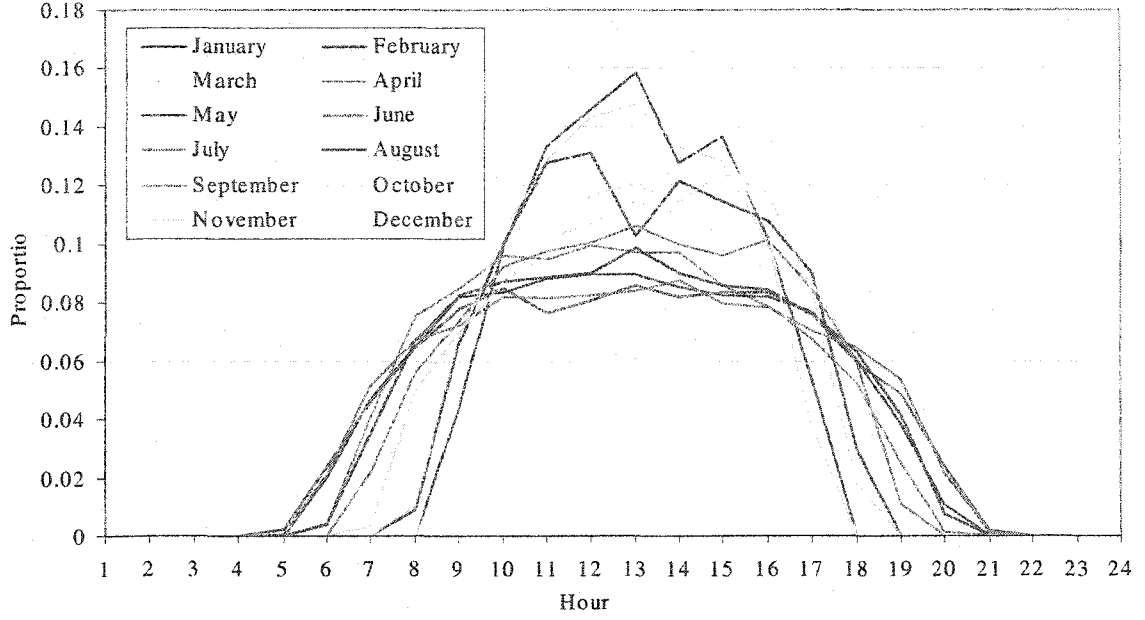


Figure 2.5: Hourly proportions of direct solar radiation for the 10-year average 15th day of each month at Fargo, ND.

the earliest extreme of i_{SR} is 5 and the latest extreme of i_{SS} is 21, varying with season, latitude, and longitude. Station values of p_i were regressed against latitude to create trend surfaces, in order to generate trend surfaces to improve their spatial interpolation. The station values for hourly totals of direct solar radiation R_{Di} in the 15th day were regressed on station latitude, longitude and elevation, taken singly and in all combinations. Then, for each month, the hourly p_i surfaces from the initial interpolation run were corrected using:

$$p_i = \frac{R_{Di}}{\sum_{i=i_{SR}}^{i_{SS}} R_{Di}} \Rightarrow \sum_{i=i_{SR}}^{i_{SS}} p_i = 1. \quad (2.22)$$

in order that any negative values introduced by the spatial interpolation algorithm were eliminated, and that hourly proportions p_i for each cell summed to one.

2.4 Results

This section presents results of the development of the R_G data set: namely 5-km resolution surfaces of the long-term mean R_G and long-term trends in R_G . Broad conclusions may be drawn from these results. R_G provides the major energy input to any evaporative process, and when applied to a surface energy budget (see Equation 2.5), is an excellent estimator of net available energy Q_N .

Figure 2.6 presents the effects of topographic correction on R_G , as expressed by the long-term mean daily rate. Figure 2.6(i) presents the uncorrected time-series determined by observations of R_G alone. Figure 2.6(ii) presents the time-series of R_G determined as the sum of R_H and topographically corrected R_D . While there are significant similarities across much of the conterminous US, significant differences arise in areas of varied topography.

Obvious in both figures is the effect of insolation's inverse latitudinal trend, particularly over the homogenous eastern US. Moving west, R_G generally increases with longitude, leading to the occurrence of the highest values in both surfaces in the desert Southwest. As regards the spatial statistics of the surfaces, both the corrected and uncorrected R_G surfaces show broadly similar means across the conterminous US: the uncorrected mean R_G is 16.1 MJ/m²/day, and the corrected mean R_G is 15.5 MJ/m²/day. As expected, though, the ranges are different: the uncorrected R_G varies from a minimum of 10.8 MJ/m²/day (in the Puget Sound region of western Washington) to a maximum of 21.5 MJ/m²/day (in southeastern Arizona); the corrected R_G varies from a minimum of 10.1 MJ/m²/day (in the Olympic Peninsula of western Washington), to a maximum of 25.4 MJ/m²/day (in the Sierra Nevada mountains of California). That the range across the

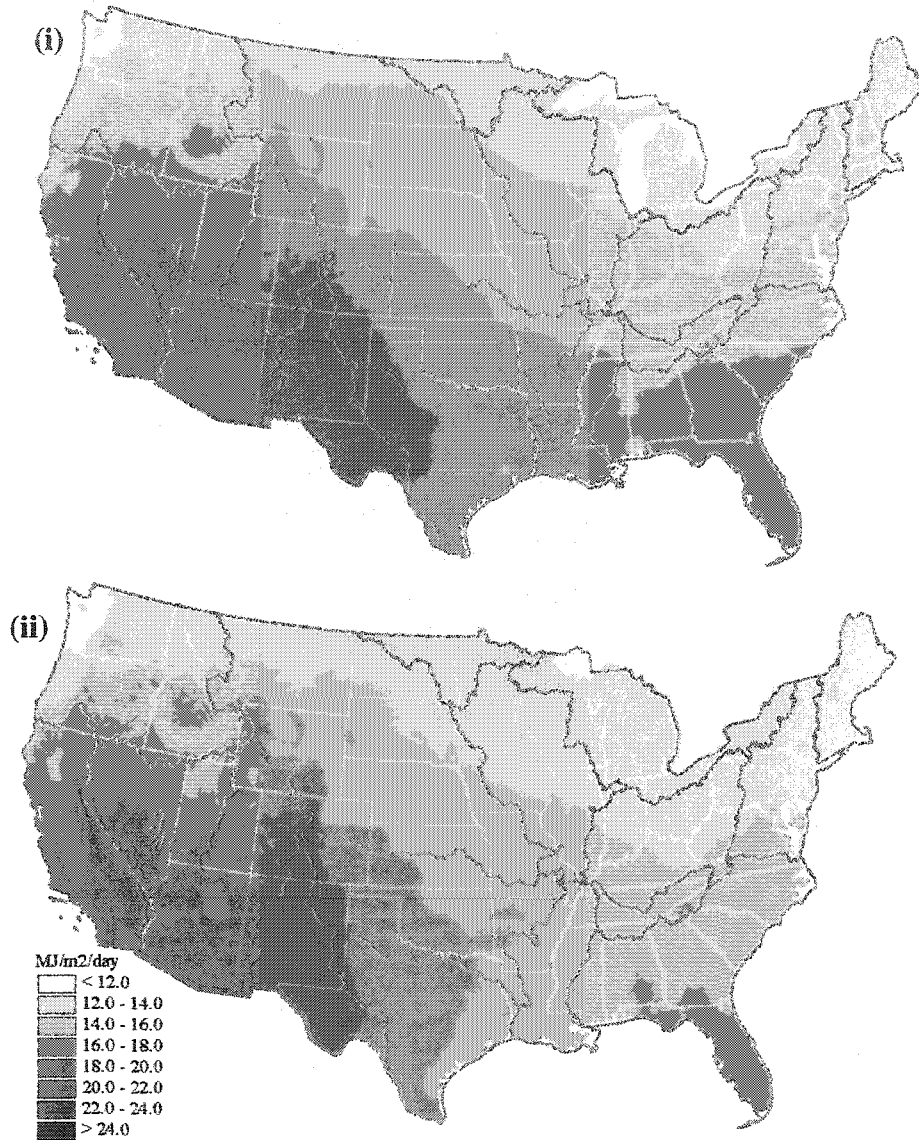


Figure 2.6: Distributed long-term mean daily R_G , spatially interpolated across the conterminous US from a 27-year (WY 1962-1988) monthly time-series of daily R_G rates, expressed at each pixel, in $\text{MJ/m}^2/\text{year}$. (i) is determined by observations of R_G alone with no topographic correction; (ii) is the sum of R_H and topographically corrected R_D . Also shown are the state- and WRR-boundaries.

corrected surface exceeds that across the uncorrected surface is a function of the increased variability in the R_D input in the former surface, particularly in the rugged terrain of the western US. This is also reflected in the variances of the overall surfaces:

1.95 MJ/m²/day for the uncorrected R_G surface; 2.10 MJ/m²/day for the corrected R_G surface. Overall, the pattern of insolation in the corrected surface is evidently more attuned to elevation, or more specifically, to the increased slopes and more varied aspects that accompany rugged terrain. This is particularly obvious in the western US, where the effects of topography on the R_D component of R_G are more pronounced: for example, the north-south oriented mountain ranges in the basin-and-range country of Nevada are evident in the topographically corrected R_G surface, but not in the uncorrected R_G surface.

Figure 2.7 presents the temporal trend in R_G , expressed as the slope of a linear fit to a 42-year annual time-series. R_G here is estimated as the sum of R_H and topographically corrected R_D : the data used in Figure 2.6(ii) is a sub-period of that used for Figure 2.7 (WY 1962-1988 in Figure 2.6; WY 1953-1994 used in Figure 2.7).

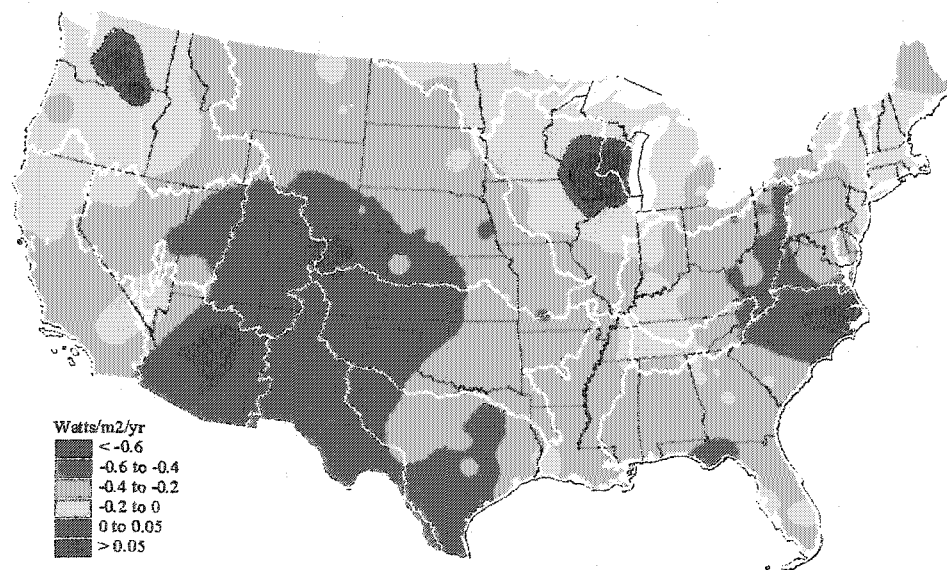


Figure 2.7: Distributed trends in R_G spatially interpolated across the conterminous US from a 42-year (WY 1953-1994) monthly time-series of observations, corrected for local topographic effects, and expressed as the slope of a linear fit to the annual time series at each pixel, in watts/m²/year. Also shown are the state- and WRR-boundaries.

On a distributed basis, the pattern of decreasing R_G is almost universal—with R_G decreasing over 97.50% of the conterminous US, with decreases pronounced in the Southwest and North Carolina. Significant exceptions to this general decrease are evident in the western Great Lakes region and the inland Pacific Northwest.

The existence of trends in R_G appears in the literature to be somewhat of a hot-button issue: predictions by GCMs are not matched by observations of decreasing short-wave irradiance at the earth's surface on the order of over 10% over the past 50 years [Gilgen *et al.*, 1998], an observed decrease in global solar irradiance of 6-12% over the period 1960-1990 for a region in northwestern Russia [Roderick and Farquhar, 2002], or of globally increasing cloudiness and precipitation [Karl *et al.*, 1996]. While this research discusses no data for Russia, averaged across the conterminous US for the period of the new data set (WY 1953-1994), a decrease in R_G of 0.298 watts/m²/year, for a 42-year decrease of 12.52 watts/m² or 14.4% of the mean is observed, thereby lending indirect support to the findings of Gilgen *et al.* [1998].

2.5 Conclusions

Towards the development of an accurate distributed data set of ET_a based on the complementary relationship as a tool for studies of climate change and variability across the conterminous US, the authors developed a methodology to compute the amount of solar radiation incident per unit area of ground surface as a function of R_H , R_D , and solar path geometry. A 42-year-long set of monthly, spatially distributed, high-resolution surfaces of Q_N corrected for topography was thereby created. This involved the collation of R_D and R_H data from three sources, the reproduction of 12 years of monthly R_H

radiation data missing from two of the sources, and the development of an algorithm to compute R_D per unit area of arbitrarily tilted ground surface. The spatial resolution of the resulting Q_N data set is determined only by the resolution of the DEM used to derive the slope and aspect surfaces. The temporal resolution was matched to that of the other input data to the ET_a model and, while it is theoretically variable, it is practically fixed by dint of the computational investment of the input surfaces to the solar radiation adjustment procedure described.

This new Q_N data set allows for long-term trend analyses in the single most important variable in determining the strength of the hydrologic cycle to be studied, as shown in *Hobbins et al.* [2001c], where trends in Q_N were analyzed as a component of trends in ET_a , allowing for verification of other earlier work concerning the trends in both ET_a and ET_{pan} [Szilagyi et al., 2001; Roderick and Farquhar, 2002]. Further, the spatial distribution of the data set allows for analysis of un-metered regions, but at a cost of generating uncertainties associated with spatial interpolation of the input data. It allows the further breakdown of climatic trends in the components of the hydrologic cycle, particularly those components of ET_a , as to both their magnitude and their spatial distribution. Such data are available for anywhere in the conterminous US and at any scale and spatial breakdown so desired: from the entire conterminous US; into water resource regions, states, climatic divisions, specific watersheds, physiographic regions; and on down to that of a single pixel. This represents a significant leap forward from previous studies, both in that a spatially distributed technique permits the examination of regional sensitivities to climate change and variability—a significant improvement over generating continental-scale averages from point values—and in that examining long-

term trends in the input climatic variables obviates any assumptions of stationarity in any component, specifically Q_N .

Further work may include an examination of the homogeneity of the input data, especially at temporal joints, the solar-shadowing effects of regional topography, and an estimation of the accuracy of the technique using the missing station interpolation test and others.

3. Developing a Homogeneous Data Series of Pan Evaporation across the Conterminous United States for Analysis of Long-Term Trends

3.1 Abstract

Pan evaporation data are gathered from two data sources for 228 pans across the conterminous US toward an examination of long-term trends in annual and warm-season totals. Using only pans that report at least 20 years or seasons of data within the period 1950-2002 produces sets of 1248 data at 44 pans from which annual trends are derived, and of 7064 data from 228 pans for warm-season trends. The data sets are characterized by their lack of completeness and, more importantly, non-homogeneity that could introduce spurious biases into analyses of long-term trends unless adjusted for. However, the metadata supposed to record events that induce potential heterogeneities at each pan, and that would therefore enable researchers to derive an adjusted, homogeneous data set, are scant and, when available, elliptical. Given the additional complicating requirement that climatically driven trends not be filtered out as sources of heterogeneity, a homogeneity adjustment that resolves understandings of both the physical dynamics and the statistical properties of the data is indicated. For each pan's time-series, then, analyses are performed to detect abrupt changes across the entire period of record at points indicated by the metadata or by the combined subjective judgment of the authors. Using the *t*-test to indicate statistically significant abrupt shifts, the time-series of 172 pans are adjusted at a total of 326 abrupt data-shifts: 280 due to pan location changes indicated by the metadata; 46 due to unspecified events. In this manner, 43% of the annual data and 55% of the warm-season data are adjusted. In a comparison of trend results from pre- and

post-adjustment data across all pans, the proportions of decreasing trends remain the same while the numbers of significant trends in the annual data drop to about a third of pre-adjustment levels.

3.2 Introduction

In order to examine the impacts of global climate change and variability on the hydrologic cycle, one must examine actual evapotranspiration (ET_a), which remains one of the most difficult variables to measure or observe directly while often being the most variable. Historically, ET_a has been estimated as a function of potential evapotranspiration (ET_p), which is itself observed directly at evaporation pans as ET_{pan} , and factored therefrom. Thus, to examine long-term trends in the hydrologic cycle, the question must be asked, “Is ET_{pan} changing?” Others have attempted to answer this question using few stations, or stations over small areas, or stations that are spatially disjoint from the region of interest (different continents, even) [Peterson *et al.*, 1995; Brutsaert and Parlange, 1998; Golubev *et al.*, 2001; Ohmura and Wild, 2002; Roderick and Farquhar, 2002; Center for the Study of Carbon Dioxide and Global Change, 2003]. The ultimate goal is to examine changes in ET_{pan} as a component of a changing hydrologic cycle in the same region (conterminous US) and over the same period (WY 1953-1994) as the other hydrologic variables.

In a potential network of hundreds of pans over 50 years, any number of adverse impacts may have created heterogeneities in the data recorded that may lead to significant biases in the results of long-term trend analyses unless they are accounted for in the data [Peterson *et al.*, 1998]. These changes are categorized in this study as either operational,

local, or regional climatic. Operational changes relate to changes in instrumentation, procedure, personnel, or station location. Local changes relate to changes in the land-use or land-cover in the area immediately surrounding the station, such as urbanization, deforestation, or irrigation. Regional climatic changes relate to the large-scale changes in the physical dynamics of the evaporative process themselves, whether due to the variability inherent in the processes, or due to climate forcing, anthropogenic or otherwise. Users of climatic data sets are informed as to the nature and timing of operational changes by metadata—data about the data—and these can be used to filter out their effects through a process referred to herein as “homogenization.” Unfortunately, metadata are often either incomplete or partially or wholly unavailable.

Peterson et al. [1998] review the homogenization of *in situ* climatological data and provide the basic motivation, stating “the difference in trends between homogeneity-adjusted and unadjusted data can be enormous at an individual station and very significant in regional analyses.” While there exist myriad techniques to detect and adjust for heterogeneities, in general the processes are convergent: for a given station, differently adjusted time-series will be more similar to each other than they are to the unadjusted time-series [*Peterson et al.*, 1998].

For the development of an homogenous ET_{pan} data set across the conterminous US, the flexibility of choice of homogenization procedure is constrained primarily by (i) the temporal completeness of the data, (ii) the quality of the metadata, and (iii) the use to which the adjusted data will be put: long-term trend detection. In the former (i), the data are remarkable for their lack of completeness: at any given station there are seasonal and multi-year gaps where either no data were recorded or insufficient data were recorded to

generate the annual, seasonal, or monthly totals of interest. In the case of the latter (ii), there were significant problems in obtaining optimal metadata, i.e., that reporting all potential sources of heterogeneities, and of that metadata that were available, they were equally confusing for what they didn't say as they were informative for what they did. These issues provoked this study's evolution of a task-specific methodology for homogeneity adjustment: one that incorporated objective statistical analyses and subjective judgment. The requirement that regional climatic heterogeneities be preserved in the data set informs the choice further, as a slightly more nuanced understanding of homogeneity than is usually the case is used. Thus, a homogeneity test is required that accounts for operational breaks, but does not filter out trends due to regional climatic changes.

The chapter proceeds as follows: first the data sources, their availability and integration are summarized; then example metadata are shown and discussed as to their contributions and shortcomings; then example time-series that combine data and metadata and outline the inherent heterogeneities are shown; then the detection and adjustment of heterogeneities—using a guided, semi-objective homogeneity analysis using all available metadata—is explained, drawing particular attention to challenges specific to the data set; then the results of the homogeneity detection are shown with their implications for the larger-scale study, comparing adjusted results with unadjusted results; finally, a summary of conclusions drawn from this work in particular and homogeneity testing in general are drawn.

3.3 Data Sources and Availability

3.3.1 Pan Evaporation Data

In order to generate the longest period from the most pans covering the largest spatial extent possible, the ET_{pan} data were collated from the following two sources, both within the National Climatic Data Center (NCDC):

- Daily Evaporation: TD-3200, Surface Land Daily Cooperative Summary of the Day [*EarthInfo*, 1998a; NCDC, 2004a].
- Total Monthly Evaporation: TD-3220, Summary of the Month Cooperative [NCDC, 2004b].

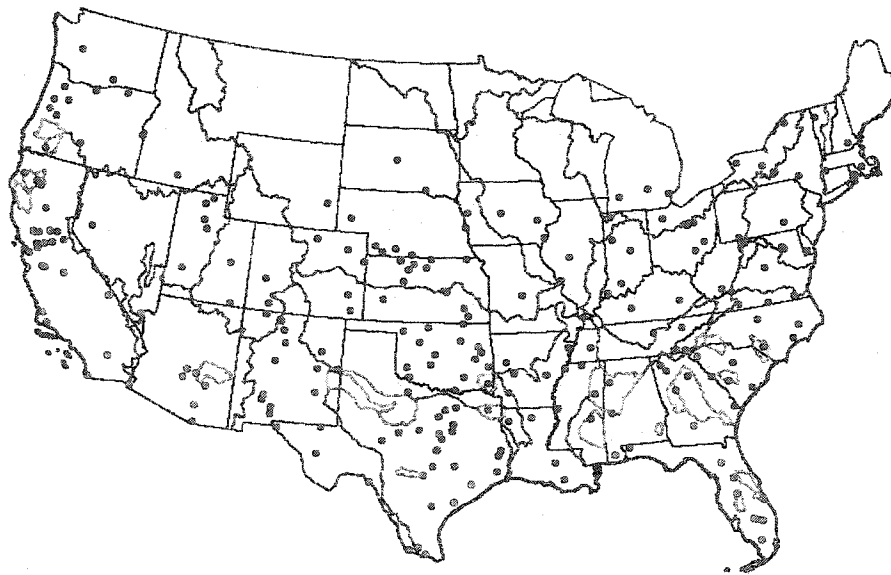


Figure 3.1: Location of the evaporation pans used in this study. Red circles indicate pans used for annual trend analysis; blue circles indicate further pans used for warm-season trend analysis. Green polygons are basins from the Hydro-Climatic Data Network (HCDN) [*Hydrosphere*, 1996; *Slack and Landwehr*, 1992] used in the analysis for Figure 3.6.

For months in which more than two-thirds of the daily data were reported, the daily data were integrated to monthly data by summing and linearly scaling up for missing days, if necessary.

The resulting integrated monthly data from TD-3200 and the reported monthly data from TD-3220 were combined to create annual data from those water years when all 12 months were reported, and warm-season (MJJASO) data from those calendar years when all six months were reported. Only pans for which at least 20 annual or seasonal totals were available for the period 1950-2002 were to be used in the proposed trend analysis. This procedure resulted in 44 pans for annual data and 228 pans for warm-season data, with average record lengths of 28.4 years and 30.9 seasons, respectively.

3.3.2 Metadata

Metadata are supposed to record the time and nature of operational changes to the station recording the data. By definition, these changes will generate heterogeneities, which may be significant and lead to significant biases in the results of long-term trend analyses. Users may use the metadata to filter out the heterogeneities from the time-series of the data. However, the metadata will not record the sorts of creeping events that lie beyond the control of the recording institution but that nonetheless may adversely impact the physical dynamics driving the phenomenon under observation. In the case of ET_{pan} , these may be such long-term changes as urbanization, deforestation, or irrigation. Unfortunately, metadata are often either incomplete or partially or wholly unavailable.

The metadata are maintained by the NCDC [NCDC, 2004d], and the analysis to be presented was carried out using all metadata available. An HTML list of dates and

coordinates is attached to the on-line data for each pan (an example of which is shown in Table 3.1). Shifts in pan-location may be inferred from the coordinates listed; other changes of unknown nature may also be inferred. Metadata break the period of record for each pan into sub-periods, without distinguishing one sub-period from another. For each sub-period, the latitude and longitude (in degrees and whole minutes) and elevation (in meters and feet, recorded to one decimal place) of the pans are recorded, allowing pan-location changes to be inferred to the extent that such low-level coordinate precision allows. For each pan, each division into sub-periods can be interpreted as a potential heterogeneity in the time-series, whether or not it was inferred-geographic in nature.

Table 3.1 indicates the sort of information that is and is not available from a station's metadata. In this example, it may be inferred that the station operated with a different name and COOP ID number from July 1, 1946 until 8 April, 1959, when it changed name but not number. On 30 April, 1959, it ceased operation. It re-started on October 1, 1980, with its current COOP ID number but at a lower location. The nature of the change that distinguishes the period October 1, 1980 to April 9, 1991 from the period 9 April, 1991 to July 16, 1992 is not recorded, but the elevation changed again during the subsequent two-week period. On June 6, 1995, the station was moved slightly west, but again, the nature of the change that distinguishes the period June 6, 1995 to July 7, 2003 from the period July 7, 2003 to the present is not recorded (it lies outside of this study's period of interest, in any case). In summary, from the metadata that are available for this station seven potential break-points in the operation of the station can be inferred: three are of unknown origin, and four are geographic in nature. Mapping these break-points onto the ET_{pan} data recorded at the station indicates that two of the geographic break-points and

one of the unknown break-points may be relevant to the homogeneity of the ET_{pan} time-series for recorded at this station. The time-series for this pan and the two geographic heterogeneities and one heterogeneity of unknown origin that are listed in Table 3.1 and that potentially influence the annual or warm-season trends are shown as solid and dashed vertical lines in Figure 3.2(iii).

Table 3.1: Example of a station's metadata (COOP ID 298535: New Mexico State University, NM) [NCDC, 2004d].

Date Began	Date Ended	Lat / Lon	Elevation (m./ft.)	COOP ID	WBAN	Call Sign	WMO ID	Type
STATE UNIVERSITY								
07 Jul 2003	Present	32°17'N / 106°46'W	1182.9 / 3881	298535	.	.	.	COOP
06 Jun 1995	07 Jul 2003	32°17'N / 106°46'W	1182.9 / 3881	298535	.	.	.	COOP
30 Jul 1992	06 Jun 1995	32°17'N / 106°45'W	1182.9 / 3881	298535	.	.	.	COOP
16 Jul 1992	30 Jul 1992	32°17'N / 106°45'W	1182.6 / 3880	298535	.	.	.	COOP
09 Apr 1991	16 Jul 1992	32°17'N / 106°45'W	1182.9 / 3881	298535	.	.	.	COOP
01 Oct 1980	09 Apr 1991	32°17'N / 106°45'W	1182.9 / 3881	298535	.	.	.	COOP
08 Apr 1959	30 Apr 1959	32°17'N / 106°45'W	1193.0 / 3914	290131	.	.	.	COOP
AGRICULTURAL COLLEGE								
01 Jul 1946	08 Apr 1959	32°17'N / 106°45'W	1193.0 / 3914	290131	.	.	.	COOP

Figure 3.2 uses four example pans to summarize the different inter-relations between data and their metadata-derived potential heterogeneities. Here it is important to look beyond two obvious features in these time-series: gaps in the time-series and the seasonal cycles. Although by definition the numerous gaps in the data imply operational changes in the stations, they are by themselves of little useful concern in the context of heterogeneity analysis. The seasonal behavior, evident in each pan's time-series and

useful in visually identifying heterogeneities, may be ignored, as it is in the annual or warm-season totals that the interest lies. Figure 3.2(i) (COOP ID 418996: Thompsons 3 WSW, TX) indicates a long record with no immediately apparent pan-impacting heterogeneities or trends. Figure 3.2(ii) (COOP ID 042319: Death Valley, CA, shows an apparent decreasing trend that ends between months 380 and 420, but no apparent heterogeneities, as inferred from the metadata. Figure 3.2(iii) (COOP ID 298535: New Mexico State University) is discussed above: it shows no immediately apparent long-term

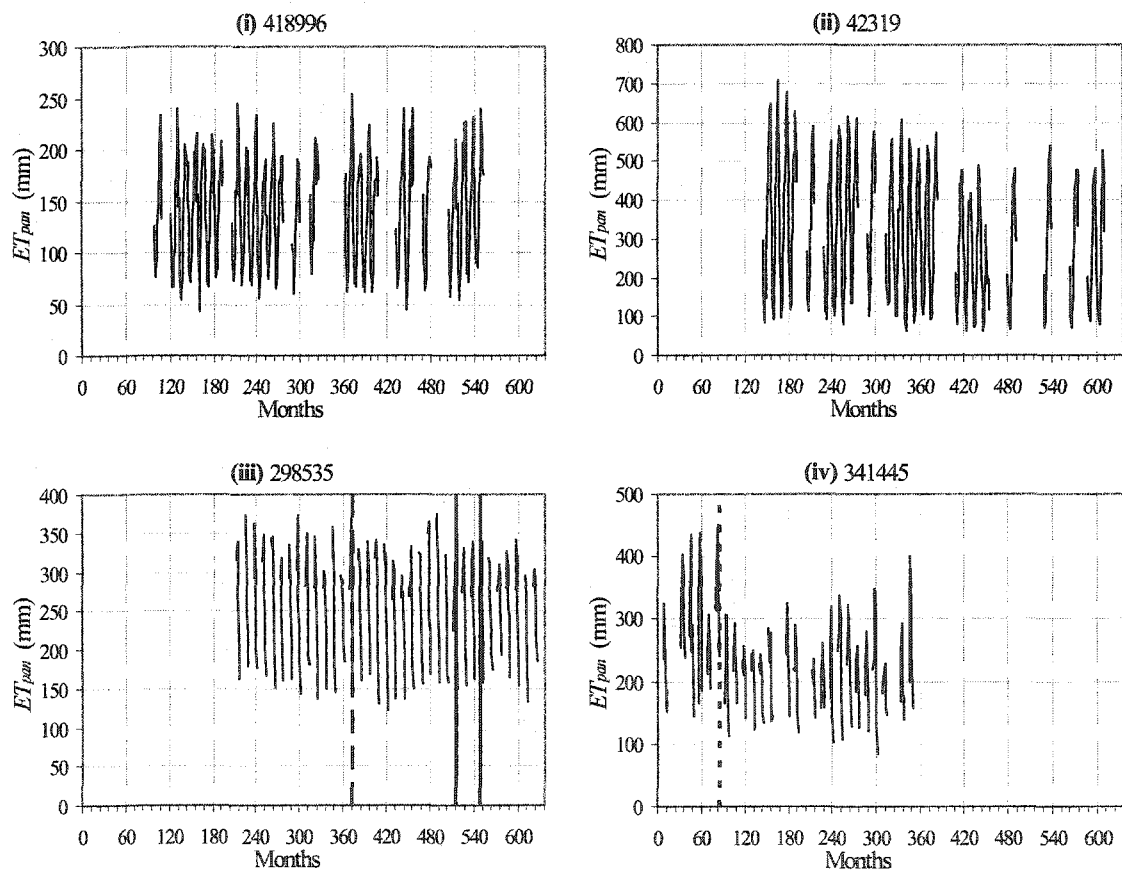


Figure 3.2: The available unadjusted monthly time-series for evaporation pans (i) COOP ID 418996, (ii) COOP ID 042319, (iii) COOP ID 298535, and (iv) COOP ID 341445. Potential break-points are indicated as vertical lines through the time-series: metadata-derived break-points of geographic origin and unknown origin by solid and dashed lines, respectively, and other apparent break-points by dotted lines.

trends but includes both types of metadata-derived heterogeneities—two geographic and one of unknown origin. Figure 3.2(iv) (COOP ID 341445: Canton, OK): the metadata for this station does not imply any impact on the ET_{pan} record, but the behavior here exhibited shows a break-point at month #86 that is too obvious to ignore in the context of its effects on long-term trend analysis at this pan.

3.4 Homogeneity Testing

The objective of this study is to remove the artificial signals of operational heterogeneities from the ET_{pan} data, leaving the variations in ET_{pan} that result from the variability inherent in the physical dynamics of the evaporative process themselves. In the absence of useful metadata about changes in pans—whether they be abrupt, through operational changes, or gradual, through trends in climatic conditions on the local scale or on the regional scale (where, in the final analysis, the real interest lies)—this chapter describes the identification of, and correction for, heterogeneities in the data used to derive trends in ET_{pan} .

This objective requires a more nuanced definition of homogeneity than standard homogeneity tests allow. A data set is sought that—similarly to the standard definition of homogeneity—is not subject to abrupt changes of operational origin, but that—now in contrast to the standard definition—still reflects evolving regional climatic conditions. Ideally, the effects of local heterogeneities would also be removed, however, it is not possible to distinguish them from the variations of interest: that is, the trends due to regional climatic change and variability. In response to this new definition, a flexible

approach is sought to testing the 228 pan time-series for homogeneity across the potential break-points.

It must be first recognized that any pan's time-series may have more than one break-point indicated in the metadata, or none at all. This is clear from Figure 3.2, where time-series (i) and (ii) have no break-points indicated, and time-series (iii) has three (the break-point indicated in time-series (iv) was not indicated in the metadata but derives from visual inspection alone). Following are the different types of heterogeneities in the unadjusted data and their associated assumptions:

Type 1—shifts in pan location recorded in the metadata. All of these break-points are assumed to result in heterogeneities in the recorded data.

Type 2—changes of unknown type recorded in the metadata. It is assumed that some of these break-points will have resulted in heterogeneities, but not all—a reflection of the possibility that the some station-changes (see Table 3.1) may have had nothing to do with the operation of the pan at the station, e.g., they may have been changes in ancillary instrumentation. These are tested statistically and those whose effects are significant are treated as heterogeneities.

Type 3—abrupt changes apparent in the recorded time-series but not recorded in the metadata. It is assumed that some of these break-points represent significant heterogeneities. These are tested statistically and those whose effects are significant are treated as heterogeneities.

The *t*-test is used to determine whether two samples bounded by break-points are likely to have come from the same two underlying populations. The *t*-test is a parametric

test, in that parameters—the mean, variance, and size—of each sub-series are used in the test [Salas, 1992]. The hypothesis that the means are the same is rejected if $T_c > T_{1-\alpha/2, \nu}$, where $T_{1-\alpha/2, \nu}$ is the $1-\alpha/2$ quantile of the Student's t distribution with $\nu = N_1 + N_2 - 2$ degrees of freedom and α the significance level of the test. N is the sub-sample size and the subscripts 1 and 2 refer to the sub-periods on either side of the break-point under test. Note that the size of each of the sub-series N_1 or N_2 plays a significant role in determining the power of the test.

In the case of this study, the test statistic, T_c is calculated as follows:

$$T_c = \frac{|\mu_2 - \mu_1|}{\sqrt{\frac{(N_1 - 1)\sigma_1^2 + (N_2 - 1)\sigma_2^2}{N_1 + N_2 - 2} \left(\frac{1}{N_1} + \frac{1}{N_2} \right)}} \quad (3.1)$$

where μ is the mean of the ET_{pan} data in the sample and σ^2 is its variance.

The t -test is then carried out at each break-point. Where the t -test implies a statistically significant difference in the mean across the break-point, the data are homogenized to the latest (in time) sub-period of the data set according to the following equation:

$$ET_{pan1}^A = \mu_2 + ET_{pan1} - \mu_1 \quad (3.2)$$

where ET_{pan1}^A indicates the homogenized, or adjusted, data, and ET_{pan1} its unhomogenized equivalent, μ refers to the sample means of the periods indicated by the subscripts 1 and 2 taken from before and after the break-point, respectively. While Equation (3.2) implies stationary processes on both sides of the heterogeneity—i.e., in sub-series 1 and 2—which is in conflict with this study's aim of examining the non-stationarity or temporal trends inherent in the data, it is the best that can be mustered.

All break-points of Type 1 are adjusted for, regardless of their statistical significance. Break-points of Types 2 and 3 that are statistically significant at the 95% level are adjusted for. In this manner, all spotted—i.e., statistically confirmed—heterogeneities and all physical shifts in the pan are adjusted for in the homogenization process.

3.5 Results

In this section the results of the homogenization procedure applied to the annual and warm-season data sets are examined as they relate to the larger context of the use for which they are intended: that of the input data for a long-term trend-analysis in *ET* rates across the conterminous US. Thus, the overall population of break-points is here summarized, then the effects of the homogenization are examined, first on the secular trend derived for an example pan, then on the population of pans used in both the annual and warm-season analysis. The effects of homogenization on a spatially interpolated warm-season ET_{pan} -trend surface are then examined. Finally, as the larger-scale goals of this dissertation include the examination of the complementary relationship between actual and potential *ET* rates first proposed by *Bouchet* [1963], a preliminary analysis of said rates after homogenization is offered, to uncover whether the complementarity discussed in *Hobbins et al.* [2003] is an artifact of a heterogeneous data set or truly represents the physics of the process.

3.5.1 Break-points: A Summary

The time-series of each of the 230 pans was homogenized across its entire period of record to account for heterogeneities as explained above. As a statistical test to confirm heterogeneity at a given indicated point, *t*-testing at 95% significance level was conducted. This resulted in the removal of 326 abrupt data-shifts at 172 pans (or 75% of the population of pans), of which 280 were due to changes in pan location, and 46 were due to unspecified changes. In this manner, 43% of annual data, and 55% of warm-season data were homogenized.

3.5.2 Trends at a Single Pan

An example of the effects of the homogenization is presented in Figure 3.3, which shows the monthly time-series for the pan at COOP ID 355160, Malheur Branch Experiment Station, OR, and the long-term trends derived from its pre- and post-homogenization data. Prior to homogenization, the warm-season data, shown in Figure 3.3(i), shows a distinct increasing trend as shown in Figure 3.3(ii), which, after the monthly data were aggregated into warm-season data, was evaluated at 8.76 mm/season/year (p -value of $7.35 * 10^{-12}$, R^2 of 0.677). After homogenization across the seven potential heterogeneities (indicated as vertical lines in Figure 3.3(i)), the trend all but disappears; to -0.02 mm/season/year (p -value = 0.979, $R^2 = 2*10^{-5}$). This result highlights the importance of examining the metadata before drawing conclusions from the raw data.

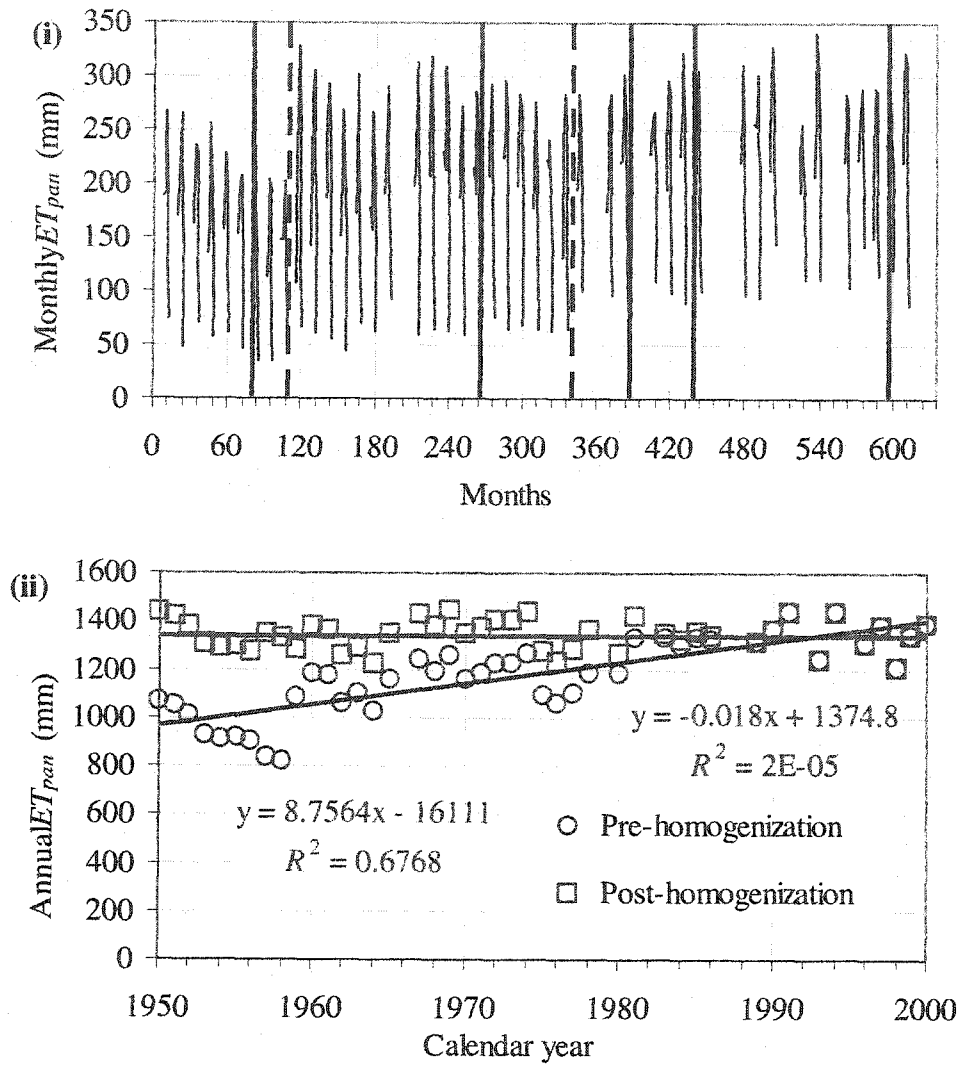


Figure 3.3: The effects of homogenization on trends derived for a single evaporation pan: (i) shows the available unadjusted monthly time-series for evaporation pan COOP ID 355160 (Malheur Branch Experiment Station, OR), including heterogeneities; (ii) shows the trends in the warm-season data, pre- and post-homogenization.

3.5.3 Trends in the Population of All Pans

Here, the effects of homogenization as applied to all pans are examined, first by comparing annual trends derived from the raw, or unhomogenized, data set to those derived from the data set after homogenization, then by doing the same with the larger set

of warm-season pans. In the annual data set there are 1248 data at 44 pans; in the warm-season data set, there are 7064 data at 228 pans. The period studied is CY 1950-2002.

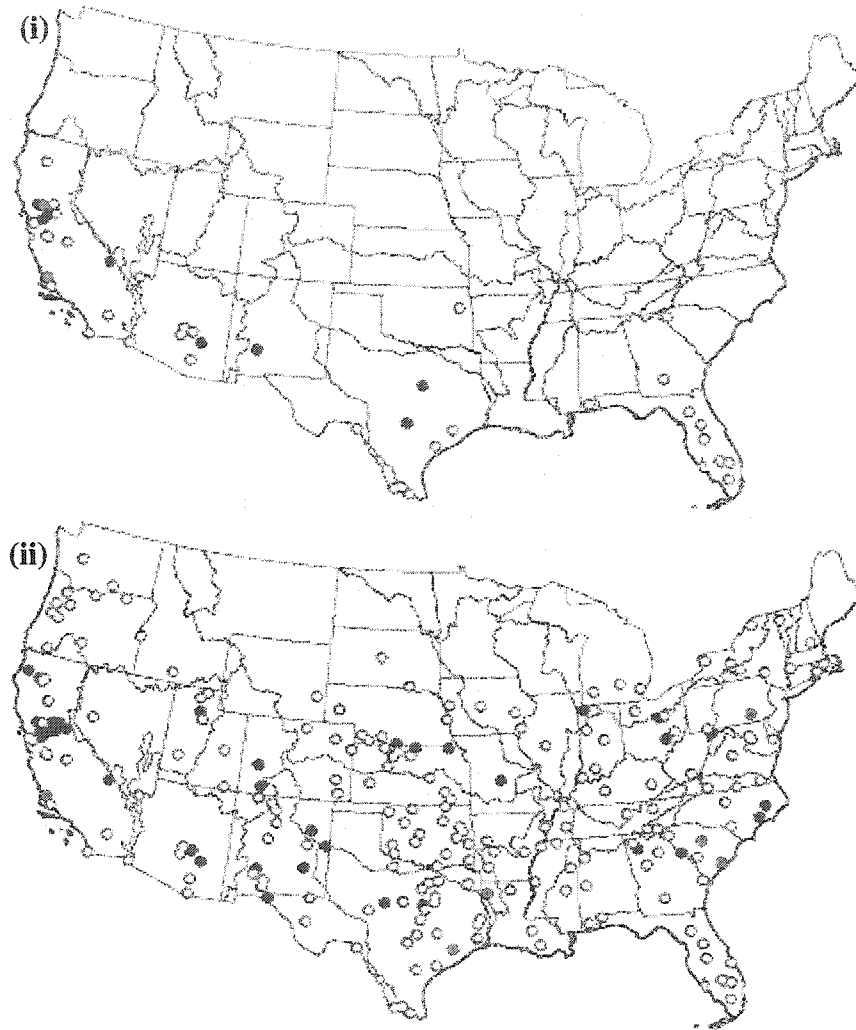


Figure 3.4: Trends in (i) adjusted annual ET_{pan} and (ii) adjusted warm-season (MJJASO) ET_{pan} across the conterminous US over the period WY 1950-2002. Increasing trends are represented by red circles, decreasing trends by blue circles. Solid circles represent pans with trends significant at 90%.

Overall, in the annual data, the effect of homogenizing the data set was to increase the proportion of pans with decreasing trends, from 57% to 64% of the pans. With regard to all (i.e., increasing or decreasing) trends significant at the 90% level, 64% were

significant in the pre-homogeneity data set, and of these 48% were decreasing; in the post-homogenized data set, only 27% of the trends were significant, and of these 75% were decreasing. In terms of the warm-season trend data, the overall effect on the proportion of pans reporting decreasing ET_{pan} trends was negligible (60% from 62%), but again, the number of pans reporting all trends significant at the 90% level was reduced from 128 to 43. As in the annual trend data, the proportion of the significant ET_{pan} trends that were decreasing increased, from 64% to 84%. Figure 3.4(i) and (ii) show the spatial distribution of the post-homogenized trends for (i) the annual trends and (ii) the warm-season trends, broken down according to direction of trend and statistical significance.

3.5.4 Spatially Distributed Warm-season Trends

One of the primary goals of this study is to examine trends in ET rates across the conterminous US, requiring interpolation of either pan data or trends derived from pan data from the station values discussed above to un-metered regions. In this section, therefore, the effects of homogenizing the ET_{pan} data on the results derived from a simple spatial interpolation scheme applied to the station trend-data are examined. An Inverse Distance Weighted (IDW) spatial interpolation method is used, wherein at each point of interpolation, the weights applied to the data from the surrounding stations are calculated simply as a function of the distances between the point of estimation and the points of observation (pans). While IDW is not generally deemed suitable for non-homogeneous regions—which in this study would be regions of strong orographic influence and other geographical or climatological contrasts—it suffices here to provide a measure of the influence of the homogenization process.

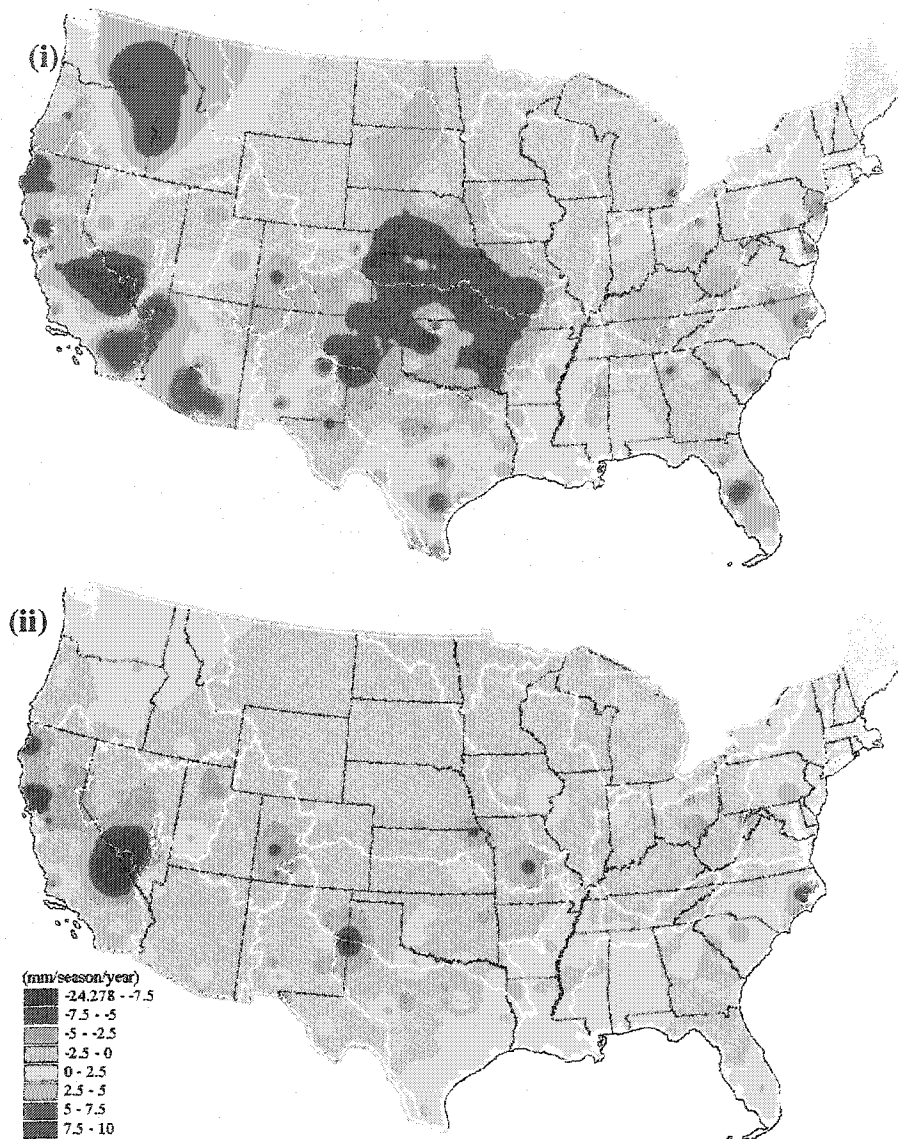


Figure 3.5: Effects of homogenization on trends derived at pans and then spatially distributed by IDW interpolation: (i) raw, unhomogenized warm-season ET_{pan} data set, and (ii) homogenized warm-season ET_{pan} data set.

Figure 3.5(i) shows the unadjusted warm-season ET_{pan} -trend data spatially interpolated across the conterminous US. This analysis shows decreasing ET_{pan} across 68% of the region, with significant exceptions in the Northwest, desert Southwest, Florida, regions around the Gulf of Mexico, and South Carolina. Trends range from -

23.664 mm/season/year to +17.021 mm/season/year, with a spatial mean of -0.802 mm/season/year and a standard deviation of 3.189 mm/season/year.

Figure 3.5(ii) shows the homogenized warm-season ET_{pan} -trend data similarly interpolated. This analysis shows ET_{pan} decreasing across 75% of the region, with significant exceptions in the Northwest, the Northeast, regions around the Gulf of Mexico, South Carolina, and southern Florida. The trends range from -24.278 mm/season/year to +5.473 mm/season/year, with a mean of -0.831 mm/season/year and standard deviation of 1.647 mm/season/year.

In comparing the spatial distribution before and after homogenization of the station-based input data, the texture of the spatial distribution remains distinctly station-oriented; probably a function of the simplicity of the IDW scheme. Beyond the texture, different parts of the country show differing effects of the homogenization procedure on the ET_{pan} -trend data. The trends across 21% of the country have changed direction (7% negative-to-positive, 14% positive-to-negative): the desert southwest and New England showed increasing trends in the raw data set, but decreasing trends in the adjusted data set. In some regions, the trends have been mitigated: the large increases in the inland Pacific Northwest and the large decrease in the High Plains have abated somewhat. In one region, the trends have intensified: in California the trends are now more intensely negative. Examining the change in the spatial statistics of the data across the complete spatial extent of the lower 48 states, the change in the mean proves negligible, but the standard deviation decreases significantly, by almost 50%. The minimum trend remained about constant, but the maximum trend has been mitigated somewhat.

Using the t -test on the point data (the population of all warm-season trends), the hypothesis that the pan-trends before and after homogenization are the same at the 95% level must be rejected (in fact, the hypothesis is accepted only at the 46% significance level), confirming that the populations are significantly different, or that the heterogeneities induced by break-points as defined above have a significant effect on the pan-trend results.

In summary, the effects of homogenizing the data set in terms of the pans themselves—the station-estimates—were far less dramatic than for the spatial distribution. In the case of the station-based estimates, the ratios of negative/positive trends were identical pre- and post-homogenization at 60/40, with 22% pans reporting a different trend-sign after homogenization, evenly split between negative-to-positive and vice-versa.

3.5.5 Confirming the Complementary Relationship

Figure 3.6 shows the relationship between ET_a and ET_p , the former derived from basin budgets (ET_a^*), and the latter from the homogenized ET_{pan} data set. ET_a^* is calculated for each basin as the difference between precipitation drawn from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) [Daly *et al.*, 1994] and runoff extracted for USGS gages at the outlets of minimally impacted basins listed in the Hydro-Climatic Data Network (HCDN) [Hydrosphere, 1996; Slack and Landwehr, 1992]. Data for a single basin-pan pair line up vertically.

In the context of trends in ET_a and ET_{pan} , Figure 3.6 may be interpreted as an ergodic-type approximation of such trends, with the response of ET to variations in precipitation

presented as a surrogate for actual temporal trends in the ET rates themselves. Each datum pair represents the paired ET rates for a single time-instance of a single basin with a given moisture availability and energy input, and the behavior that is known as the “Complementary Relationship” (described in Section 1.2.1 and Figure 1.2) is clearly visible. Figure 3.6 constitutes the first observational evidence in support of the complementary relationship hypothesis.

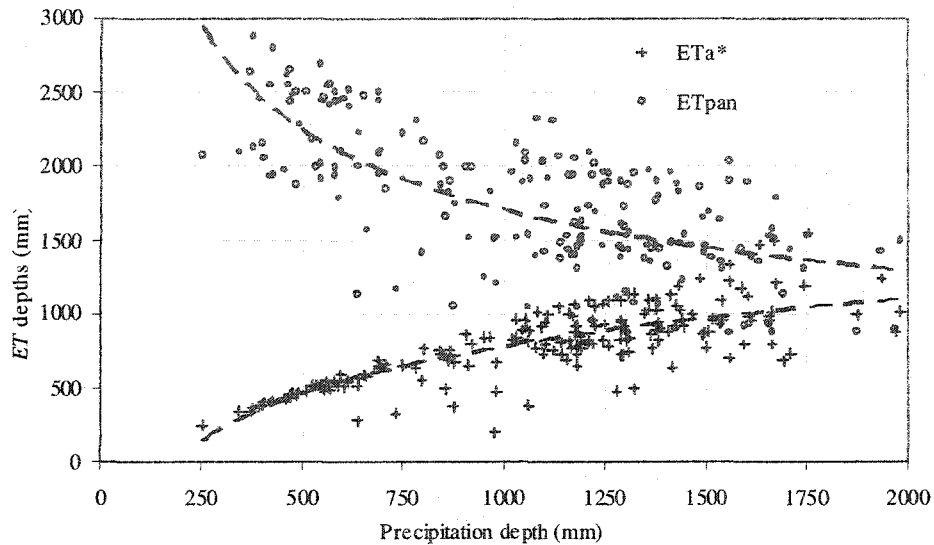


Figure 3.6: The observed complementary relationship in point annual depths of adjusted ET_{pan} and water budget-derived, basin-wide annual depths of ET_a^* for their surrounding basins.

3.6 Conclusions

Regardless of its homogeneity, using ET_{pan} data for estimation of distributed long-term trends is subject to several limitations relating to the spatial and temporal distribution of the pans and to the physical representativeness of the data themselves. First, there is a pronounced spatial and seasonal bias in the ET_{pan} record. This is evident

in Figure 3.1, which indicates that warm-season pans are located throughout much of the conterminous US, whereas annual pans are limited only to those areas where seasonal freezing of the pans is not an issue. Thus, one is limited to either a spatially limited but temporally thorough data set, or the spatially thorough but temporally limited obverse. Second, in using ET_{pan} as predictors of ET_p —and therefore of ET_a —one is exposed to the vagaries of the ambient conditions that determine ET_{pan} : many or most pans are situated in urbanized areas or where local climatological conditions are influenced by spatial heterogeneity of the upwind reach of the evaporation pan. In observing an average increase or decrease in ET_{pan} at a particular site, one may simply be observing the long-term effects of temporal changes in land-use immediately upwind of the pan, such as a change in land-use (e.g., urbanization, irrigation, or deforestation), and may therefore be inadvertently mis-diagnosing simple effects of such local changes as long-term climatological trends on a regional scale.

Complicating the development of a task-specific homogenization procedure are factors relating to the quality of the metadata, to the continuity of the data themselves, and to this study's definition of homogeneity. First, the metadata were of limited utility: they were incomplete, confusing, and often inexplicative. While they gave *a priori* indications of some heterogeneities, they only hinted at the meanings of others, and entirely ignored yet others (that were visually obvious), leading to the assumption that not all the story about the data was being told and that, in the absence of any other independent or objective information, subjectivity would have to play an important part in the analysis. Second, the ET_{pan} data themselves were drawn from incomplete time-series. Finally, this study's definition of homogeneity was unorthodox. As the eventual

aim of this study is to examine solely those trends due to regional climatic forcing that remained after operational shifts had been filtered out, an *a priori* assumption of non-stationarity had to be made that, under normal circumstances, precludes homogeneity. This meant that many standard, off-the-shelf homogeneity tests were unsuitable, as they would filter out such trends as this study aimed to examine.

Having developed and applied a guided semi-objective homogeneity test, it was necessary to adjust for homogeneity 43-55% of data, at 75% of the pans. While the assumptions inherent in the t-test—that the mean and variance of the data in the sub-periods are stationary—runs counter to the assumption of trends in the data, this source of error is conservative as trends at a given pan will tend to be under-estimated when they are derived from data thus homogenized. In a comparison of trend results for pre- and post-adjustment data across all pans some differences were noted in the details: the proportions of decreasing trends remained fairly static: annual 57% to 64%, warm-season 62% to 60%; the numbers of significant trends in the annual data dropped from 64% to 27%, and from 56% to 19% in the warm-season data. However, these differences were not together significant enough to confuse or change the conclusions of the trend analysis.

Having first observed the complementary relationship between actual and potential *ET* fluxes in a preliminary study of trends in *ET* rates conducted using un-adjusted, non-homogenized data [Hobbins *et al.*, 2003], this complementarity in the homogenized data set has here been validated, thereby confirming that this behavior is not merely an artifact of noisy, heterogeneous data.

Based on a spatial interpolation of the trend-data derived for each pan, it is worth noting how trends derived at a few stations affect the spatial distribution. This highlights the importance of homogeneous data when applying it to un-metered areas, that is, through the process of spatial interpolation, where any biases become spread across the map [Peterson *et al.*, 1998].

As rich as the temptation is, in a digital age, to interpret the world in a binary fashion—zero or one, off or on, extant or extinct—data are not to be taken at such face-value. There is much that goes into the physics, the recording, and the reporting of data that either is not itself recorded or reported, or is difficult to impossible to find. In ET_{pan} data, direct recorded evidence of heterogeneities were found (e.g., a physical shift in the pan clearly reported in the metadata), but much more often, only shadows of such events were found in the metadata (e.g., dates reported with no event associated), and mere inferences of such events (e.g., jumps in the time-series itself that are not reported in any fashion in the metadata). Thus, it is important to conclude that, over trusting the raw data completely and blindly simply by dint of its binary existence, examining the metadata comes as a very poor improvement. It is necessary further to seek potential heterogeneities that may have not been reported in the metadata but that are subjectively evident. Such a method maximizes the amount of metadata from both sources: it tests all available reported metadata and makes available subjective metadata that is not reported and, in both cases, confirms the events to which they refer on an objective statistical basis.

In summary, given additional complications of scant metadata and incomplete data time-series, and requirements that climatically driven trends not be filtered out as sources

of heterogeneity, it must be concluded that resolving understandings of both the physical dynamics and the statistical properties of the data set must be incorporated into a middle-ground approach that combines objective rigor and subjective judgment.

4. Climate Change Analysis using a Complementary Relationship Model of Regional Evapotranspiration with Advective Calibrations based on Water Budget-derived Evapotranspiration and Pan Evaporation.

4.1 Abstract

To establish a baseline for the study of the effects of climate change and/or variability on evapotranspiration, a methodology for rigorous examination of past trends in actual evapotranspiration (ET_a) is proposed within the context of the hypothesis of a complementary relationship, which allows for estimation of ET_a by simple, physically based models that account for feedbacks in land surface-atmosphere dynamics. Two different parameterizations of the wind function of the Advection-Aridity model [Brutsaert and Stricker, 1979] are used. One is calibrated such that modeled ET_a matches basin-derived evapotranspiration (ET_a^*) at 655 hydrologically undisturbed test-basins across the conterminous US; the other such that modeled potential evapotranspiration (ET_p) matches point observations of pan evaporation (ET_{pan}) across the southern US. Long-term trends in ET_a are broken down into its climatic components in the context of the complementary relationship, with no assumptions made about the temporal stationarity of either component. Both calibrations are used to model spatially distributed, monthly ET_a for a 42-year period at a 5-km resolution over the conterminous US, and both time-series are verified against ET_a^* , in 655 test-basins across the conterminous US in the case of the ET_a^* -based calibration, and in 207 southern test-basins in the case of the ET_{pan} -based calibration. The performance of the general model in estimating long-

term trends in annual ET_a and its observed components is verified across the gamut of spatial scales.

4.2 Introduction

In the face of climatic change and variability, water resource-managers need to examine and, perforce, model an uncertain hydrologic cycle; a cycle in which ET_a —being subject to the gamut of meteorological dynamics, from wind speed, temperature, humidity, and air pressure to insolation—is perhaps the most variable and sensitive to climatic change, yet remains the most difficult to model.

The dearth of direct analysis of ET_a is primarily due to the difficulties inherent in calculating ET_a and the complications of scale; of trend analyses of ET_a (as opposed to ET_p), there are almost none. Understanding of the processes at the basin-wide or regional scale necessary for use by hydrologists and climate and ecological modelers is limited, and the ability to estimate regional ET_a has largely been constrained by traditional paradigms that rely on dubious assumptions about the nature of moisture dynamics in the soil, vegetative, and atmospheric components of the land surface-atmosphere interface, whereby most models treat ET_p as an independent climatic forcing process and derive ET_a estimates through non-physical, locally parameterized relationships thereof [e.g., Morton, 1983]. ET_a is often modeled either as a simple, often empirical function of ET_{pan} observed at nearby weather stations, or by ground-based models that tend to rely on the gross simplifications mentioned.

These difficulties point to the need for models of regional ET_a that consider the evaporative system as an integrated whole, that bypass the poorly understood dynamics

within each component, and that incur minimal data requirements about the nature of the land surface. Such a regional ET_a model must fulfill various criteria. As regards formulation, it must be physically based and spatially distributed (or at least lumped at a scale close to the physical limitations of the hypothesized dynamics), well-calibrated with a near-zero mean error and no bias with respect to its input data, and independent of assumptions of stationarity in other components of the hydrologic cycle. As regards its applicability, it must operate over a wide range of climates, especially in regions where there are little or no direct observational data and in varied and often extreme topographies, and at a range of spatial scales and over time-periods useful to water managers. Complementary relationship models are such models.

Past research [Hobbins *et al.* 2001a, 2001b; Sugita *et al.*, 2001] has shown that the proper and accurate parameterization of the advective component is the *sine qua non* of any physically based ET model. This component is encoded as the drying power of the air (E_A), which is generally calculated by multiplying some measure of the air's humidity by a wind function ($f(U_2)$) that describes the variation of vapor transfer of the air as a function of wind speed (U_2). While there exists a theoretical expression for $f(U_2)$, it is too cumbersome to be of practical utility in the estimation of ET_a on a regional scale. Thus, every study since the seminal work on the calibration of pan evaporimeters by Penman [1948] has selected from existing parameterizations or developed new ones. The parameterization choices are generally predicated on, for example, how such factors as the temporal resolution of modeling and consequent assumptions on vertical stability at small scales [Katul and Parlange, 1992; Parlange and Katul, 1992a; Parlange and Katul, 1992b] or at large scales [Sugita *et al.*, 2001] coincide with modeling goals, or on the

data availability and quality [Kohler and Parmele, 1967; Morton, 1983]. The purposes of this study require a parameterization of $f(U_2)$ that can be spatially distributed and that will yield regional ET_a estimates over the entire conterminous US. This requirement and the types of data available over the temporal and spatial extent of the study suggest the following two $f(U_2)$ -parameterization options:

- (i) An ET_a^* -based parameterization that matches modeled ET_a to ET_a^* observed at hydrologically undisturbed basins, which has been previously attempted with some success by Hobbins *et al.* [2001b], but on a limited temporal extent, using fewer basins to calibrate to, and without the intention of using the resulting ET_a data set to examine secular trends.
- (ii) An ET_{pan} -derived parameterization that matches the ET_p component of the complementary relationship to ET_{pan} observations. Here, ET_a is described as a function of ET_{pan} again, but in the context of a complementary relationship.

Both of these approaches have their advantages—spatial and temporal extents and data availability, in particular—and both incur the expense of physical assumptions that constrain their applicability. The development of these two parameterizations of $f(U_2)$ by both methods (i) and (ii) is described in this chapter, and their application examined with regard to both the development of, and secular trends in, an ET_a time-series.

Recognizing the need to generate ET_a data and ET_a -trend data across un-metered regions, the use of a complementary relationship model that requires no ground-based data is combined with $f(U_2)$ parameterized from observations gathered from all over the conterminous US. Thus, spatially distributed input fields are derived at a spatial

resolution as close to the smallest physically defensible (as close to the smallest extent at which complementary relationship dynamics operate as possible) that computational power limitations will allow. As the analysis is not limited to stations, trends in modeled ET_a may be represented at any spatial breakdown desired.

This chapter of the dissertation, then, offers a complementary relationship model for use as a tool for a baseline study of the effects of climate change and variability and presents the findings of a study of long-term trends in ET_a across the conterminous US. A summary of the recent work of others in this field yields a framework that motivates the study, which then addresses the demand for analyses of the various effects of trends in the components of ET_a [Ohmura and Wild, 2002]—the energy flux and the advective flux—on trends in ET_a , avoiding any assumptions of stationarity in either component of ET_a that have bedeviled past trend analyses.

The hypothesis of the complementary relationship is summarized, with particular attention paid to the role of advection in the evaporative process and its specific conception with the framework of the complementary relationship. In an examination of trends in both basin-derived actual ET (ET_a^*) and pan-derived potential ET (ET_{pan}), and in their component fluxes, it is shown that observed trends in ET_a^* are only explicable in the context of the complementary relationship. Trends in input variables are examined as to their spatial distributions, especially as they support or refute the complementary relationship hypothesis and the work of others.

Observations of ET_a^* and ET_{pan} are used to parameterize two versions of one of the most common complementary relationship models—the Advection-Aridity approach first proposed by Brutsaert and Stricker [1979]—and two parameter sets for the problematic

$f(U_2)$ factor of the advective component are developed; one that is basin-based, the other that is pan-based. Using each version, monthly 42-year time-series of ET_a are produced at a 5-km resolution over the conterminous US. The performances of these two parameterizations in replicating observed ET_a^* at a large suite of test-basins across the conterminous US are verified and compared. The modeled ET_a data sets are then used to estimate long-term trends in ET_a at a variety of spatial scales: over the whole conterminous US, for Water Resource Regions (WRRs), Accounting Units (AUs). Finally, suggestions are offered as to how best to combine the information contained in both parameter sets to improve the ET_a model performance.

4.3 Recent Research into Trends in Evapotranspiration

As stated in Section 1.2.5, there has until recently been a dearth of studies of trends in ET_a , and when ET in any form has been studied, it has not been ET_a at a regional scale. Recently, however, more attention has been paid to the estimation of trends in ET_a : *Brutsaert and Parlange* [1998] briefly outline a resolution of the so-called “Pan Evaporation Paradox” in favor of the complementary relationship hypothesis; *Szilagyi* [2001] and *Szilagyi et al.* [2001] and *Roderick and Farquhar* [2002] go so far as to use observations to examine the role that the complementary relationship plays in such trends in ET_a and its components; and *Ohmura and Wild* [2002] suggest avenues for further research. These studies have been described in Section 1.2.5; here their results and conclusions are examined only as they provoke the work in this study.

4.3.1 Brutsaert and Parlange [1998]

Brutsaert and Parlange [1998] state that ET_{pan} is globally observed to be decreasing, counter to predictions of increased ET_a by GCMs and concurrent with increasing precipitation and cloudiness: evidence of an apparent “pan evaporation paradox.” In a heuristic fashion, they argue that talk of such a paradox, results from misapprehension of ET_{pan} as an indicator of climate change. They outline the hypothesis of a complementary relationship between regional ET_a and ET_p as an explanation for this paradox, but do so without referring to any data or observations specifically—this study fills that gap by rendering this hypothesized complementarity an observational fact.

4.3.2 Szilagyi [2001] and Szilagyi et al. [2001]

Other than those of the author, the first attempts to determine large scale trends in ET_a in the context of the complementary relationship were published by *Szilagyi* [2001] and *Szilagyi et al.* [2001], who estimated long-term trends in regional ET_a across the conterminous US using a complementary relationship model, with long-term ET_{pan} observations as predictors of ET_p .

Szilagyi et al. [2001] noted a 6% increase in warm-season (MJJASO) ET_a (derived from warm-season ET_{pan}) over the period 1948-1996, in conjunction with an 11% increase in precipitation. They examined the causes of such trends with regard to the determining climatological input variables—temperature and humidity as indicated by the vapor pressure deficit (V_{dif})—and generated ET_a^* estimates for six large-scale basins (covering ~50% of the land area of the conterminous US), whereupon they observed an increase in ET_a^* over the same period, but only to the tune of 3%. *Szilagyi et al.* [2001]

assume that there is no long-term trend in Q_N , and that therefore, changes must come from changes in E_A , which is to say either V_{dif} or U_2 (see Chapter 1). They conclude that the complementary relationship over-estimates increases in ET_a over the period, but they do not examine the effect of their assumption of no long-term change in Q_N , which could negate this apparent error. The reasons for making such a far-reaching assumption are not clear: while the paper acknowledges an increase in cloudiness over the same time-period, it does not then conclude that this *must* affect the energy available at the ground surface for evaporation and therefore decrease—in the case of increasing cloudiness—all evaporative measures: ET_w , ET_p and ET_a . Indeed, they go on to conclude that, while there has been a significant increase in predicted ET_a (to coincide with the observed increase in precipitation), there has been no increase in V_{dif} . Thus there must be either a decrease in U_2 or a *decrease* in cloudiness, counter to their acknowledgement of increasing cloudiness. However, the available data are never examined to support or refute their claim. As they imply, this methodological assumption may explain the difference between their watershed-based and complementary relationship-based ET_a -trend estimates, leading their application of the complementary relationship to over-estimate such trends. The study described in this dissertation improves upon the methodologies of Szilagyi [2001] and Szilagyi *et al.* [2001], as such trends in all components of the ET_a expression are examined— V_{dif} , U_2 , and Q_N .

That estimates of ET_a^* -trends derived by Szilagyi [2001] and Szilagyi *et al.* [2001] apparently support their conclusions that the complementary relationship over-estimates ET_a -trends must be regarded with some skepticism in the light of their choice of basins. Regions at the climatic extremes are not represented—none are in the arid southwest or

the hyper-humid northwest. Further, they compare point estimates of ET_a -trends with areal estimates of ET_a^* -trends derived by averaging approximately half of the conterminous US into the six basin-estimates.

In comparing the ET_{pan} data with meteorological data gathered at the nearest SAMSON stations, *Szilagyi et al.* [2001] run afoul of the spatial disjoint between the pans and the climatological stations. *Hobbins* [2000] and *Hobbins et al.* [2001b] examined the use of long-term point ET_{pan} data to interpolate for a surface of ET_p , but found that the ET_{pan} stations were, in general, significantly removed from the stations (SAMSON) recording the aerological conditions; a mean difference of over 1000 m was reported; potentially distance enough to contravene the assumption that the meteorological stations record data that reflect the driving atmospheric dynamics at the pans. Further, their use of ET_{pan} as a proxy for ET_p or as a predictor of ET_a involves a correspondence that is flawed by methodological constraints [*Hobbins et al.*, 2001b]. These constraints include the vagaries of the ambient conditions that determine ET_{pan} , wherein many or most pans are situated in urbanized areas or where local climatological conditions are anthropogenically influenced. In the light of these issues, one must conclude that an observed trend in ET_{pan} at a particular site may lead one to mis-diagnose the simple effects of local changes—urbanization, irrigation, or deforestation, for example—as long-term climatological trends on a regional scale.

While *Szilagyi et al.* [2001] represents a good starting paper, the methodologies and restricted assumptions in this study represent significant improvements. First, in choosing the NCDC data set from which to draw their data, *Szilagyi et al.* [2001] were unable to generate a complete record of data: the period 1965-1983 was missing from their record,

and U_2 data were missing before that. The study described in this dissertation suffers no such gaps in the record, using complete records for all of the climatologic and hydrologic variables from 1953 to 1994. Second, in this study, surfaces of input variables are generated at every pixel for the entire conterminous US, through spatial interpolation from many more stations. This distributed technique permits the examination of regional sensitivities to climate change and variability at any spatial breakdown: WRRs, states, climatic divisions, specific watersheds or physiographic regions, down to the single pixel. This represents an improvement over generating continental-scale averages from spatially biased point values, as in *Szilagyi et al.* [2001], and avoids the problem of the spatial disjoint between pans and the meteorological stations.

4.3.3 Roderick and Farquhar [2002]

Roderick and Farquhar [2002] observe a different expression of the “pan evaporation paradox” by noting that rising global mean temperature is matched by counterintuitively decreasing ET_{pan} , and they examine two possible resolutions of the paradox: first through the complementary relationship in ET , and second through a decrease in irradiance at the earth’s surface, due to increasing pollution, leading to a less vigorous hydrologic cycle. They state that the complementary relationship explanation is unsatisfactory for the following two reasons: that ET_{pan} in non-water limiting environments is also decreasing, that is, ET_{pan} and ET_a are decreasing, and that V_{dif} across the conterminous US has remained constant over the last 50 years.

In response to their first reason for negating the effects of the complementary relationship, one must note that while the complementary relationship dynamic may be

hypothesized to hold everywhere; it is only in water-limited environments that it is obvious. In fact, as will be shown in Sections 4.5 and 5.5, this observation of decreasing ET_{pan} and decreasing ET_a supports their observation of decreasing irradiance without contravening the complementary relationship hypothesis. Their second reason for discounting the complementary relationship—and their central tenet—hinges on two observations: (1) that V_{dif} across the conterminous US has remained constant over the last 50 years: an observation examined (and refuted) in Section 4.5. and (2) a decrease in global solar irradiance R_G in northwestern Russia (they estimate $R_G \approx 1.25Q_N$) of 2-4%/decade, or δR_G of $-315 \text{ MJ/m}^2/\text{year}$, which is the evaporative equivalent of δET_{pan} of -90 to -155 mm/year (the range results from the range in values of Δ , which is temperature-dependent), which brackets the mean decrease in annual ET_{pan} of 110 mm observed at seven pans in the region. These observations lead *Roderick and Farquhar* [2002] to conclude that trends in ET_{pan} are due solely to trends in Q_N , and not to trends in E_A , and that the complementary relationship is therefore not an important dynamic in determining trends in ET_{pan} or, by extension, in ET_a . This is in marked contrast to *Szilagyi et al.* [2001] who, as shown above, assume exactly the opposite: that there are no trends in Q_N , and that trends in ET_a are due solely to trends in E_A .

The results and conclusions reported by *Szilagyi* [2001], *Szilagyi et al.* [2001], and *Roderick and Farquhar* [2002] immediately provoke the following questions: is a significant trend in Q_N observed across the conterminous US, contrary to *Szilagyi et al.* [2001] but in support of *Roderick and Farquhar* [2002]; is a significant trend in E_A observed, contrary to *Roderick and Farquhar* [2002]; are observed trends in Q_N and E_A ,

when considered together and spatially concurrent, contradictory to or supportive of observed trends in ET_{pan} and ET_a^* in the US and, if so, how so?

4.3.4 Ohmura and Wild [2002]

Perhaps in an attempt to force the science to resolve these contradictory assumptions and explanations for the “pan evaporation paradox,” *Ohmura and Wild* [2002] editorialize in the journal *Science* that it is the trend in ET_a that is important, and that ET_{pan} evaporation is only relevant if it offers clues as to the direction of trends in ET_a . They further raise two important issues that are addressed as specifically as possible in this dissertation. First, they state:

“that the direction of the evaporation trend is not determined by temperature alone. That a warmer atmosphere does not necessarily produce more evaporation can be seen in the fact that hemispheric evaporation is much more substantial in winter than in summer under the present climate.”

Second, they call for an examination of ET_a in the context of both its radiative and advective components:

“The diurnal temperature range (DTR) must be separated into two components: one due to the 24-hour periodicity and the other due to the non-24-hour variation. The former represents the effect of the diurnal cycle in radiation; the latter indicates the strength in advection. This treatment makes it possible to determine to what extent the trend in

evaporation is due to changes in radiation fields or in the strength of advection.”

It is the latter suggestion that is addressed herein (the T data are at a temporal resolution insufficient to examine DTR).

4.3.5 Ozdogan and Salvucci [2004]

In a study of the long-term effects on ET rates of regional scale land-use change in a semi-arid region, *Ozdogan and Salvucci* [2004] find that a 23-year, ten-fold increase in irrigated agriculture coincided with a decrease in ET_p modeled from the Advection-Aridity model and observed warm-season ET_{pan} , from 14 mm/day to 7 mm/day. From a sensitivity analysis of the effects of Q_N , air temperature, E_A , V_{dif} , and U_2 on trends in modeled ET_p they conclude that δET_p is not sensitive to δQ_N but is sensitive to δE_A and that, further decomposing the trends, U_2 is more powerful in its effects on ET_p than is V_{dif} . They ascribe the former weak dependence to the complex interplay of relationships in the surface energy budget, wherein negative feedbacks abound and mediate trends in ET_a ; for example, increasing regional ET_a leads to increased cloudiness, which drives down R_G , which then drives down the energy available at the surface, reducing the energy available for ET_a .

On the other hand, energy budget considerations indicate a route for the strong dependence of δET_p (and hence δET_a) on δU_2 : *Ozdogan and Salvucci* [2004] cite work by *Alpert and Mandel* [1986], who found that the decreasing albedo and increasing roughness accompanying reverse-desertification (i.e., irrigation in hyper-arid/arid areas) lead to a decrease in sensible heating due to a partitioning of Q_N in favor of latent heat

flux. This in turn leads to lower differential heating which itself leads to gross effects on air circulation. *Alpert and Mandel* [1986] found that a combination of albedo decreases and roughness increases following intense irrigation development in a hyper-arid area of Israel led to a lower variability in wind speed.

The direct effect of U_2 is to modify eddy diffusivity: increasing U_2 leads to increasing eddy diffusivity, and increasing turbulence, which, all else equal, increase ET_p and lead to a complementary decrease in ET_a . *Ozdogan and Salvucci* [2004] suggest four further reasons to explain the strong correlation of δU_2 and δET_p : first, the oasis effect, wherein irrigation affects local wind circulation in both magnitude and direction; second, and akin to the findings of *Alpert and Mandel* [1986], that the growth of irrigated crops results in increased surface roughness over large distances; third, that their wind speed instrumentation is affected by local shielding, either by crop growth or by trees planted specifically to reduce wind speeds over the crops; and fourth, that wind speed is decreasing due to climatological factors acting on a regional or supra-regional scale unrelated to local ET_a changes.

Ongoing work by *Ozdogan and Salvucci* will, when published, report on modeling of their observations with a mesoscale model that incorporates instability considerations. Their new results will highlight the extent to which the complementarity of ET rates depends on changes in wind speed and will indicate a high pressure anomaly that significantly slows the prevailing winds over the study area [*Salvucci*, personal communication, 2004].

4.4 Advection and the Complementary Relationship

4.4.1 The Complementary Relationship

The theory of the complementary relationship in regional evapotranspiration, first proposed by *Bouchet* [1963], considers ET_p to be a function of feedback processes between limitations of water availability at the land surface and the evaporative power of the overlying atmosphere. This allows regional ET_a to be modeled using only data that describe the conditions of the over-passing air; no locally optimized coefficients are necessary. The approach thereby avoids the difficulties inherent in coupling surface and free atmosphere phenomena in the soil-plant-atmosphere system. The utility and scientific merits of complementary relationship models have been shown by numerous studies [*Morton*, 1965, 1975, 1976, 1978, 1979, 1983; *Brutsaert and Stricker*, 1979; *Hobbins et al.*, 1999, 2001a, 2001b].

The hypothesis of a complementary relationship states that in homogeneous regions—over areas of a regional scale away from any sharp environmental discontinuities, where moisture availability is spatially uniform, and where assumptions of a well-mixed atmospheric boundary layer and negligible upwind edge-effects hold well—there exists a feedback mechanism between actual and potential ET rates. Under these conditions, all the energy at the surface that, due to limited water availability or soil moisture, is not taken up in the process of ET_a (q_1) increases the temperature and humidity gradients of the over-passing air and leads to an increase in ET_p (q_2) equal in magnitude to the decrease in ET_a .

$$q_1 = q_2 \tag{4.1}$$

In conditions where ET_a equals ET_p , this rate is referred to as the wet environment evaporation (ET_w). The complementary relationship is illustrated by Figure 4.1 and described by:

$$ET_a + ET_p = 2ET_w. \quad (4.2)$$

Under traditional paradigms, this equality (4.1) does not hold, and instead ET_p is held to be independent of soil moisture conditions; while ET_a falls below ET_p , ET_p does not rise above ET_w .

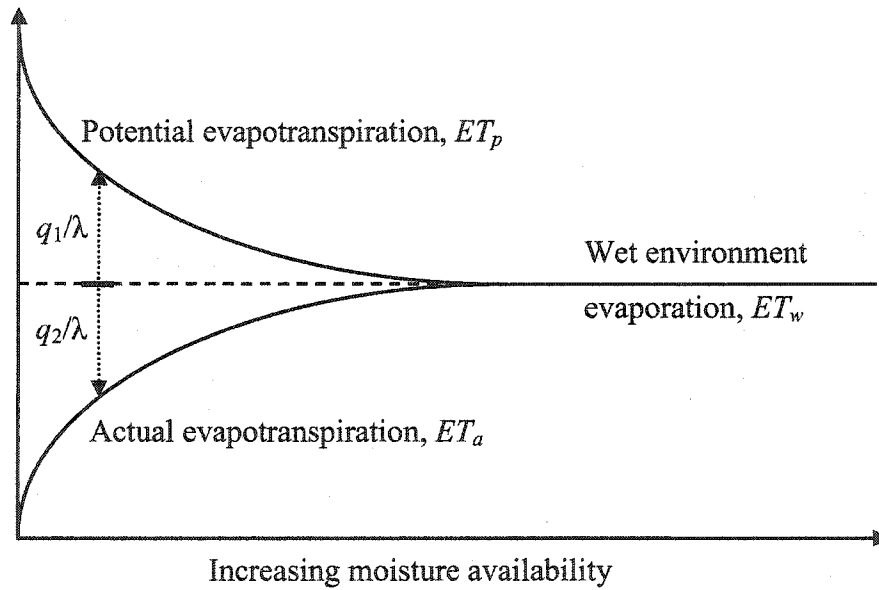


Figure 4.1: Schematic representation of the complementary relationship in regional evapotranspiration.

In this study, using independent observations of ET_{pan} and ET_a^* , which represent ET_p and ET_a , respectively, the first empirical evidence for the complementary relationship hypothesis is provided (see Chapter 5).

4.4.2 The Advection-Aridity Model

The most widely used models of the complementary relationship are those based on the Advection-Aridity approach first proposed by *Brutsaert and Stricker* [1979] and described in detail there and in *Hobbins et al.* [2001b]. It is this approach that forms the basis of all modeling in this study; it is summarized here as it elucidates the conceptual basis of the complementary relationship.

The Advection-Aridity approach combines the effects of regional advection on ET_p with the hypothesis of a complementary relationship between ET_p and ET_a . In this model, ET_w is calculated based on derivations of the concept of equilibrium evapotranspiration under conditions of minimal advection, first proposed by *Priestley and Taylor* [1972], and shown in Equation (4.3), and ET_p is calculated by combining information from the energy budget and water vapor transfer in the Penman equation (4.4). ET_a is then calculated as a residual of Equation (4.2). The *Priestley and Taylor* [1972] equation is:

$$\lambda ET_w = \alpha_{PT} \frac{\Delta}{\Delta + \gamma} Q_N \quad (4.3)$$

where λ represents the latent heat of vaporization, Δ is the slope of the saturated vapor pressure curve at air temperature, and γ is the psychrometric constant. The value of the Priestley-Taylor coefficient α_{PT} has been studied in various land-cover types and at a range of temporal scales [*Priestley and Taylor*, 1972; *McNaughton and Black*, 1973; *DeBruin and Keijman*, 1979; *Morton*, 1983]. Recognizing the variability in estimates for this empirical parameter, its calibration was the focus of much of the work in *Hobbins et al.* [2001b], and the value obtained therein ($\alpha_{PT} = 1.3177$) was used in this study.

The familiar expression of the Penman equation for ET_p is:

$$\lambda ET_p = \frac{\Delta}{\Delta + \gamma} Q_N + \lambda \frac{\gamma}{\Delta + \gamma} E_A. \quad (4.4)$$

The second term of this combination approach represents the effects of large-scale advection in the transfer of water vapor, and takes the form of a scaled factor of an aerodynamic vapor transfer term E_A , also known as the “regional drying power of the air.”

It is important to note that it is in the conception of the advective component E_A that the distinction between ET_a -estimation methods based on the complementary relationship and those on traditional paradigms lies. Traditional paradigms consider the over-passing air divorced from the surface and therefore conceive of the E_A term to be independent of ET_a : a higher E_A term indicates that ET_a from areas upwind is lower, and vice-versa. However, in the complementary relationship, the E_A term depends on ET_a . Under this proper treatment of regional-scale advection, the E_A term then reflects the effects of regional advection on ET_a after the evaporating surface has been brought into equilibrium with the over-passing air by the feedbacks across regional-scale land-surface atmosphere interfaces encoded in the complementary relationship. In the complementary relationship hypothesis, then, the drying power of the air over a region is greater when there has been less evaporation into the air (due to a regional drying trend) and the boundary layer has been well-mixed, and decreased when regional ET_a is increased (due to regional wetting).

In either conception, however, E_A is a product of the vapor pressure deficit (V_{dif} or $e_a^* - e_a$) and a “wind function” of the speed of the advected air $f(U_r)$, of the form:

$$E_A = f(U_r)(e_a^* - e_a). \quad (4.5)$$

In Equation (4.5), U_r represents the wind speed observed at r meters above the evaporating surface, and e_a^* and e_a are the saturation vapor pressure and the actual vapor

pressure of the air at r meters above the surface, respectively. The calibration of $f(U_r)$ is described in Section 4.4.4.

Combining the expressions for E_A (4.5), ET_p (4.4), and ET_w (4.3) in the expression of the complementary relationship (4.2) yields the following expression for ET_a :

$$\lambda ET_a = (2\alpha - 1) \frac{\Delta}{\Delta + \gamma} Q_N - \lambda \frac{\gamma}{\Delta + \gamma} f(U_r) (e_a^* - e_a) \quad (4.6)$$

where the two driving dynamics behind ET_a are now clear: the first term on the right represents the influence of the energy budget; the second term the local wetness. It is these dynamics and their effects on trends in ET_a that form much of the subject matter of this chapter of the dissertation.

4.4.3 Data Sources

This section describes the sources of data used to estimate trends in ET_a^* and ET_{pan} (Section 4.5.2), to divide them up into their components (Section 4.6.2), and to calibrate (Section 4.4.4) and run (Section 4.6) the Advection-Aridity model of ET_a . As they are all the same data sources, they are all discussed here for convenience. The relevant data networks are shown in Figure 4.2.

4.4.3.1 Basin-derived Evapotranspiration ET_a^*

The basin-derived estimate of ET_a^* is used to perform the ET_a^* -based calibration (Section 4.4.4.1), to estimate trends in ET_a^* (Section 4.5), and to verify the performance of both the ET_a^* -based and ET_{pan} -based calibrations of ET_a (Section 4.6).

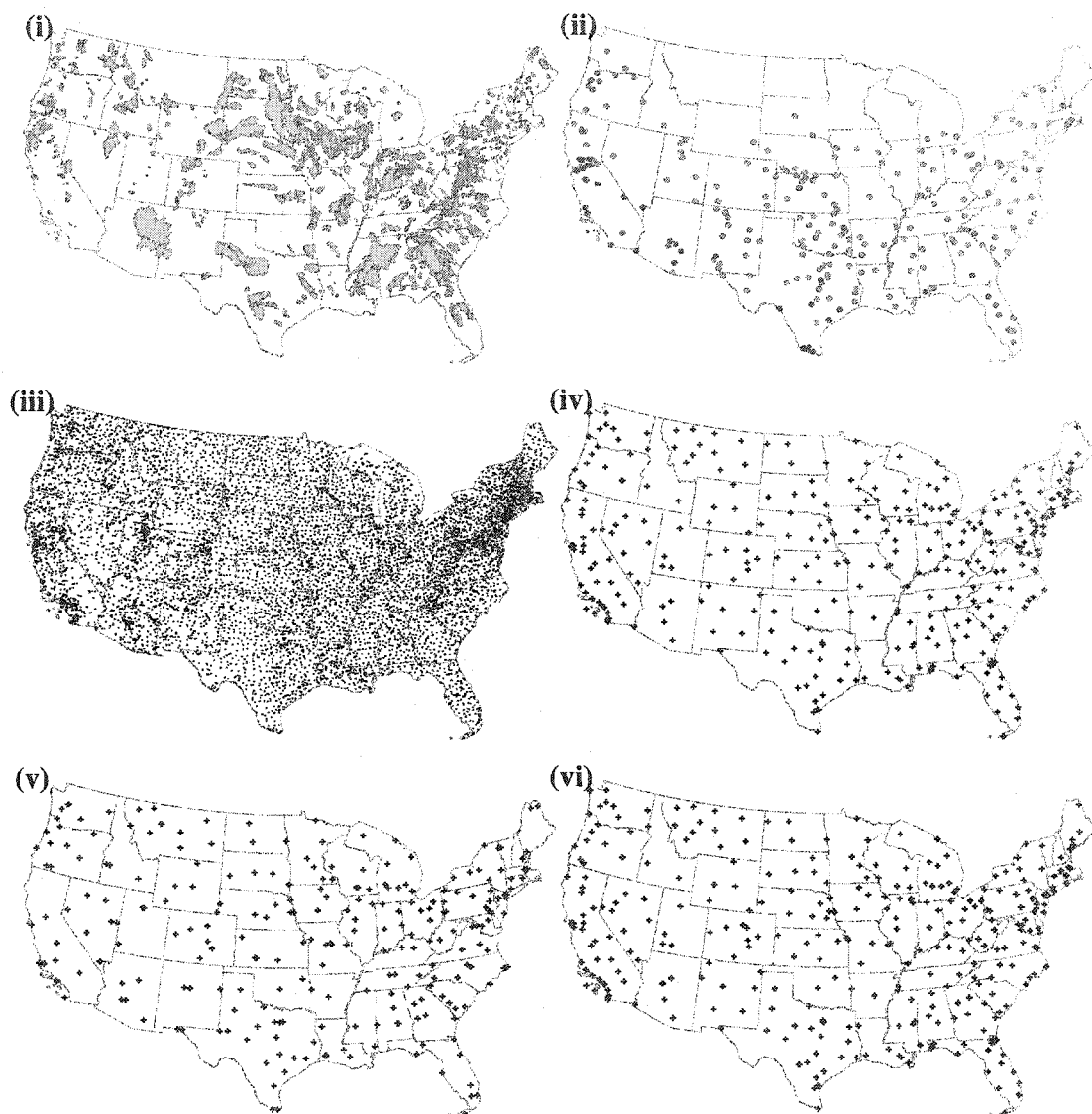


Figure 4.2: Data networks across the conterminous US. (i) shows locations of the 655 test-basins used to develop ET_a^* estimates. (ii) shows locations of pans used to develop ET_{pan} data (blue circles represent annual stations, red circles represent warm-season stations). (iii) to (vi) show locations of stations used for the following Advection-Aridity model inputs: (iii) temperature; (iv) humidity; (v) solar radiation, and (vi) wind speed.

Observed ET_a^* time-series were derived for WY 1953-1994 as annual precipitation less annual streamflow annual ET_a^* data for 655 hydrologically undisturbed basins across the continental US (see Figure 4.2(i)), constituting 1.5×10^6 km² or 19.4% of the conterminous US. This is done in the manner of *Eagleson* [1978], by expressing the natural water balance at a basin-scale as:

$$R_s + R_g = P - ET_a^* - \Delta S_s - \Delta S_g \quad (4.7)$$

where R represents flows from the basin, P represents the precipitation input, ΔS represents changes in storage, and the subscripts s and g indicate dynamics in the surface and groundwater domains, respectively. Assuming stationarity conditions for the climatic forcing, the long-term (i.e., climatological), large-scale water balance for an undisturbed basin should lead to negligible net changes in overall basin moisture storage. For a control volume including the ground surface and transpiring canopy and extending to the groundwater aquifer, the long-term, steady-state, water balance can be expressed as:

$$ET_a^* = P - R \quad (4.8)$$

which yields the estimate of ET_a^* , where R , the basin yield, now includes contributions from both surface R_s and groundwater R_g flow, and is estimated by the observed streamflow.

The precipitation data were drawn from the “Parameter-elevation Regressions on Independent Slopes Model (PRISM)” [*Daly et al.*, 1994]. This data set combines climatological and statistical concepts in an objective precipitation interpolation model, and currently contains data at a grid-cell size of 4 km and a monthly time-step for the period 1940–1999. PRISM was selected as it yielded better results (i.e., lower cross-validation bias and absolute error) than kriging techniques [*Daly et al.*, 1994], and was

assumed to be the best available estimate of precipitation fields, particularly over the complex terrain that dominates large portions of the western US. The streamflow data were extracted for USGS gages listed in the “Hydro-Climatic Data Network (HCDN)” [Hydrosphere, 1996; Slack and Landwehr, 1992], which was created to facilitate studies of surface water hydrology. The data set contains only those basins with little or no anthropogenic influence, and contains data for 1,659 gauging stations. Digitized basin boundaries corresponding exactly to the areas draining to the HCDN gages were made available by the NWS and were used to extract data from the PRISM (precipitation) and Advection-Aridity model output and intermediate surfaces.

4.4.3.2 Pan Evaporation ET_{pan}

The ET_{pan} data were drawn from daily and monthly pan evaporation data recorded at 228 pans in the NCDC Summary of the Day [EarthInfo, 1998a; NCDC, 2004a] and NCDC Summary of the Month [NCDC, 2004b] data sets, respectively (see Figure 4.2(ii)). Limiting analyses to pans that reported at least 20 complete years or warm seasons (MJJASO) within the period 1953-1994 produced sets of 12396 monthly data at 43 pans from which the annual trends were derived; and of 72660 data from 228 pans for the warm-season trends, where a datum is a single year’s or season’s observation at a single pan. The data were homogenized to account for abrupt shifts in ET_{pan} measurements resulting from changes in pan-location or type, or other changes that could otherwise artificially bias the results [Peterson *et al.*, 1998]. For each ET_{pan} time-series, a homogeneity analysis was performed to detect abrupt changes across the entire period of record as indicated by the metadata [NCDC, 2004d] accompanying the raw data or by

statistical tests (i.e., t -test and double-mass curve analyses) indicating statistically significant abrupt shifts at the 95% level. The time-series of 164 pans were homogenized around 228 abrupt data-shifts. In this manner 49% of the annual data and 61% of the warm-season monthly data were homogenized. This homogenization process is discussed in detail in Chapter 3.

4.4.3.3 Modeled Actual Evapotranspiration ET_a

To produce a spatially distributed ET_a time-series, the model requires input data on solar radiation, wind speed, average temperature, humidity, albedo, and elevation (see Figure 4.2(iii)). Solar radiation data were drawn from 258 stations in the “Solar and Meteorological Surface Observation Network (SAMSON)” [NOAA, 1993], SOLMET [NCDC, 2001], and “NCDC Airways Solar Radiation” [EarthInfo, 1998b] databases. The development of the solar radiation input for the derivation of Q_N is described in detail in Chapter 2 and in Hobbins *et al.* [2004b]; in summary, it is derived from the sum of diffuse radiation and direct radiation seasonally corrected for the effects of local slope and aspect. Solar radiation surfaces were interpolated using the the inverse distance-weighted (IDW) method described in Hobbins [2000]. Wind speed data were drawn from 568 stations in the SAMSON [NOAA, 1993] and “NCDC Surface Airways” [EarthInfo, 1998b; NCDC, 2004c] databases. Most wind speed surfaces were interpolated using IDW, with ordinary kriging preferred for those WRRs and months where it proved possible. Average temperature was estimated as the mean of the average monthly maximum and average monthly minimum temperatures drawn from 9271 stations in the “NCDC Summary of the Day” [EarthInfo, 1998a; NCDC, 2004a] database. Temperature

surfaces were interpolated by ordinary kriging of the station data, with the semivariogram choice optimized according to the characteristic distance method explained in *Hobbins* [2000]. Humidity data were drawn from 324 stations in the SAMSON [NOAA, 1993] and “NCDC Surface Airways” [*EarthInfo*, 1998b; NCDC, 2004c] databases in the form of dew-point temperatures. Humidity surfaces were interpolated using ordinary kriging. Average monthly albedo surfaces based on Advanced Very High Resolution Radiometer (AVHRR) data were taken from *Gutman* [1988]. The elevation data were extracted from a 30-arc-second DEM.

While it would be instructive to examine trends in ET_a modeled at stations, the input data networks are so different in their spatial distributions and temporal coverages as to render such a station-based estimation impossible. Instead a distributed approach was adopted here, and the selected spatial resolution was based on a balance of computational burden and a desire to examine trends at the smallest scale at which the complementary relationship is assumed to hold (*Bouchet* [1963] specifies scale-lengths on the order of hundreds of meters). Thus, surfaces of the input variables (temperature, humidity, solar radiation, and wind speed), intermediate variables (Q_N and E_A), and output variables (ET_a) were generated either by applying spatial interpolation techniques to the point observations of the input variables or running the model at each pixel in the case of the intermediate and output variables. All spatial interpolation and analyses were conducted at a 5-km cell size (that of the DEM after its transformation to the Albers Equal Area projection used for the GIS-based analysis) for the conterminous US on a monthly basis over the period WY 1953-1994. The spatial interpolation procedures used are detailed in *Hobbins et al.* [2001a]. It should be noted that variables with a high degree of spatial

variability but recorded at sparse networks (e.g., wind speed) are necessarily going to be less well predicted by spatial interpolation than variables with a high degree of spatial variability recorded at dense networks (e.g., average temperature) and variables with lower spatial variability recorded at sparse networks (e.g., solar radiation).

The distributed ET_a surfaces resulting from the application of the model to the spatially interpolated input surfaces permit the examination of trends in ET_a across a wide range of scales, from continental down to the scale-length imposed by the physics of the process (on the order of hundreds of meters [Bouchet, 1963]). Further, the component fluxes—the radiative flux and the regional advective flux—could be examined for trends, thereby avoiding the simplifying assumptions of stationarity in one or other component of ET_a ; assumptions that will be shown to have led previous workers to questionable conclusions [Szilagyi, 2001; Szilagyi et al., 2001; Roderick and Farquhar, 2002].

4.4.4 The Wind Function and its Calibration

The wind function $f(U_r)$ is either theoretically or empirically derived. Brutsaert and Stricker [1979] suggested the following theoretical expression for the wind function under neutral—i.e., a stable atmospheric boundary layer—conditions:

$$f(U_r) = \frac{\psi a_v k_{vK}^2 U_r}{R_d T \ln[(z_2 - d_0)/z_{0v}] \ln[(z_r - d_0)/z_{0m}]} \quad (4.9)$$

In Equation (4.9), ψ is the ratio of the gas constant of dry air R_d to that of water vapor R_v , a_v is the ratio of the eddy diffusivity to the eddy viscosity under neutral conditions, k_{vK} is the von Kármán constant, z_{0m} and z_{0v} are the roughness lengths for momentum and water vapor, respectively, T is the air temperature in K, z_2 is the height at which e_a is

measured, d_0 is the displacement height, and z_r is the height of the wind speed measurement.

However, in the context of modeling monthly regional ET_a with the complementary relationship, the confounding effects of atmospheric instability acting over short time-periods and the onerous data requirements rule out such theoretical formulations. Much other work has been done in the agricultural arena to calibrate or reformulate the proposed wind function for use in the combination or Penman equation (e.g., *Allen* [1986], *Van Bavel* [1966], *Wright* [1982]). These agriculturally oriented formulations operate on limited spatial and temporal scales, do not hypothesize feedbacks of a regional nature, and require local parameterizations of resistance and canopy roughness. Thus, they are not applicable in predicting regional ET_a . *Penman* [1948] originally suggested the following empirical linear approximation for $f(U_r)$ using wind speeds measured at 2 m above the surface and therefore denoted by $f(U_2)$:

$$f(U_2) = 0.26(1 + 0.54U_2) \quad (4.10)$$

which, for wind speeds at 2 m elevation in m/sec and vapor pressures in mb, yields E_A in mm/day. This formulation of $f(U_2)$ was used in the Advection-Aridity model operating at a temporal scale of a few days [*Brutsaert and Stricker*, 1979]; in doing so, *Brutsaert and Stricker* [1979] ignored any effect of atmospheric stability in the wind function term. (While the numerical factor in the original expression in *Brutsaert and Stricker* [1979] is 0.35, the factor 0.26 in Equation (4.10) is used here for dimensional homogeneity in the units shown.)

As shown in *Hobbins et al.* [1999, 2001a, 2001b], the original Advection-Aridity model as formulated by *Brutsaert and Stricker* [1979] and using the wind function shown

in Equation (4.10) is strongly biased with respect to the advective input—increasingly under-estimating ET_a with increasing mean annual wind speed, especially for wind speeds above 4 m/sec—and that this bias may be removed by proper selection of the wind function $f(U_r)$. *Hobbins et al.* [2001b] reparameterized and recalibrated the model on a regional, seasonal basis across the conterminous US, recognizing that the effects of atmospheric instability and the onerous data requirements rule out theoretical formulations of the wind function $f(U_2)$, and instead suggesting an empirical linear approximation for $f(U_r)$, of the form:

$$f(U_r) \approx f(U_2)_{i,WRR} = a_{i,WRR} + b_{i,WRR} U_2 \quad (4.11)$$

where U_2 is mean monthly wind speed at 2 meters above the ground, a and b are respectively the intercept and slope of the linear approximation, and the subscripts i and WRR respectively represent the month and region (water resource region, in this example) of application. This new regional and seasonal parameterization yielded estimates of ET_a with near-zero errors when compared to independent long-term estimates of ET_a^* across 139 basins representing the gamut of climatic regimes in the conterminous US. While these results indicated the utility of complementary relationship models in general, they demonstrated the sensitivity of the performance of the Advection-Aridity model to the choice of formulation of $f(U_2)$ and the necessity to calibrate said $f(U_2)$ to provide spatially distributed, accurate, and unbiased estimates of ET_a .

In parameterizing the $f(U_2)$ on a regional basis, the following two issues must be resolved: (1) defining an $f(U_2)$ -parameterization technique at the points where data are available, and (2) providing parameter sets for areas where no data are available, i.e., defining a spatial distribution procedure. In this chapter, two techniques for

parameterizing $f(U_2)$ are examined: one based on the use of observations of ET_a^* as independent estimates of ET_a , similar to *Hobbins et al.* [2001b]; the second using observations of ET_{pan} as independent point-estimates of ET_p . Both methods back-calculate values for $f(U_2)$, either explicitly or implicitly, and these are then regressed on observations of U_2 to create the two parameters a and b necessary to fully describe the relationships shown in Equation (4.11). Each method then relies on a different procedure whereby these parameter sets are distributed across the conterminous US. The Advection-Aridity model is then reformulated to reflect the new $f(U_2)$ relationships. In the next sections, both calibrations are described and the assumptions and drawbacks inherent to each discussed.

4.4.4.1 ET_a^* -based Calibration

This section describes the water-budget based calibration of the ET_a model. Henceforth, the model so calibrated and results so generated will be referred as being “ ET_a^* -based.” In order to optimize the parameters (a and b , for intercept and slope, respectively) of the linear wind function $f(U_2)$ shown in Equation (4.11), the following estimation procedure was adopted. First it was specified that, in each test-basin, the ET_a model:

$$\lambda ET_a = (2\alpha - 1) \frac{\Delta}{\Delta + \gamma} Q_N - \lambda \frac{\gamma}{\Delta + \gamma} (e_a^* - e_a) (a + bU_2) \quad (4.12)$$

match the observations of ET_a^* such that

$$ET_a = ET_a^* = P - R \quad (4.13)$$

where terms are defined in Section 4.4.3.1. Here it should be noted that negligible net changes in overall basin moisture storage in the long-term (i.e., the climatological mean) are predicated on the assumption of stationary conditions for climatic forcing.

In order to specify consideration of a 42-year time-series, Equations (4.12) and (4.13) may be expressed in the following matrix form:

$$\mathbf{E} = \mathbf{W} + \mathbf{A}\mathbf{X} + \mathbf{B}\mathbf{Y} \quad (4.14)$$

where:

$$\mathbf{E} = ET_{ai} = P_i - R_i, \quad i = 1, \dots, 42 \quad (4.15)$$

$$\mathbf{W} = (2\alpha - 1) \frac{\Delta_i}{\Delta_i + \gamma_i} \frac{Q_{Ni}}{\lambda}, \quad i = 1, \dots, 42 \quad (4.16)$$

$$\mathbf{X} = \lambda \frac{\gamma_i}{\Delta_i + \gamma_i} (e_a^* - e_a)_i, \quad i = 1, \dots, 42 \quad (4.17)$$

$$\mathbf{Y} = \lambda \frac{\gamma_i}{\Delta_i + \gamma_i} (e_a^* - e_a)_i U_{2i}, \quad i = 1, \dots, 42 \quad (4.18)$$

The constants A and B represent a and b in the wind function of the formulation of ET_a in Equation (4.12), and will preserve the long-term mean of each basin's ET_a^* observations in modeled ET_a . Post-multiplying by the transposes of each of the known vectors $\mathbf{X}$ and $\mathbf{Y}$, and taking expectations yields a pair of simultaneous equations that may be used to estimate the values of the parameters A and B as functions of the variances and covariances of $\mathbf{W}$, $\mathbf{X}$, and $\mathbf{Y}$.

Post-multiplying by the transposes of $\mathbf{X}$ and $\mathbf{Y}$ respectively:

$$\mathbf{E}\mathbf{X}^T = \mathbf{W}\mathbf{X}^T + \mathbf{A}\mathbf{X}\mathbf{X}^T + \mathbf{B}\mathbf{Y}\mathbf{X}^T \quad (4.19)$$

and

$$\mathbf{E}\mathbf{Y}^T = \mathbf{W}\mathbf{Y}^T + \mathbf{A}\mathbf{X}\mathbf{Y}^T + \mathbf{B}\mathbf{Y}\mathbf{Y}^T \quad (4.20)$$

and then taking expectations:

$$E[EX^T] = E[WX^T] + AE[XX^T] + BE[YX^T] \quad (4.21)$$

and

$$E[EY^T] = E[WY^T] + AE[XY^T] + BE[YY^T] \quad (4.22)$$

or, dropping the matrix notation:

$$S_{EX} = S_{WX} + AS_{XX} + BS_{YX} \quad (4.23)$$

and

$$S_{EY} = S_{WY} + AS_{XY} + BS_{YY} \quad (4.24)$$

where, for example, S_{WX} represents the covariance matrix of the two indexed time-series W_i and X_i , and S_{XX} represents the variance matrix of the indexed time-series X_i . All covariances and variances are known. This pair of simultaneous equations permits the estimation of the values of the scalars A and B , which are then respectively the values of the intercept a and the slope b in the parameter set $\{a,b\}^{\text{BASIN}}$ describing $f(U_2)$ in the basin.

To create a distributed $\{a,b\}$ parameter set—one in which each 5 km x 5 km pixel across the conterminous US contains its own $\{a,b\}$ set—a combined objective-subjective technique was used. A series of four nested layers were overlain across the conterminous US, describing distributed $\{a,b\}$ parameter sets derived over increasingly coarse spatial extents; from that of the 655 test-basins in the finest layer (see Figure 4.3(i)) to that of 4-digit HUC-aggregates (see Figure 4.3(iv)). Each successive layer filled in gaps in the $\{a,b\}$ parameter set distributed across the preceding finer layer. The first, finest layer consists of pixels describing the $\{a,b\}^{\text{BASIN}}$ parameter sets at each of the 655 test-basins (shown in whole Figure 4.2(i) and in part in Figure 4.3(i)) by applying the sequence for

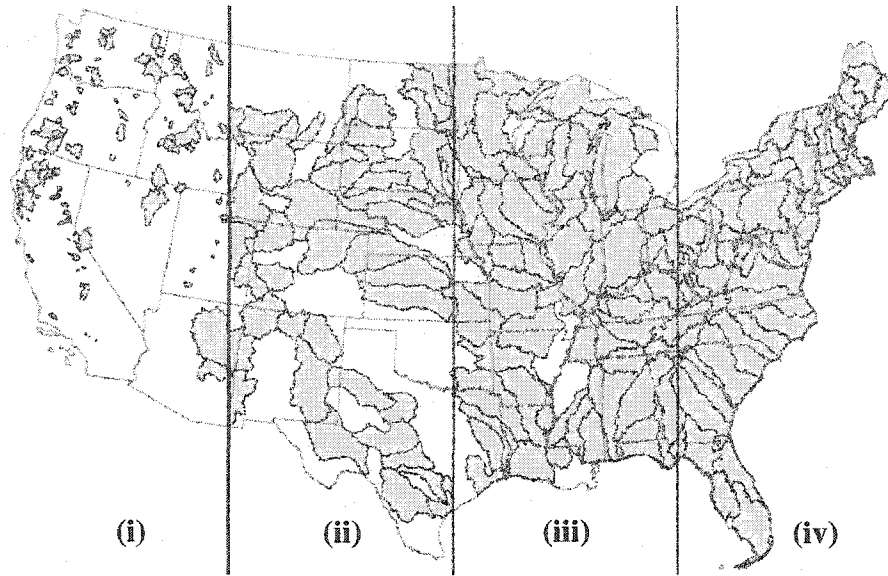


Figure 4.3: The distribution technique for ET_a^* -based $f(U_2)$ s. Shaded areas indicate where $\{a,b\}$ parameter sets have been distributed at each stage into each of the following areas, from left to right: (i) the test-basins; (ii) the 6-digit HUC-aggregates that contain test-basins; (iii) the 4-digit HUC-aggregates that contain test-basins; and (iv) all 4-digit HUC-aggregates.

parameterization described above (Equations 4.12 to 4.24) using data drawn only from the test-basin. In this layer; no $\{a,b\}$ information was available in the interstices. The second layer consists of those 6-digit HUC-aggregates (65% of 334: shown in Figure 4.2(ii)) that contained test-basins. At each of these 6-digit aggregates, the data used to calibrate the $\{a,b\}$ parameter set were gathered from any test-basins lying within the 6-digit aggregate, and no information in the interstices that comprised the remaining 35% of the 6-digit aggregates. The third layer comprises those 4-digit HUC-aggregates (80% of the 204: shown in Figure 4.2(iii)) containing test-basins, and here, the same procedure was followed, with the data used to calibrate the $\{a,b\}$ parameter set being gathered from the test-basins that lay within the 4-digit aggregate, and no information in the interstices

that comprised the remaining 20% of the 4-digit aggregates. The final layer consists of the remaining 4-digit HUC-aggregates (20% of the 204: shown in Figure 4.2(iv)), for which parameter sets were estimated using data gathered from proximal and/or climatologically similar test-basins. The layers were then combined in the order described, with the $\{a,b\}$ parameter set for each 5-km x 5-km pixel across the conterminous US being drawn from the first layer in the sequence that contained information for that pixel.

The primary assumption of the ET_a^* -based calibration technique is that ET_a can be described as the difference between stationary P and R processes (both of which invoke their own uncertainties and, one of which—precipitation—is modeled, rather than observed), and that in the long-term and over integer multiples of years, storages in the basin are stationary.

Although the year-to-year storage changes that are neglected in estimating annual ET_a^* (Equation 4.13) will be non-zero and therefore will add noise to the estimates in E , they would be negligible in modeling ET_a on a long-term mean annual basis (i.e., climatological mean annual, or the mean over this study's 42-year time-period) for undisturbed basins. However, in predicting the year-to-year time-series of ET_a necessary for trend analyses, if the climatic forcing (i.e., as reflected in the basin variables) is non-stationary—the possibility that this study aims to examine, after all—then the noise imparted by contravention of this assumption may not be serially uncorrelated or normally distributed, and may therefore introduce a significant bias to the parameter set, rendering both annual ET_a estimates and ET_a -trend estimates inaccurate.

4.4.4.2 ET_{pan} -based Calibration

This section describes the pan evaporation-based calibration of the ET_a model. Henceforth, the model so calibrated and the results so generated will be referred as being “ ET_{pan} -based.” The central premise of this calibration is that at a point in a homogeneous region (i.e., one of scale lengths on the order of 1-10 km or areas on the order of 10-100 ha [Bouchet, 1963]), the complementary relationship indicates that a free-water surface—an evaporation pan, in this context—will evaporate at the potential rate ET_p . Thus, if the temperature, humidity, and solar radiation are known, ET_{pan} observations can be used as estimates of ET_p in Equation (4.4) to back-calculate the value of the drying power of the air E_A , and hence, the value of $f(U_2)$ in Equation (4.11). Combining Equations (4.4) and (4.11) yields the following expression for back-calculating $f(U_2)$ for each month i at each pan:

$$f(U_2)_i = \left(ET_{pan_i} - \frac{\Delta_i}{\Delta_i + \gamma_i} \frac{Q_{Ni}}{\lambda} \right) \frac{\Delta_i + \gamma_i}{\gamma_i (e_a^* - e_a)_i} \quad (4.25)$$

The resulting values of $f(U_2)$ are then compared to the observed U_2 to generate the relationship between U_2 and $f(U_2)$ using a least-squares fit.

In the warm-season $f(U_2)$ parameterization, 5980 ET_{pan} data from 228 pans were used, and only for months May through October (i.e., Water Months 1 and 8–12), as these were the only months for which homogenized ET_{pan} data were available. In the annual $f(U_2)$ parameterization, 1033 ET_{pan} data from 43 pans were used, with all months calibrated. The ramifications of the spatial distributions of the annual and warm-season pans are discussed below.

To distribute the $\{a,b\}_i^{\text{PAN}}$ parameter set across the conterminous US such that each 5 km x 5 km pixel had a unique set of monthly values of $f(U_2)$ parameters, the $\{a,b\}_i^{\text{PAN}}$ parameter sets developed at the 43 pans using the above technique were spatially interpolated using a simple IDW technique.

Beyond assumptions relating to the homogeneity of the ET_{pan} data set, which are addressed in Chapter 3 and *Hobbins et al.* [2004b], the primary assumption of the ET_{pan} -based calibration is that ET_{pan} observations are point representations of regional integrations of the forcing dynamics on ET_p . The use of ET_{pan} as a perfect estimator of ET_p , or as a direct (via the traditional paradigm) or indirect (via the complementary relationship) predictor of ET_a , is a problematic correspondence, in practice. Many or most pans are situated in urbanized areas or where local climatological conditions are anthropogenically influenced. In such areas, the heterogeneity of the reach upwind of the pan may negate the assumption of a well-mixed region that is homogeneous with respect to water availability and topography and therefore may confound the complementarity of ET_a and ET_{pan} . Further, in the context of trend analyses, and in using ET_{pan} as predictors of ET_p —and therefore of ET_a —one is exposed to the vagaries of the ambient conditions that determine ET_{pan} . Thus, in observing a long-term change in ET_{pan} at a particular site, one may simply be observing the long-term effects of urbanization around the pan, or a change in land-use (e.g., irrigation or deforestation) and may therefore be inadvertently mis-diagnosing simple effects of such local changes as long-term climatological trends on a regional scale.

A further drawback of using ET_{pan} in this calibration relates to the spatial and temporal limitations of the data set. Year-round monthly ET_{pan} data are only available

from pans in the southern tier of states; from Florida to California. Across the other regions of the conterminous US, ET_{pan} data are limited to the warm season, and even there, there are no data in much of the northern tier: warm-season pans are absent from Montana, North Dakota, Minnesota, Wisconsin, and Maine. These spatial and temporal biases limit any ET_{pan} -based ET_a surface to either freeze-free areas or freeze-free periods. Both are discussed in following sections in this chapter. Accordingly, and with regard to modeling ET_a , the spatial extent of the annual ET_{pan} -based ET_a model was limited to areas defined by a 400-km radius around each pan adjusted northwards where appropriate to include the boundaries of nearby states.

In the light of these issues, one must conclude that the assumption that the ET_{pan} data accurately represent aerological conditions over homogenous areas large enough for the complementary relationship potentially limits the accuracy of trend analyses of ET_{pan} -based ET_a .

Figures 4.4 (i) and 4.4(ii) compare the two $f(U_2)$ parameters sets: that based on a least-squares calibration of the monthly time-series of modeled ET_a to the ET_a^* based on water-budgets in the test-basins (described in Section 4.4.4.1), and that based on a monthly linear regression calibrating monthly sets of modeled ET_p to monthly ET_{pan} values from the annual set of 43 evaporation pans (described in Section 4.4.4.2). Figures 4.4 (iii) and (iv) compare the corresponding sets of $f(U_2)$ functions. The parameter sets used for comparison are drawn from the spatially coincident basin-pan pairs, that is, the 23 test-basins that enclose the 25 pans (the other test-basins do not enclose pans, and the other pans are not located within test-basins). Note that in the case of the ET_a^* -based calibration, each test-basin has single, year-round values of a and b (intercept and slope

in Equation (4.11), respectively), whereas in the case of the ET_{pan} -based calibration, values of a and b are derived for each pan on a monthly basis. To compare like with like, at each of the 25 pans, the average of the 12 monthly $\{a,b\}_i^{PAN}$ values is taken to represent a faux-annual $\{a,b\}^{PAN}$ set to compare to the set of 23 annual $\{a,b\}^{BASIN}$ values.

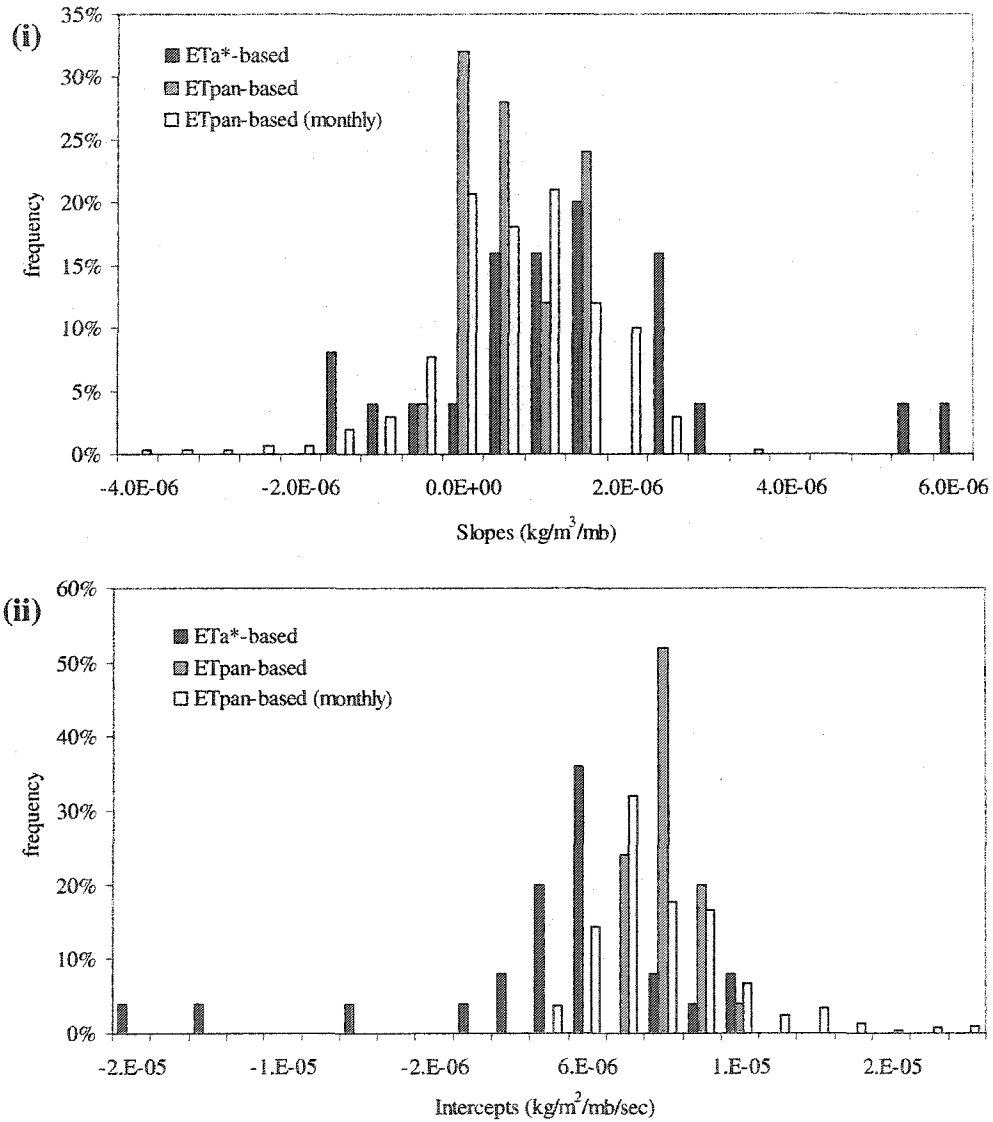


Figure 4.4: Comparison of the $f(U_2)$ parameter-populations estimated by calibration to ET_a^* and annual ET_{pan} at all pan/test-basin coincident pairs: (i) distributions of the slope parameter-values; (ii) distributions of the slope parameter-values; (iii) variation of the ET_a^* -based wind functions; and (iv) variation of the ET_{pan} -based wind functions.

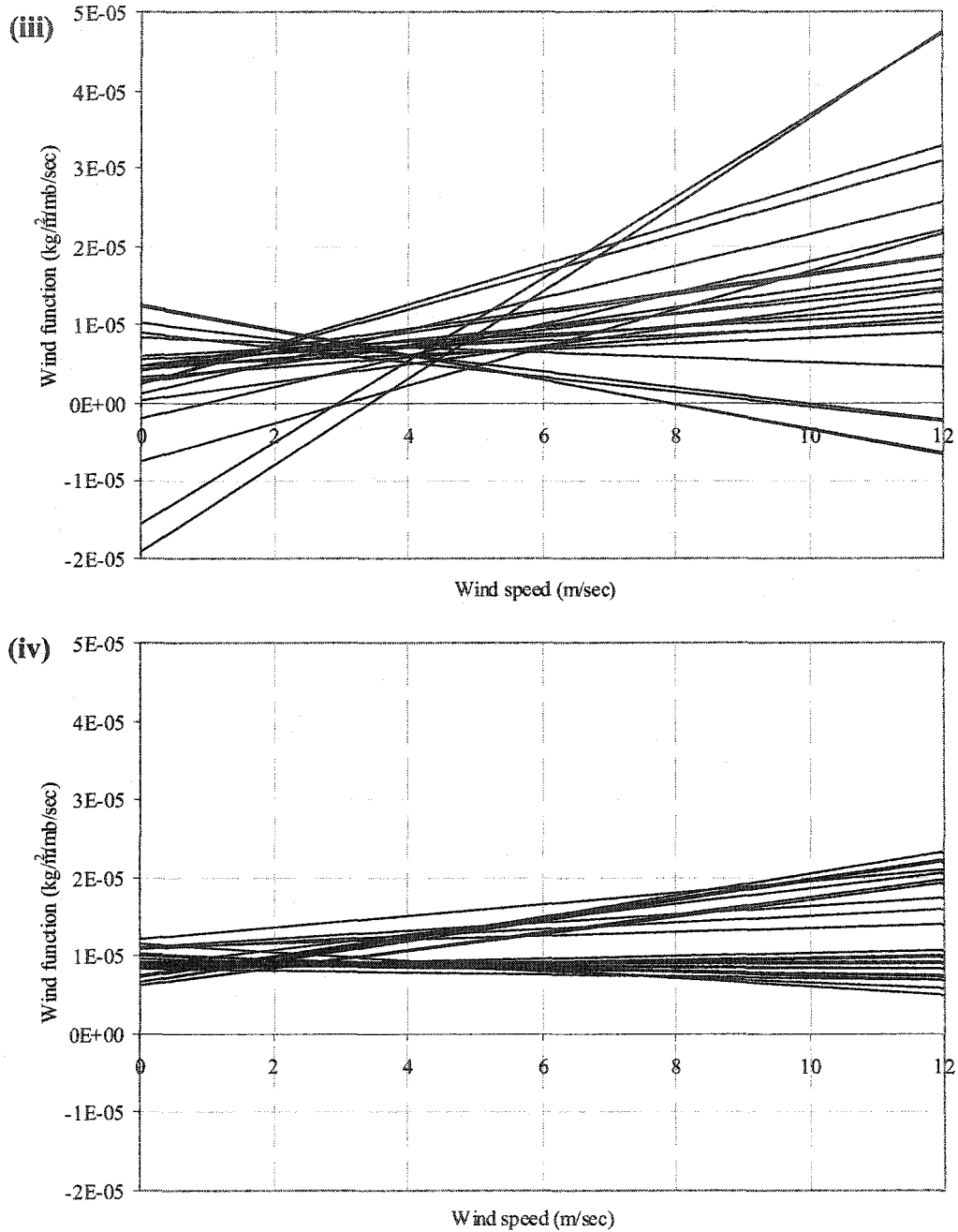


Figure 4.4 (cont.): Comparison of the $f(U_2)$ parameter-populations estimated by calibration to ET_a^* and annual ET_{pan} at all pan/test-basin coincident pairs: (i) distributions of the slope parameter-values; (ii) distributions of the slope parameter-values; (iii) variation of the ET_a^* -based wind functions; and (iv) variation of the ET_{pan} -based wind functions.

Figures 4.4(i) and 4.4(ii) present histograms of slope and intercepts, respectively, of the $f(U_2)$ for the 23 test-basins and for the 25 pans, the latter presented both as “annual” and the actual monthly values. As the populations of each of the three parameters sets presented are different, the y -axis represents relative frequencies. It is clear from the graphs and supported by statistical analyses (i.e., skewness tests of normality at the 5% significance level) that the ET_a^* -based and ET_{pan} -based parameter sets are very different: the ET_a^* -based slope parameters are normally distributed, but its intercept parameters are not; neither the monthly ET_{pan} -based slope or intercept parameters are normally distributed; but both the annualized ET_{pan} -based slope and intercept parameters are normally distributed. In the ET_a^* -based parameters sets, there are distinct and distant tails of high positive slopes and low negative intercepts. The effects of these parameter distributions are clear in Figures 4.4(iii) and 4.4(iv), where $f(U_2)$ s are plotted for the ET_a^* -based calibration and the ET_{pan} -based calibration, respectively. The U_2 -range is bounded by the minimum and maximum U_2 observed across the entire spatial and temporal extent of its time-series. The annual ET_a^* -based wind functions vary widely: some start negative and increase with rising U_2 , while still others start positive but become negative with increasing U_2 : physically, a negative $f(U_2)$ would imply wetting of the surface with air movement, while a negative $df(U_2)/dU_2$ (or slope $b < 0$) would imply that increasing U_2 reduces the potential for an evaporating surface to transfer vapor to the air, both of which are physically indefensible on the time-scales of months. Here negative $f(U_2)$ and $df(U_2)/dU_2$ are artifacts of one of the main drawbacks inherent in the calibration method: the assumption that ET_a^* can be estimated on a monthly basis by the difference between basin-wide P and R at the outlet, and the storage changes that are otherwise

ignored (Equation 4.13) on a long-term basis are affecting the month-to-month ET_a^* deleteriously, introducing noise into the $f(U_2)$ parameter population. The annualized ET_{pan} -based $f(U_2)$ s shown in Figure 4.4(iv) are much more tightly clustered, and, while there are some negative $df(U_2)/dU_2$ (or $b < 0$), all $f(U_2)$ s remain positive across the range of U_2 . The monthly $f(U_2)$ would, of course, be more widely dispersed (Figures 4.4(i) and 4.4(ii) indicate a few negative intercepts and slopes in the monthly parameter set), but they would still remain more tightly clustered than those from the annual ET_a^* -based calibration. On the basis of this qualitative analysis, it is clear that the parameter sets differ greatly depending on calibration technique, and that the ET_{pan} -based parameter set is more physically defensible, as it is derived more closely from direct observations and relies on fewer assumptions. The performance of the parameter sets against observations from other components in the hydrologic cycle is discussed in Section 4.6.

4.5 Observed Trends

4.5.1 Trend Analysis Methodology

A variety of methods was used to examine the temporal trends in annual quantities of ET_{pan} , ET_a^* , and the input and intermediate components (Q_N , U_2 , V_{dif} , and ET_a^* -, ET_{pan} - and ET_{pan}^{ws} -based E_A), and output series of modeled ET_a (ET_a^* -based and ET_{pan} -based ET_a). First, least-squares linear regression permitted quantification of trends over spatial averages that allowed the most direct comparisons to the work of others (work described in Section 1.2.5 and summarized in Section 4.3). Second, the Mann-Kendall test, which is often used to test for trends in hydrological time-series [Lettenmaier *et al.*, 1994] and

provides a ready measure of trend significance and direction, was applied at each 5 km x 5 km pixel distributed across the conterminous US to generate all results shown in subsequent trend surfaces (Figures 4.5, 4.9 to 4.13, 4.21, and 4.22). While the least-squares linear regression trend test is simple and presumed to be familiar to all, the Mann-Kendall test is less so, and is therefore described below. First the standard Mann-Kendall test is defined, then the constraints on the power of the test are summarized, with particular attention paid to the effects of auto-correlation such as is observed in the time-series tested in this study. Finally, the development of the critical Mann-Kendall statistics that account for auto-correlation is detailed.

The Mann-Kendall test statistic (Z-statistic) is non-dimensional, measuring the direction of a succession of x_i 's with time and thereby offering information as to the direction of observed trends and a measure of their significance, but providing no quantification of the magnitude of the trend in the units of the time-series under study. The Z-statistic at each pixel is developed by first accumulating the sum S of the series of *signum* functions of each x_i against all successive x_j 's:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (4.26)$$

where n is the length of the x_i time-series and $\text{sgn}(\cdot)$ is the *signum* function defined as,

$$\text{sgn}(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases} \quad (4.27)$$

The expected value and variance of S are given by Equations (4.28) and (4.29), respectively:

$$E[S] = 0 \quad (4.28)$$

$$\text{Var}(S) = \{n(n-1)(2n+5) - \sum_i t(t-1)(2t+5)\}/18 \quad (4.29)$$

where the second term represents an adjustment for tied or censored data, t representing the number of data in each tie. The test statistic Z is then given by:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases} \quad (4.30)$$

As a non-parametric test, no assumptions as to the underlying distribution of data are necessary. The Z -statistic is then used to test the null hypothesis (H_0) that the data are identically distributed random observations and not time-dependent. Ordinarily—that is, assuming no serial dependence (i.e., assuming zero correlation) in the time-series beyond that directly resulting from trends— H_0 of no trend cannot be rejected at the α -significance level if the following condition applies:

$$|Z| < U_{1-\alpha/2} \quad (4.31)$$

where $U_{1-\alpha/2}$ is the $1-\alpha/2$ quantile of the standard normal distribution. Otherwise, H_0 must be rejected at the α -significance level in favor of the alternative hypothesis of a positive (or negative) trend if the Z -statistic exceeds the critical value of U in a positive (or negative) direction. The confidence level for this study was set at 95%, yielding a critical value of $|Z|$ of 1.96 for uncorrelated series.

The power of the Mann-Kendall test in the analysis of monotonic trends in a time-series—that is, the probability of correctly rejecting H_0 and therefore correctly identifying an existing trend—is a function of sample size, trend magnitude, pre-assigned significance level, variability within the time-series [Yue *et al.*, 2002], and—more

importantly in the context of this study—the degree of serial dependence, or autocorrelation within the time-series.

Sample size is fixed at 42 (i.e., WY 1953-1994) for the annual series examined in this study. The presence of trends may be masked by the variability within the time-series, with test power being reduced by large variability (i.e., large coefficients of variation), and increased for time-series with less variation. At a given significance level, the Mann-Kendall test becomes more powerful at detecting stronger absolute (i.e., either upward or downward) trends than at detecting smaller ones. This is true for time-series that are non-normally distributed—as many hydrologic series are. However, for some distributions, the relationship between power and absolute trend is weak (e.g., for log-normally distributed time-series, the power remains constantly low across the range of actual trends), thereby complicating analyses of trends in different types of series (e.g., precipitation and streamflow), or for sites that have different distributions or different shape parameter-values for a given distribution. For greater significance levels (or smaller confidence levels), the power increases across the range of trends, but more so for greater absolute trends than for smaller. This squares with the idea that for a given time-series, a trend is more likely to be rejected at lower significance levels, and more likely to be identified at a higher significance level.

Most importantly, while non-parametric tests, such as the Mann-Kendall test, are thought to represent the statistics of non-normally distributed data better than parametric tests, one of the primary assumptions in their application remains that of serial independence [Yue *et al.*, 2002]. The impact of serial correlation on the power of the Mann-Kendall test is itself a function of trend magnitude, sample size, and correlation

magnitude [Yue and Wang, 2002], increasingly so for lower sample sizes and lower trend magnitudes. For low sample sizes (Yue and Wang [2002] suggest $n < 50$), positive correlations increase the probability of trends being detected, that is, one is more likely to reject H_0 and conclude that a trend exists, falsely or not; negative correlations decrease the probability of detection, that is, one is more likely to accept H_0 and conclude that no trend exists, again, falsely or not.

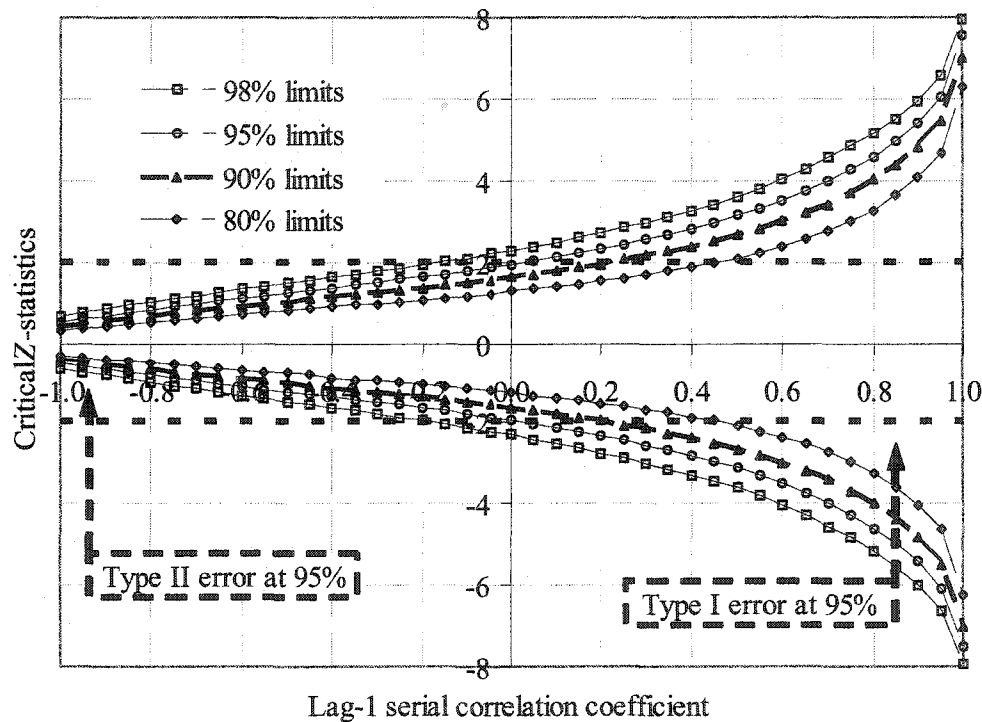


Figure 4.5: Critical Z-statistics for various serial correlations and significance levels, derived from 50,000 simulations of an AR(1) process of length $n = 42$. Horizontal dashed lines delineate 95% limits for uncorrelated series; error-regions invoked by their use in correlated series are indicated.

Using the AR(1) process—essentially adding white noise to a process of known lag-1 serial correlation—it can be shown that negative correlation has a mitigating effect on underlying trends (see Figure 4.5) and reduces the variance of the population of Z-

statistics around its zero-mean, leading to increasingly constricting limits for increasingly negative correlations. The opposite is true for positively correlated series: the variance of the population of Z-statistics is increased around its zero-mean, leading to increasingly divergent limits for increasingly positive correlations. As indicated by the variety of limits across confidence limits ranging from 80% to 98%, lowering the confidence (or raising the significance) has the obvious effect of increasing the probability of detecting a trend, but increasingly so for increasingly positive—or decreasingly negative—correlations.

Another way of looking at the effect of serial correlation on trend-detection is to examine the difference between assuming zero correlation on series that are known *a priori* to be correlated. As indicated by the regions between the dashed horizontal lines indicating the 95% limits for uncorrelated series and the divergent bold lines indicating the 95% limits for series with lag-1 correlations between -1 and +1 (see Figure 4.5), falsely assuming a process is not correlated may lead to errors of a type dependent on the actual correlation in the series, as follows: (i) an increased probability of type-I errors (i.e., rejecting the null hypothesis when it is true) for series that are positively correlated, and (ii) an increased probability of type-II errors (i.e., accepting the null hypothesis when it is false) for series that are negatively correlated. Thus, assuming no correlation in a time-series leads to under-detection of trends in negatively correlated series, and over-detection of trends in positively correlated series, which is next shown to be the case over the majority of the conterminous US for ET_a^* -based annual ET_a : it is, in fact, the case for all series under examination herein.

It is suspected *a priori* that the time-series under examination are not serially independent, but that there exist significant serial correlations on an annual basis. Traditionally, detecting and testing for the significance of correlation involves the application of confidence limits to the correlogram, which displays the correlation structure of a time-series, by plotting the correlation of data across a time-lag as a function of the time-lag. The confidence limits at the γ confidence level (or α significance level; $\gamma = 1 - \alpha$ probability bounds for $\rho_j = 0$) are defined by:

$$\left[-\frac{U_{1-\alpha/2}}{\sqrt{N}}, \frac{U_{1-\alpha/2}}{\sqrt{N}} \right], \quad (4.32)$$

which, when applied to a 42-year annual time-series for $\alpha = 5\%$, or at the 95% confidence level, yields limits of $[-0.3024, 0.3024]$. Thus, at the 5% significance level, values of ρ_j within these limits indicate no correlation at lag- j ; values of ρ_j above these limits indicate positive correlation; and values of ρ_j below these limits indicate negative correlation at lag- j .

In the case of the spatially distributed data in this study, the initial suspicion of serial correlation in the data series is borne out by Figure 4.6, which is presented ahead of time as an example of the correlation structure that may exist within the data: in this example, ET_a^* -based ET_a is used. In the manner of a correlogram, but displayed in the spatial domain rather than the more familiar temporal domain, each sub-figure, or “correlomap,” represents the lag- j correlation coefficient of ET_a^* -based ET_a for a particular value of j from 1 to 12 at each 5 km x 5 km pixel across the conterminous US. Immediately apparent from these correlomaps is the short-term memory of the process. At lag-1, 64% of the country shows a significant positive correlation, particularly in the western and

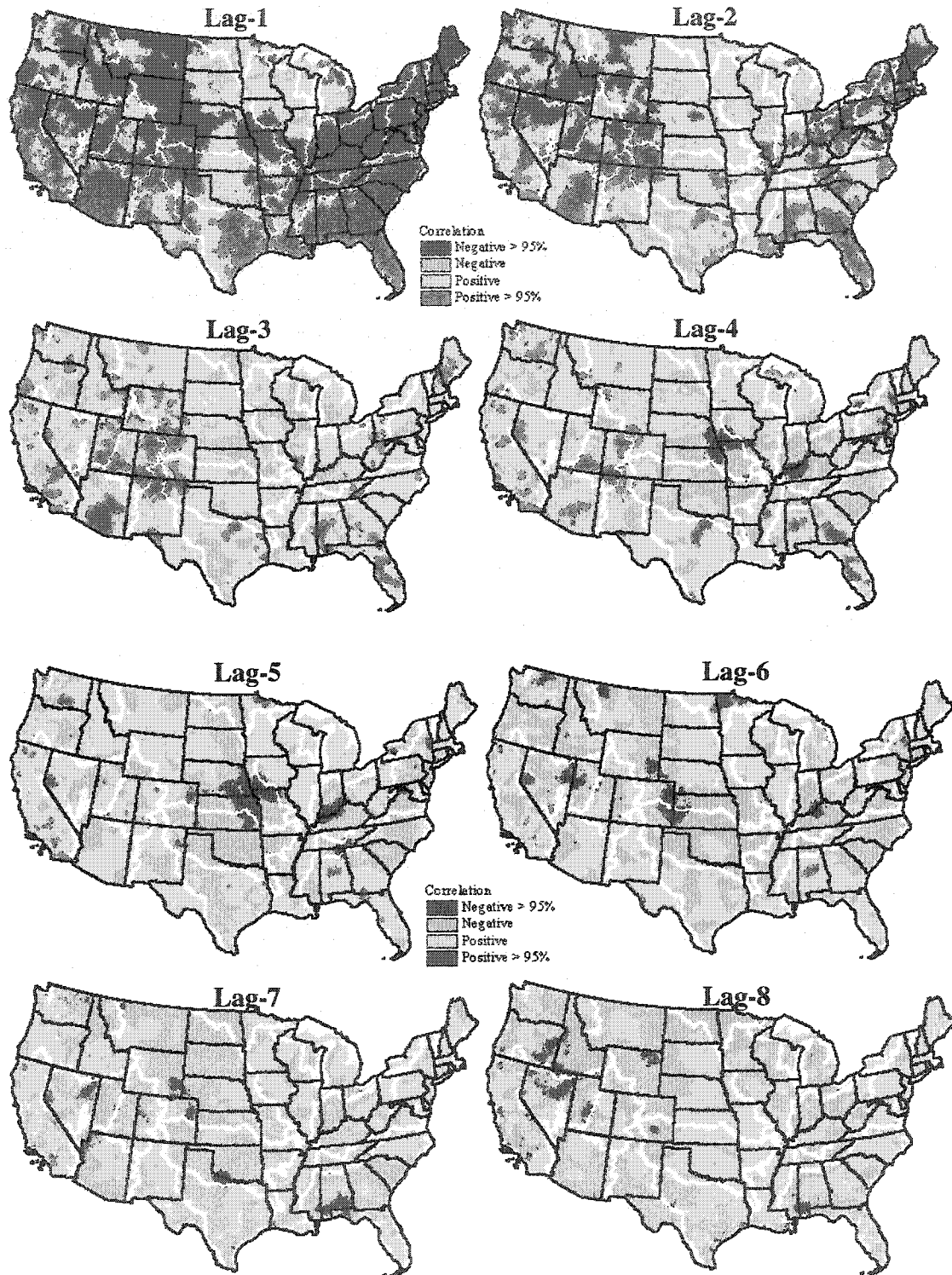


Figure 4.6: Lag- j serial correlation coefficients for annual ET_a^* -based ET_a across the conterminous US, for $j = 1 \dots 12$. Dark colors indicate significant correlation at the 95% level: red positive, blue negative. Also shown are the state- and WRR-boundaries.

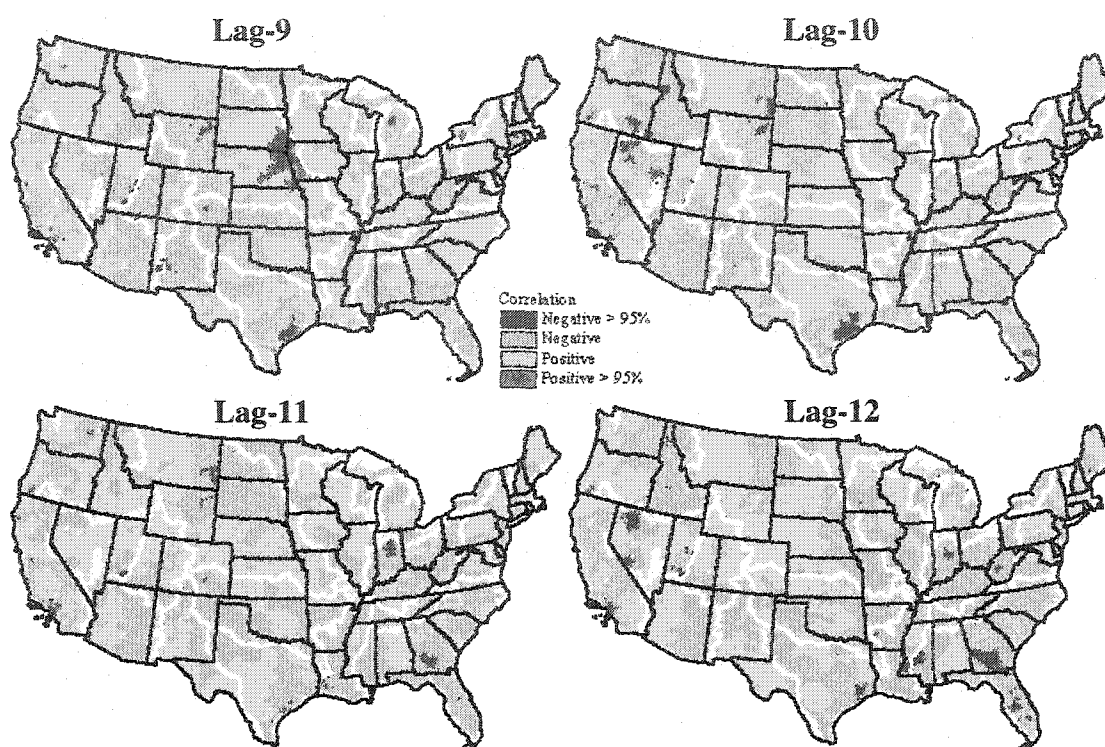


Figure 4.6 (cont.): Lag- j serial correlation coefficients for annual ET_a^* -based ET_a across the conterminous US, for $j = 1 \dots 12$. Dark colors indicate significant correlation at the 95% level: red positive, blue negative. Also shown are the state- and WRR-boundaries.

eastern thirds. At lag-2, this memory has decayed significantly within the central third and to about 50% of each of eastern and western thirds. At still higher lags, the positive correlation decays further, all but disappearing by lag-4, at which point negative correlations begin to appear in isolated and transitory pockets. Further correlomaps express no apparent spatial structure in the correlation. The spatially distributed correlation structures for each input, intermediate, and output variable are summarized for each variable in Figure 4.7, which shows the proportion of the area of the conterminous US that exhibits significant serial positive or negative correlation at each j . Note that the large areas of significance mapped for ET_a^* -based annual ET_a in Figure 4.6 and summarized for other annual variables in Figure 4.7 result from spatial correlation in

each annual iteration of the time-series as well as the temporal correlation, as the surfaces directly or indirectly bear the spatial correlation structure of the point networks of input data.

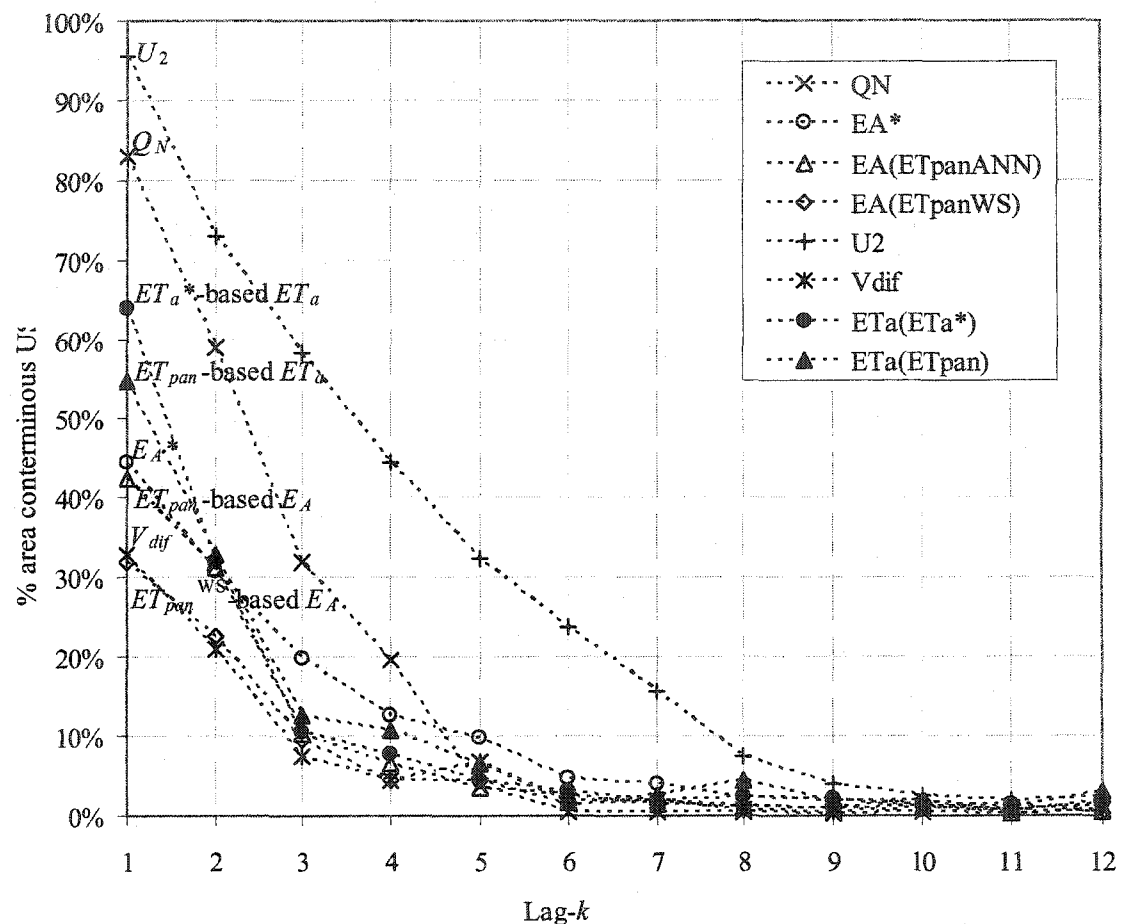


Figure 4.7: Areal proportions of the conterminous US with significant (at the 95% level) positive or negative lag- j serial correlation coefficients, for $j = 1 \dots 12$ for annual input, intermediate, and output variables: Q_N , ET_a^* -based E_A , ET_a^* -based E_A , U_2 , V_{dif} , ET_a^* -based ET_a , and ET_{pan} -based ET_a .

Having shown that the series under study are significantly correlated, at least for short lags, it remains to account for this correlation in the trend analyses. Typically, use of the Mann-Kendall test in the detection of trends in time-series that are serially correlated has

involved first rendering the time-series uncorrelated by applying a process known as “pre-whitening.” This most commonly takes the form of reducing the raw data by subtraction of an auto-correlated trend, the parameters of which are estimated from the raw data. The trend is commonly an autoregressive lag- p (AR(p)) process, of the general form:

$$x_i = \mu + \sum_{j=1}^p \phi_j (x_{i-j} - \mu) + \varepsilon_i \quad (4.33)$$

where x_i is the i 'th value of x in the time-series, μ is the mean of the time-series, j is a time-index, p is the order of the autoregressive process (or the number of previous years of data to which any given year's raw datum is assumed to be statistically related), ϕ_j are the autoregressive coefficients, and ε_i is an uncorrelated series independent of x_i , which, if random and normally distributed is called “white noise.”

A more general form of the time-series under analysis—one that allows for a trend in the mean and autocorrelation in the series—may be written as follows:

$$x_i = \mu(i) + \sum_{j=1}^p \phi_j (x_{i-j} - \mu(i-j)) + \varepsilon_i \quad (4.34)$$

where $\mu(i)$ and $\mu(i-j)$ are deterministic functions of the time-indices i and j , which is to say that they represent a generalized—and therefore potentially non-stationary—mean, or a trend in the mean. An x_i series generated using no deterministic function in the mean—i.e., one with constant μ —will still exhibit short-term trends that result solely from autocorrelation. Conversely, an x_i series generated using a non-stationary mean and zero autocorrelation will still exhibit autocorrelation solely due to the trend in the mean. Writing the x_i series in this fashion (Equation 4.34) illustrates the interconnectedness or intractability of trends and correlation, demonstrating that to define a trend in the

presence of autocorrelation is essentially to distinguish between autocorrelation and non-stationary means—a distinction that is, to a great degree, subjective.

Most frequently, and in this study in particular, an AR(1) process is assumed to represent the autocorrelation structure in the series—a subjective choice predicated mainly on the parsimony of parameters, and their ease of estimation and application on a spatially distributed basis. Parameter-estimation for AR(p) processes proceeds simply and is described in detail in *Salas et al.* [1997].

To pre-whiten the data, Equation (4.33) is rearranged such that the residual ε_i series may be calculated, which is then assumed to represent the uncorrelated portion of the series under analysis, and is then tested for trends. However, given the difficulties in distinguishing a trend from correlation, the data are not pre-whitened in this study for reasons following. First, pre-whitening significantly affects trend calculations, lowering any trend if positive AR(p) is removed, and inflating it if negative AR(p). Thus, the slope estimated from a pre-whitened series is not the estimate of the true slope of the series. *Yue and Wang* [2002] conclude that pre-whitening may not be of much interest in a practical, water resource management-oriented context, as the true trend is of more interest than the statistically "purer" one. Second, in the analysis of temporal trends in spatially distributed data, time-series may exhibit serial correlations that are, at the simplest level, significant and non-significant or, more confoundingly, significantly positive and negative, between adjacent pixels. Accounting for such cases, which are frequently seen in Figure 4.6, generating spatially distributed surfaces of AR(p) processes, perhaps, regardless of the significance of correlation, or going further and using different processes in different pixels based on the significances of their lag- j

correlation coefficients—an AR(1) process in one pixel, an AR(2) process in an adjacent pixel, say—would add overwhelming complexity to the analysis, and run the risk of over-fitting trends, thereby diluting any conclusions drawn.

To obviate complexification, a more relaxed approach that allows for potential correlation in the time-series in question and then estimates the significance of the true trend—rather than attempting to strip out the correlation beforehand—was adopted. Based on the correlograms in Figure 4.6, the statistics of which are demonstrated for all variables under study in Figure 4.7, and to avoid the aforementioned under- and over-detection of trends in series that are falsely assumed to be correlated, all Mann-Kendall trend analyses of distributed data in this study are predicated on the assumption that all input, intermediate, and output processes may be considered AR(1) with ϕ_1 varying between -1 (absolute negative year-to-year correlation, rare in hydrologic time-series) and +1 (absolute positive correlation), of the form shown in Equation (4.33). An AR(1) process was specified to resolve the abovementioned issues raised for pre-whitening spatially distributed data. Thus, for each pixel's time-series, the critical Z-limits that define significant trends at the 95% confidence level are calculated with reference to that pixel's estimated ϕ_1 parameter-value and the limits shown in Figure 4.5, with linear interpolation between the data points on the curve.

4.5.2 Trends in ET_{pan} and ET_a^*

In this section the long-term time-series of ET_a^* derived from Equation (4.8) and ET_{pan} homogenized in Chapter 3 are examined for long-term trends. The causes of such trends are examined by decomposing them into their driving dynamics, and then

examining the components' trends to see if, when combined in the context of the complementary relationship, they predict the resulting trends in ET_a^* . As trends in the component fluxes combine to produce the same trends in ET_{pan} in the complementary relationship as they do in the traditional paradigm, such an examination of component trends in ET_{pan} would not be informative.

Figure 4.8(i) indicates the spatial distribution, direction, and significance of ET_a^* trends in the 655 test-basins. Few basins show trends that are significant at the 95% level as measured by the Mann-Kendall statistic: only 2.9% are significantly decreasing, and 9.0% significantly increasing. Of the remaining basins, 43.2% are insignificantly decreasing, and 44.9% increasing. Broadly, basins in the Midwest and South show decreasing ET_a^* , while those in the High Plains and desert Southwest show increasing ET_a^* . The rest of the conterminous US is a heterogeneous mix of increasing and decreasing ET_a^* , with neither predominating.

Figure 4.8(ii) and 4.8(iii) show the distribution, direction, and significance of ET_{pan} trends in the annual and warm-season pans, respectively. Of the 43 annual pans, 60.5% show the decreasing ET_{pan} trend reported widely in the literature [e.g., *Chattopadhyay and Hulme*, 1997; *Peterson et al.*, 1995; *Brutsaert and Parlange*, 1998; *Roderick and Farquhar*, 2002]; of the 9 pans with significant trends (at the 95% level using the Mann-Kendall test-statistic), 77.8% are decreasing. Of the 228 warm season pans, 58.8% show decreasing ET_{pan} ; of the 33 pans with significant trends, 84.8% are decreasing.

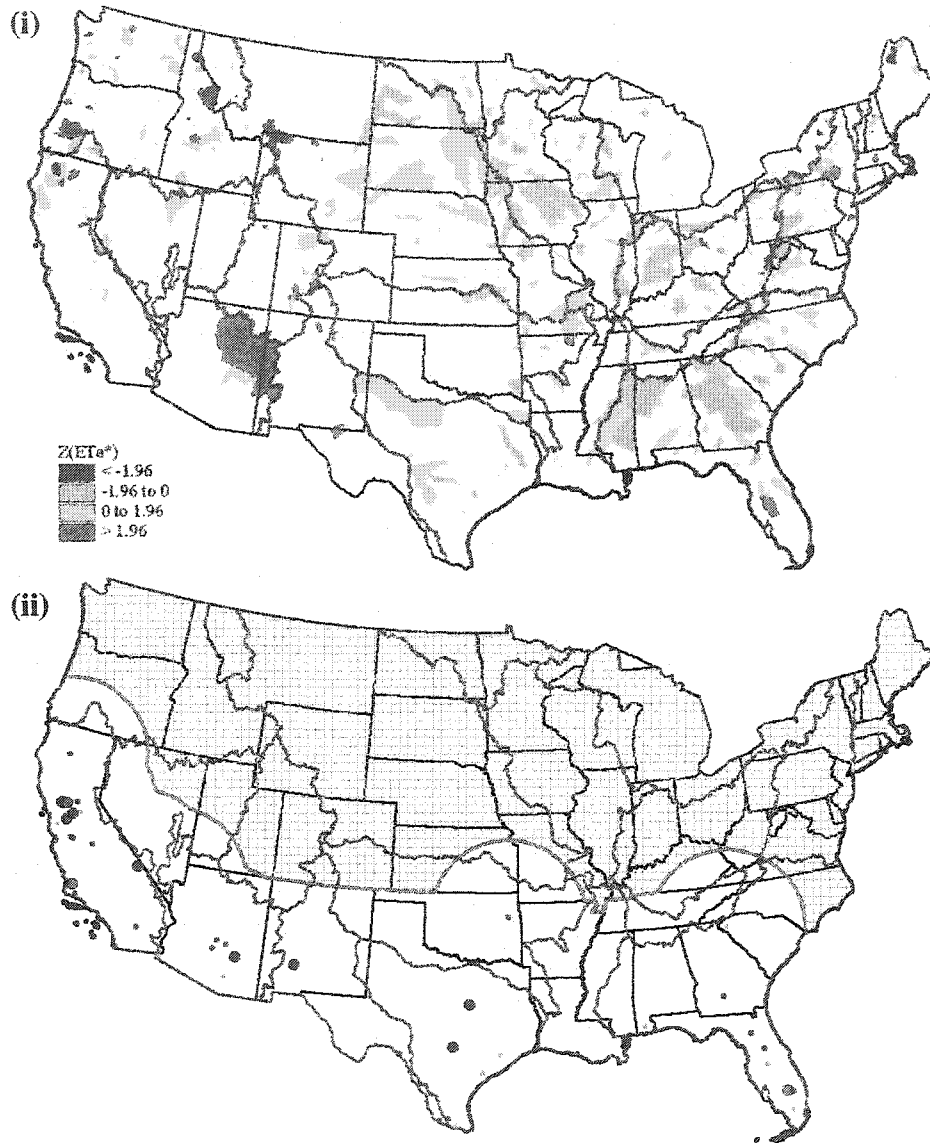


Figure 4.8: Trends in (i) annual ET_a^* in the 655 test-basins; (ii) annual ET_{pan} at the 43 annual pans; and (iii) warm-season ET_{pan} at the 228 warm-season pans. Trends are estimated using the Mann-Kendall test. Statistically significant trends (assuming no serial correlation) at the 95% confidence level have (i) $|Z(ET_a^*)|$, (ii) $|Z(ET_{pan})|$; or (iii) $|Z(ET_{pan}^{ws})| > 1.96$. Also shown are state- and WRR-boundaries and, in (ii), the southern region.



Figure 4.8 (cont.): Trends in (i) annual ET_a^* in the 655 test-basins; (ii) annual ET_{pan} at the 43 annual pans; and (iii) warm-season ET_{pan} at the 228 warm-season pans. Trends are estimated using the Mann-Kendall test. Statistically significant trends (assuming no serial correlation) at the 95% confidence level have (i) $|Z(ET_a^*)|$, (ii) $|Z(ET_{pan})|$; or (iii) $|Z(ET_{pan}^{ws})| > 1.96$. Also shown are state- and WRR-boundaries and, in (ii), the southern region.

Due to the discontinuous nature of annual and warm-season pan data, the correlation-adjusted Mann-Kendall Z-statistic limits (see Section 4.5.2) were not used to generate the data shown in Figures 4.8(i)-(iii), as the estimated correlation coefficients would be uncertain; instead the data were assumed to be uncorrelated.

Following is a first-order determination of what drives the trends in ET_a^* and ET_{pan} just observed. Here, the driving equations for ET_a are examined in a general sense that encodes both components dynamics of ET_a —the regional drying power of the air E_A in the vapor transfer component, and the energy flux driving the system in the radiative component Q_N —acting under any paradigm, including that of the complementary

relationship. Starting from a general functional expression for ET_a shown in Equation (4.6) and making no assumptions about the temporal stationarity of the slope of the saturation vapor pressure curve at air temperature Δ or the psychrometric constant γ , but assuming that E_A and Q_N are independent functions, ET_a can be expressed as follows:

$$\lambda ET_a(t) = f\{Q_N(t), E_A(t), \Delta(t), \gamma(t)\}. \quad (4.35)$$

Therefore, the most general expression for temporal trends in ET_a , regardless of the actual formulation of ET_a (complementary relationship or traditional paradigm) is:

$$\lambda \frac{d\langle ET_a \rangle}{dt} = \frac{\partial \langle ET_a \rangle}{\partial Q_N} \frac{d\langle Q_N \rangle}{dt} + \frac{\partial \langle ET_a \rangle}{\partial E_A} \frac{d\langle E_A \rangle}{dt} + \frac{\partial \langle ET_a \rangle}{\partial \Delta} \frac{d\langle \Delta \rangle}{dt} + \frac{\partial \langle ET_a \rangle}{\partial \gamma} \frac{d\langle \gamma \rangle}{dt}. \quad (4.36)$$

With the further assumption that there is no change in either γ or Δ , that is to say, assuming the following holds:

$$\frac{d\Delta}{dt} = \frac{d\gamma}{dt} = 0, \text{ or } ET_a(t) = f\{Q_N(t), E_A(t)\} \text{ and } \Delta, \gamma \neq f(t) \text{ and } \lambda ET_a = f(Q_N, E_A). \quad (4.37)$$

Then differentiating Equation (4.37) with respect to time yields the temporal trend in ET_a expressed as a function of trends in its components:

$$\lambda \frac{dET_a}{dt} = \frac{\partial ET_a}{\partial Q_N} \frac{dQ_N}{dt} + \frac{\partial ET_a}{\partial E_A} \frac{dE_A}{dt}. \quad (4.38)$$

This study examines and reports on time-trends in both these primary components, avoiding the further limiting assumptions of stationarity in either the Q_N [Szilagyi *et al.*, 2001] or E_A [Roderick and Farquhar, 2002] components.

The critical difference in the effects of component trends on trends in ET_a between traditional paradigms and complementary relationship models is observed in their functional relationship to trends in the E_A component. In traditional paradigms, ET_a is

often estimated as a function of ET_p or ET_{pan} and some measure of moisture availability, as follows:

$$ET_a = f(ET_p, \text{soil moisture}) \quad (4.39)$$

with trends in ET_a taken to be a positive function of trends in ET_p , and therefore a positive function of trends in E_A . However, this is not the case in complementary relationship-based estimates of ET_a . In such estimates, the E_A term reflects the effects of the feedback between regional advection—the drying power of the over-passing air—and ET_a as limited by water availability at the evaporating surface: when the feedbacks across the land-surface-atmosphere interface have brought the two into equilibrium, a greater drying power of the air then implies that there has been less evaporation into the air. In traditional paradigms, the feedbacks are ignored, and more moisture is presumed to evaporate into the air simply as a result of the air being drier. The proper treatment—encoded in the complementary relationship—of the effects of advection on regional scales with full mixing in the boundary layer is displayed in terms of trends in ET_a as follows:

$$\frac{\partial ET_a}{\partial E_A} = -\frac{\gamma}{\Delta + \gamma} \quad (4.40)$$

Thus, in contrast to traditional paradigms, under the complementary relationship hypothesis, trends in ET_a are a negative function of trends in E_A . The influence of the complementary relationship—as it is here formulated in the Advection-Aridity model described in Equation (4.6)—on trends in ET_a is made evident by substituting the partial derivatives in Equation (4.38) and expressing the trends in ET_a as the time-rates of change (Equation 4.41a) or the long-term changes (Equation 4.41b) over the period of record. This leads to:

$$\delta ET_a = (2\alpha - 1) \frac{\Delta}{\Delta + \gamma} \delta Q_N - \frac{\gamma}{\Delta + \gamma} \delta E_A, \quad (4.41a)$$

and

$$\Delta ET_a = (2\alpha - 1) \frac{\Delta}{\Delta + \gamma} \Delta Q_N - \frac{\gamma}{\Delta + \gamma} \Delta E_A. \quad (4.41b)$$

This, then, yields two component trends: δQ_N , which represents the trend in the available energy; and δE_A , which represents the trend in drying power of the air. The effects of these two component-trends as they combine in the complementary relationship may be more clearly seen in Figure 4.9.

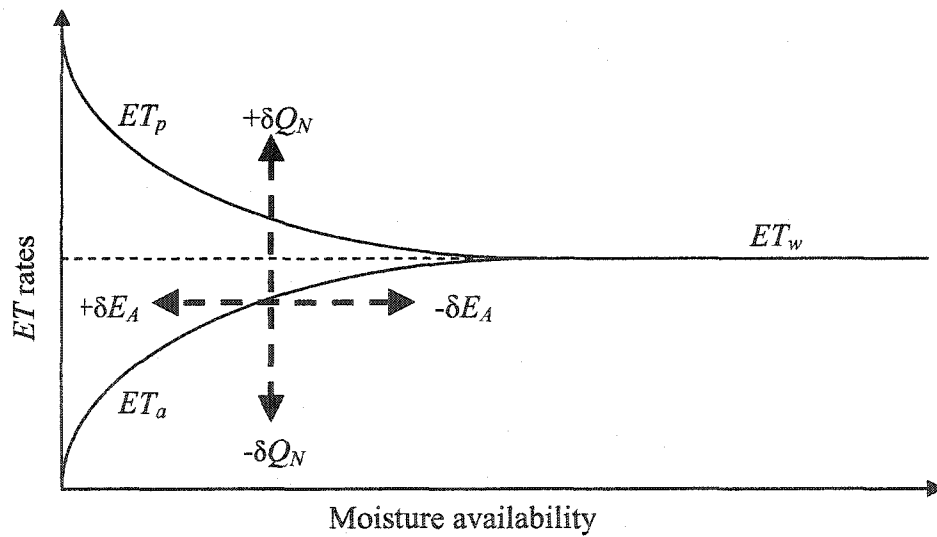


Figure 4.9: The effects of trends in the components of ET_a in the context of the complementary relationship. Arrows marked “ δE_A ” and “ δQ_N ” indicate the effects on ET_a of trends of the indicated signs in E_A and Q_N , respectively.

In Figure 4.9, the first cause of trends in ET_a , a long-term change in the regional drying power of the air (ΔE_A) in the absence of a change in the energy budget, is akin to moving horizontally along the paired curves, as shown by the arrow marked “ ΔE_A .”

According to the complementary relationship, increasing the wetness of an evaporating surface (or decreasing the regional drying power of the air E_A) moves the ET_a - ET_p pair to the right along both ET_a and ET_p , towards convergence of their respective curves, while decreasing wetness moves the pair to the left, towards divergence of the curves. This dynamic may be indicated by the Mann-Kendall test statistic for the E_A time-series, $Z(E_A)$: if, for a particular basin, $Z(E_A)$ is negative, then the basin is becoming wetter from the first effect; drier for a positive $Z(E_A)$. (The spatial distribution of $Z(E_A)$ is shown in Figure 4.12 and discussed later in this section.)

The second cause—a long-term change in the long-term net available energy (ΔQ_N) in the absence of a change in wetness—shifts both the horizontal line representing ET_w and the curve representing ET_p upwards in the case of increasing Q_N , or downwards in the case of decreasing Q_N . Correspondingly, and in accordance with the complementary relationship, the curve representing ET_a will shift in a similar direction, as shown by the arrow marked “ ΔQ_N ” in Figure 4.9. As shown in Equation (4.3), ET_w is purely a function of the available energy Q_N , and is therefore unaffected by changes in basin wetness alone. This dynamic may be indicated by the Mann-Kendall test statistic for the Q_N time-series, $Z(Q_N)$: if, for a particular basin, $Z(Q_N)$ is negative, then the net available energy for evaporation in the basin is decreasing from the second effect; increasing for a positive $Z(Q_N)$ (The spatial distribution of $Z(Q_N)$ is shown in Figure 4.11 and discussed in the next section.)

It is important to recognize that, physically, these two dynamics cannot be taken in isolation, but instead occur within the framework of complex feedback mechanisms beyond those that underpin the complementary relationship as it is currently formulated.

For instance, the effect of a long-term decrease in the available energy, indicated here by a negative trend in Q_N , may be an increase in soil moisture and thereby a decrease in V_{dif} in the over-passing air, which leads, in turn, to a lowering of the regional drying power of the air, and hence a negative trend in E_A .

In the following sections, the trends in these components are examined as they combine together across basins to produce trends observed in basin-derived ET_a^* , and according to their spatial distributions across the conterminous US.

4.5.3 ET_a^* and Component Trends in Hydrologically Undisturbed Basins

In order to examine the existence of the complementary relationship reflected in the trends in ET_a and its component fluxes, the water-budget observations of ET_a^* (see Section 4.5.1) are examined. Examining trends in annual ET_a^* and its Q_N and E_A components in the hydrologically undisturbed basins drawn from the set of 655 test-basins across the conterminous US shown in Figure 4.4(i), demonstrates the power of the complementary relationship hypothesis over the traditional, or non-complementary paradigms, both in predicting ET_a and in the analysis of long-term ET_a trends. The results for the trends in ET_a^* , Q_N , and E_A are summarized in Table 4.1.

The results for the combinations of trends in the 655 basins across the entire conterminous US derived using the ET_a^* -based E_A formulation (first column) and those across the subset of 207 basins in the Southern region derived using the ET_{pan} -based E_A formulation (second column) are similar. Of these combinations of trends, 48.7% / 45.4% (ET_a^* -based E_A / ET_{pan} -based E_A) display trends in ET_a^* that can be explained by both the traditional paradigm that holds that ET_p is independent of ET_a and by the complementary

Table 4.1: The signs of long-term trends in annual ET_a^* , Q_N , and E_A for 42 years across hydrologically undisturbed basins in the conterminous US. Possible explanations represent whether the combinations of trends in Q_N and E_A explain the trend in ET_a^* within the context of (C) the complementary relationship hypothesis, or (T) a traditional relationship between ET_a and ET_p , respectively: ✓ = explained, ✕ = not explained. The first column refers to the ET_a^* -based calibration of E_A in the 655 test-basins across the conterminous US, the second column to the ET_{pan} -based calibration in the 207 test-basins across the southern region.

% of basins in combination		sign[Z(..)]			Possible combinations	
Conterminous US (655 basins)	Southern US (207 basins)	E_A	Q_N	ET_a^*	C complementary relationship	T traditional paradigm
0.3	0	+	+	+	✓	✓
2.8	0	-	+	+	✓	✓
7.6	10.6	+	-	+	✕	✓
43.2	44.0	-	-	+	✓	✕
0	0	+	+	-	✓	✕
0.5	0	-	+	-	✕	✓
2.4	11.1	+	-	-	✓	✓
43.2	34.3	-	-	-	✓	✓

relationship between ET_a and ET_p . However, the trends in a further 43.2% / 44.0% basins can *only* be explained as a result of the complementary relationship acting. In these basins, the trends in E_A and Q_N are both negative, indicating a decrease in the drying power of the over-passing air (through a decrease in either V_{dif} or $f(U_2)$), which tends to reflect increasing regional ET_a , and a decrease in the local radiative flux, which tends to decrease local ET_a , the balance of which trends results in an increase in local ET_a . Applying these two component trends in the context of the monotonically increasing

relationship between ET_a and ET_p central to the traditional paradigm, wherein the complementary effects of regional advection are ignored, could only produce a decrease in ET_a^* in these basins, contrary to what is observed. Trends in the remaining (8.1% / 10.6%) basins are explicable within the context of the traditional paradigm, but not in the context of the complementary relationship. Possible explanations for these latter contradictory basins are as follows: (i) the trends are insignificant, i.e., the indicated trend statistics represent the mean of a noisy data set, and there is, in fact, no contradictory dynamic at work; and (ii) the differences in data-generation, although all three components represent the spatially integrated mean for each basin, the Q_N and E_A data result from spatial interpolation from observations that may have been made at some distance from the basins, while the ET_a trend data are derived from a mixture of observations integrating across the basin (streamflow) and spatially interpolated, modeled data (precipitation).

Figure 4.10 indicates the relative trends in the driving factors behind trends in ET_a^* for each of the (i) 655 test-basins across the conterminous US and (ii) 207 basins in the southern US, with each quadrant representing a different combination of influences driving trends in ET_a . Basins in the lower-left quadrant are experiencing decreasing Q_N and increasing E_A , a combination that, in the context of the complementary relationship, decreases ET_a^* . These basins, located in areas indicated as pixels that are simultaneously negative in Figure 4.11 and positive in Figure 4.12, should—through the complementary relationship dynamic—constitute a subset of the negative basins in Figure 4.8(i). Basins in the upper-right quadrant correspond to the opposite effects—increasing Q_N and decreasing E_A —thus indicating a increasing trend in ET_a and, for a good observation-

model match, an increasing trend in ET_a^* . The other two quadrants indicate mixed effects on ET_a^* ; with Q_N and E_A both increasing or both decreasing. Basins in these quadrants would then be represented as either positive or negative basins in Figure 4.8(i), with the sign depending on which of the two component trends is more powerful.

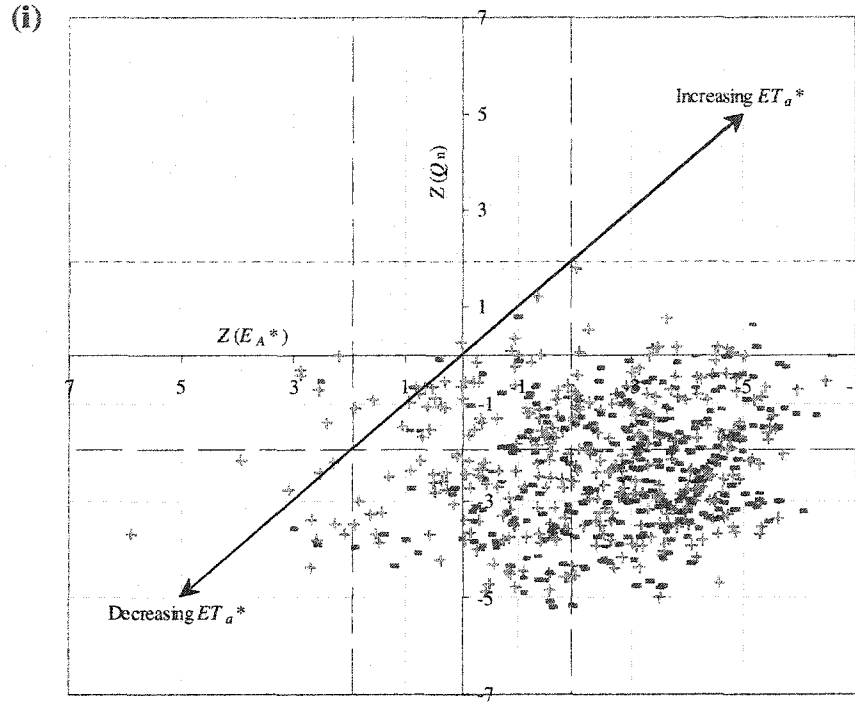


Figure 4.10: Orthogonal plot of Mann-Kendall test statistics for the Q_N and E_A components of ET_a^* lumped across the test-basins. The $Z(E_A)$ term is calculated using the $f(U_2)$ derived from (i) the ET_a^* -based calibration in 655 basins across the conterminous US, and (ii) the ET_{pan} -based calibration in 207 basins in the southern US, in both cases plotted in reverse—positive left, negative right—to coincide with the effects shown in Figure 4.9. Red “+” symbols indicate increasing ET_a^* rates, blue “-” symbols decreasing ET_a^* rates. Dashed lines indicate the 95% confidence limits for uncorrelated time-series.

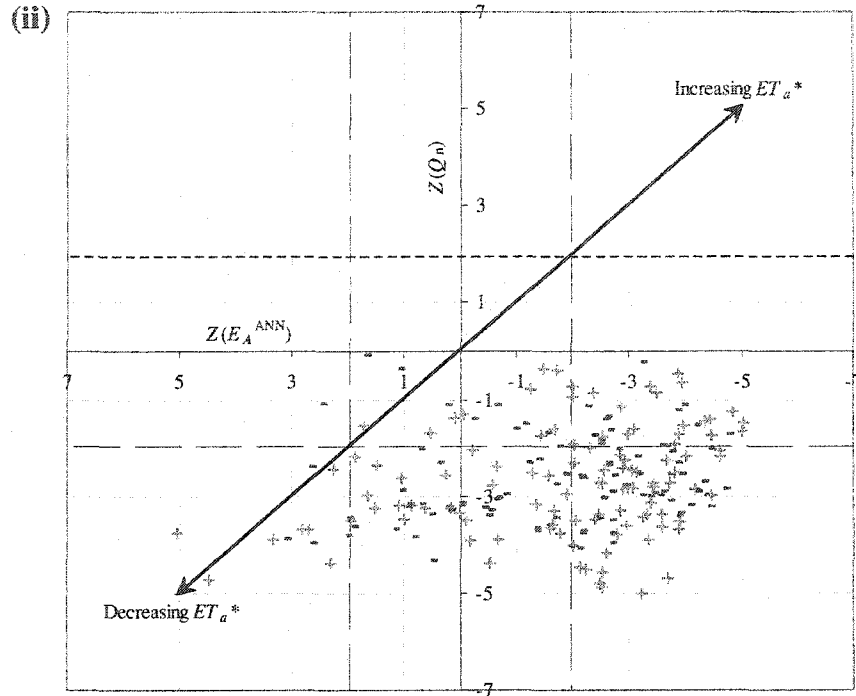


Figure 4.10 (cont.): Orthogonal plot of Mann-Kendall test statistics for the Q_N and E_A components of ET_a^* lumped across the test-basins. The $Z(E_A)$ term is calculated using the $f(U_2)$ derived from (i) the ET_a^* -based calibration in 655 basins across the conterminous US, and (ii) the ET_{pan} -based calibration in 207 basins in the southern US, in both cases plotted in reverse—positive left, negative right—to coincide with the effects shown in Figure 4.9. Red “+” symbols indicate increasing ET_a^* rates, blue “-” symbols decreasing ET_a^* rates. Dashed lines indicate the 95% confidence limits for uncorrelated time-series.

4.5.4 Distributed Trends in Q_N , E_A , U_2 , and V_{dif}

In this section, trends in each of these components are examined individually, both as to their spatial distributions and, when possible, how they compare to results reported by other workers.

Figure 4.11 presents the long-term trend in the energy available at the evaporating surface, expressed as the spatially distributed Mann-Kendall test-statistics of the time-

series of annual depth-equivalent rate of Q_N . Q_N represents the driving energy to any evaporative process; it is partitioned into sensible heat H and latent heat flux λET_a . The existence of trends in Q_N is primarily driven by trends in incident solar radiation, the existence of which appears in the literature to be somewhat of a hot-button issue: *Roderick and Farquhar* [2002] mention “considerable skepticism” toward a widespread 50-year decrease in global solar radiation in the face of evidence of a decrease on the order of 10-20% reported by *Stanhill and Cohen* [2001] and *Gilgen et al.* [1998], a 30-year decrease of 6-12% in northwestern Russia [*Peterson et al.*, 1995; *Golubev et al.*, 2001], and globally increasing cloudiness and precipitation [*Karl et al.*, 1996]. Such skepticism may result from the fact that observations of decreasing shortwave irradiance at the earth’s surface are not matched by predictions by GCMs. However, earlier GCMs did not include negative shortwave forcing by aerosols, while radiation models in current GCMs often do not account for all the factors affecting scattering and absorption by aerosols and clouds [*Stanhill and Cohen*, 2001].

While this study uses no data from Russia that would enable a direct comparison to be drawn there, averaged across the conterminous US for a similar period (1953-1994), a decrease in Q_N equivalent to 1.851 mm/year² of evaporation is observed, for a total decrease of 7.52% of the long-term mean, which corresponds almost exactly to the 0.34+/-0.07 W/m²/year global decrease reported by *Stanhill and Cohen* [2001] and thereby lends support to these findings of diminishing irradiance. By area, 97.8% of the area shows decreasing Q_N (21.2% statistically significant at the 95% level, 76.6% not significant); the remaining 2.2% of the area is increasing (0.01% statistically significant at the 95% level, 2.2% not significant).

Stanhill and Cohen [2001] report that the decrease in global irradiance has been accelerating since 1958, particularly in the northern hemisphere, with the maximum decrease occurring around 35°N, coinciding with the latitudes of maximum insolation, fossil fuel consumption, industrial activity, and population. Describing R_G as a factor of the radiation incident at the top of the atmosphere and an exponential sum of atmospheric transmissivities due to Rayleigh scattering, absorption by gases, water vapor, aerosols, and clouds, *Stanhill and Cohen* [2001] find the decrease in R_G to be a function both of increasing aerosols and cloudiness taken separately and of the combination effect of increased aerosol loading in clouds.

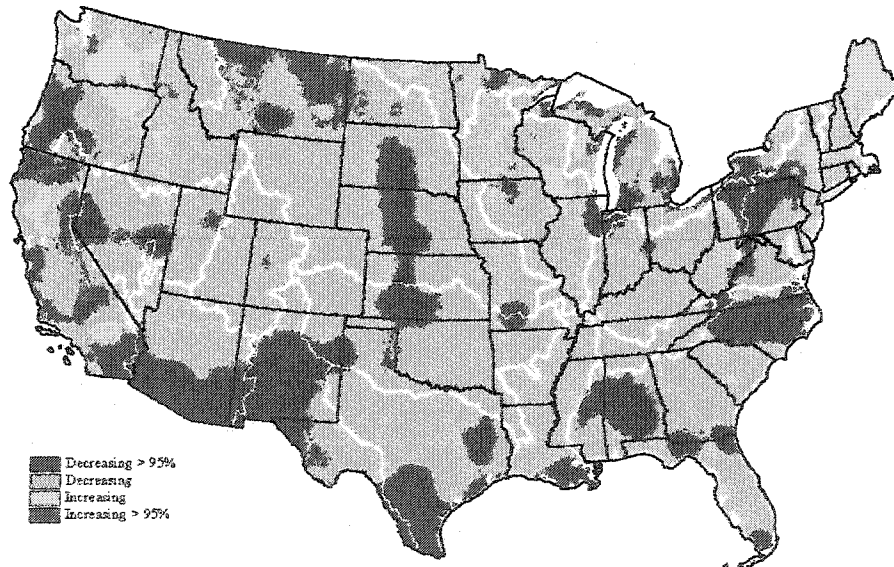


Figure 4.11: Distributed trends in annual Q_N across the conterminous US, as measured by the Mann-Kendall test statistic $Z(Q_N)$ of the 42-year time-series. Dark colors indicate statistically significant trends at the 95% confidence level: red increasing, blue decreasing. Also shown are state- and WRR-boundaries.

On a distributed basis, the pattern of decreasing Q_N is almost universal, with large areas of significantly decreasing Q_N in the High Plains, the desert Southwest, California

and Oregon, and along the Gulf of Mexico and Atlantic coasts. Although Figure 4.11 does not make this distinction, the decrease in Q_N is particularly pronounced in Arizona and North Carolina. There are few non-significant exceptions: the inland Pacific Northwest and smaller areas scattered around southern and northern California, Wisconsin, and New York and New Jersey.

Figure 4.12 presents the long-term trend in the the drying power of the air E_A , expressed as the spatially distributed Mann-Kendall test-statistics of the E_A time-series. E_A is calculated as a product of two factors: V_{dif} of the over-passing air, which is a measure of its ability to hold further moisture, and the wind function $f(U_2)$, the empirically derived expression that relates wind speed U_2 to the removal of said moisture from the evaporating surface. Discussed here are only the two annual E_A trend surfaces—those shown in Figure 4.12(i) and (ii), which show trends in E_A based on the ET_a^* -based and annual ET_{pan} -based $f(U_2)$ -calibrations, respectively (Figure 4.12(iii), which shows the trends in E_A based on the warm-season ET_{pan} -based $f(U_2)$ calibration, is, in any case, markedly similar to Figure 4.12(ii)). The overall picture for trends in the drying power of the air is somewhat complicated in both the ET_a^* -based and ET_{pan} -based cases, although between them, there do exist broad similarities: in both cases, E_A in the eastern US is predominantly and significantly decreasing, while across the western US, both trend patterns are more heterogeneous, in terms of both direction and significance.

Turning to the ET_a^* -based calibration; by area, 84.5% of the conterminous US shows decreasing trends (41.9% significant at the 95% level, 42.6% not significant), and the remaining 15.5% of the area is increasing (3.7% significant at the 95% level, 11.8% not significant). With the exception of a few areas in New England, down the Atlantic coast

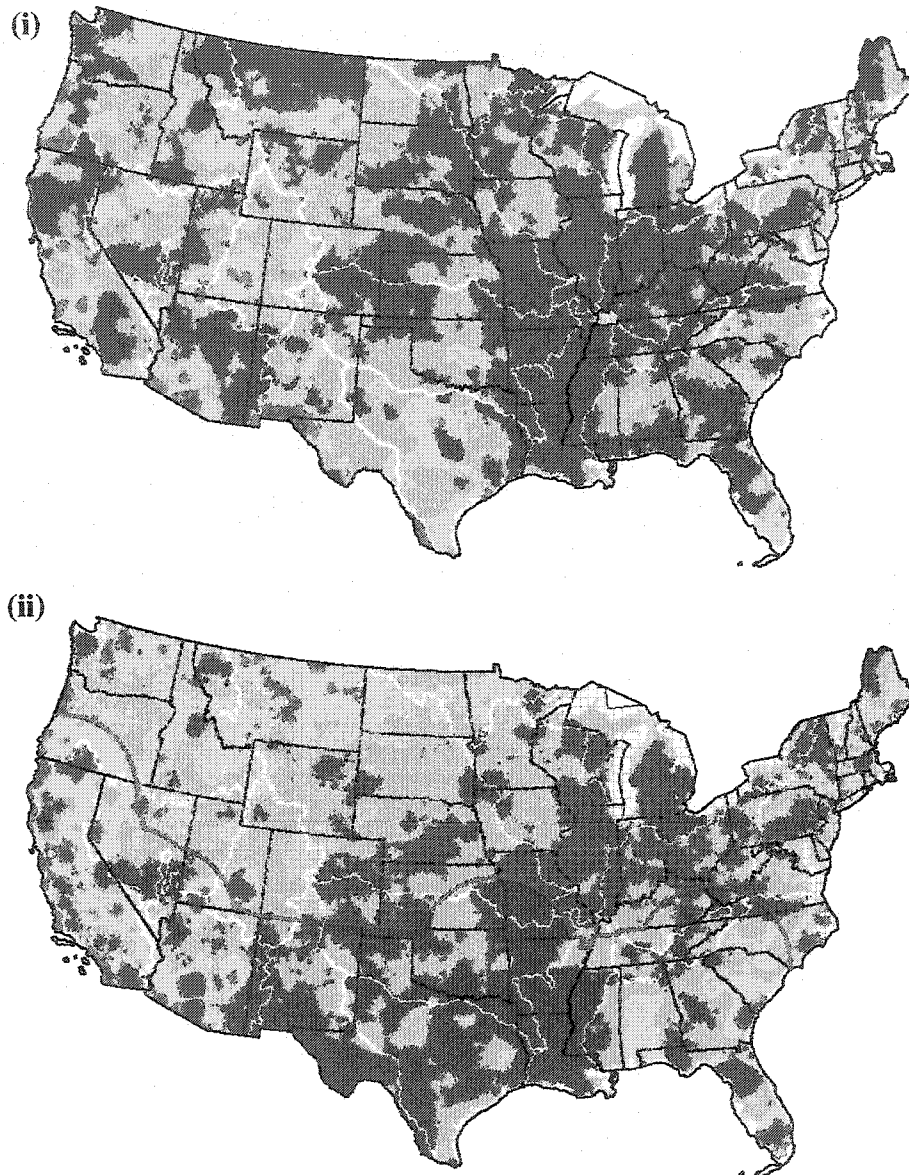


Figure 4.12: Distributed trends in annual E_A across the conterminous US, as measured by the Mann-Kendall test statistic $Z(E_A)$ of the 42-year time-series using $f(U_2)$ calibrated to (i) ET_a^* ; (ii) ET_{pan} ; and (iii) ET_{pan}^{WS} . Dark colors indicate statistically significant trends at the 95% confidence level: red increasing, blue decreasing. Also shown are state- and WRR-boundaries and, in (ii), the southern region.

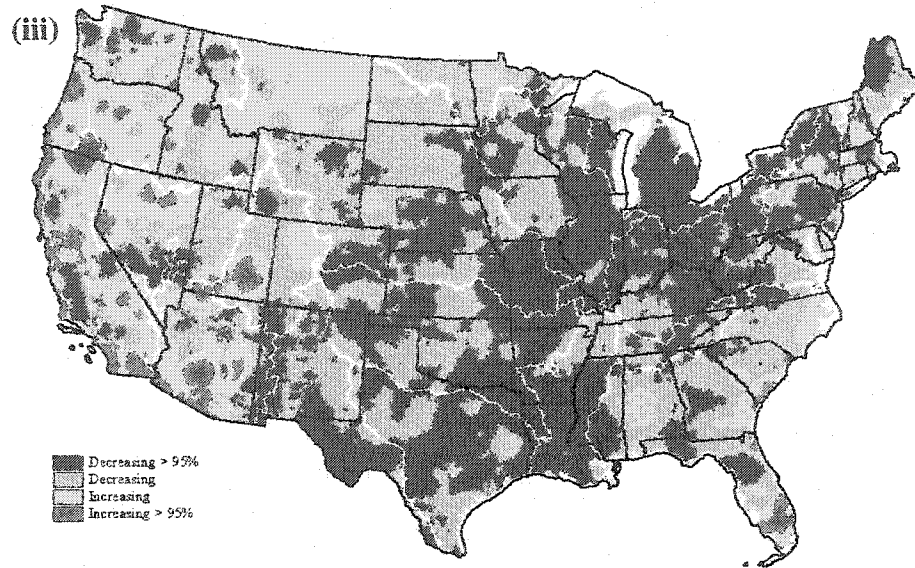


Figure 4.12 (cont.): Distributed trends in annual E_A across the conterminous US, as measured by the Mann-Kendall test statistic $Z(E_A)$ of the 42-year time-series using $f(U_2)$ calibrated to (i) ET_a^* ; (ii) ET_{pan} ; and (iii) ET_{pan}^{WS} . Dark colors indicate statistically significant trends at the 95% confidence level: red increasing, blue decreasing. Also shown are state- and WRR-boundaries and, in (ii), the southern region.

and in southern Florida, E_A across the eastern half of the conterminous US is decreasing, and significantly so. Areas of significantly increasing E_A are found across most of Montana, patches in coastal Oregon and portions of California, Utah, Arizona, New Mexico, and Texas. Spatially averaged across the entire conterminous US, the decrease over the 42-year period of record is 12.5%.

The ET_{pan} -based calibration, although over the southern region only, shows similar areal statistics: E_A is decreasing across 79.2% (42.5% significant at the 95% level, 36.7% not significant), and increasing across 20.8% (4.5% significant at the 95% level, 16.3% not significant). Similarly to the southern region of the ET_a^* -based E_A trend distribution shown in Figure 4.12(i), across the central portions of the southern region, ET_{pan} -based

E_A is decreasing and significantly so. In the eastern third of the region, significantly increasing patches are scattered along the Atlantic coast and in southern Florida. Across the western portions, areas of significantly increasing E_A stretch along the Pacific coast, and in southern portions of Arizona and Utah. Spatially averaged across the southern region, the decrease over the 42-year period of record is 11.0%.

A decrease in E_A can be due either to a decrease in wind speed U_2 or to increasing humidity, which, in this study would be measured by decreasing V_{dif} . All else equal, the latter case would reflect an increase in ET_a . *Roderick and Farquhar* [2002] claim that E_A across the conterminous US has been stationary over the last half-century to equal zero: following, their results and conclusion are verified by examinations of trends in both the factors of E_A : U_2 and V_{dif} .

Figure 4.13 displays the distributed trends in wind speed U_2 . Remarkable here is the consistency with which U_2 appears to be decreasing: 95.2% of the conterminous US, (53.0% significant at the 95% level, 42.3% not significant). Only 4.8% of the area (mostly surrounding a few SAMSON stations from which the data were gathered) shows increasing U_2 (0.3% significant at the 95% level, 4.5% not significant). The spatial mean U_2 has decreased at a rate of -0.012 m/sec/year (p -value < 0.001). Whether this remarkable decrease in U_2 is due to sampling errors, heterogeneities in the data as discussed in the context of ET_{pan} in Chapter 3, or reflect a broad climatological phenomenon is open to further investigation. This finding appears at first glance to be counter-intuitive: all else equal, an accelerating hydrologic cycle, that is, a more energetic land surface-atmosphere system, would appear necessarily to lead to increasing winds. However, it is supported by observations made during reverse-desertification in Israel

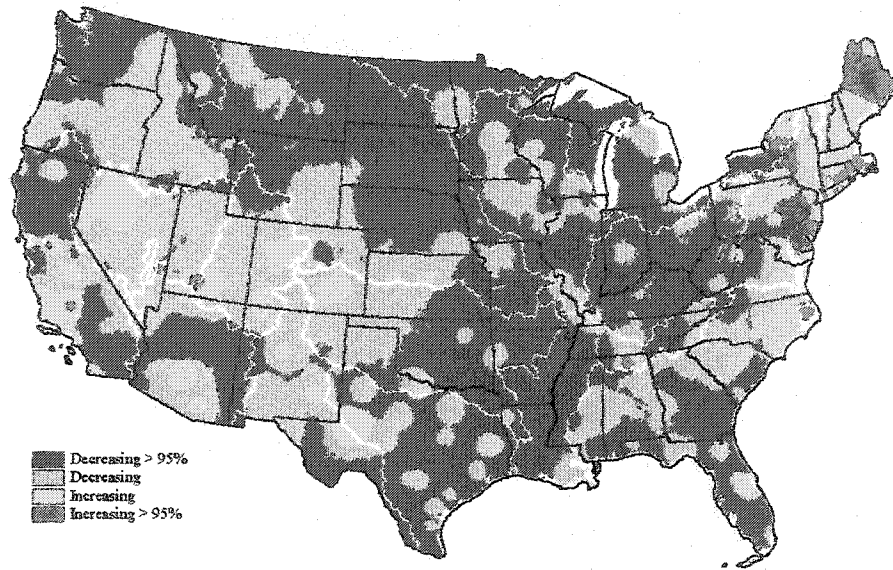


Figure 4.13: Distributed trends in annual U_2 across the conterminous US, as measured by the Mann-Kendall test statistic $Z(U_2)$ of the 42-year time-series. Dark colors indicate statistically significant trends at the 95% confidence level: red increasing, blue decreasing. Also shown are state- and WRR-boundaries.

[Alpert and Mandel, 1986] and, more recently, during large-scale irrigation development in southeastern Turkey [Ozdogan and Salvucci, 2004].

Alpert and Mandel [1986] noted that agricultural development of hyper-arid areas in Israel through irrigation decreased albedo and increased surface roughness, a combination that decreased sensible heating and increased latent heat flux. They surmise that the decrease in sensible heating leads to lower differential heating which itself leads to gross effects on air circulation, particularly evident in a lower variability in wind speed.

In their study of the long-term effects of regional scale irrigation on local ET_{pan} rates, Ozdogan and Salvucci [2004] conclude that δET_p is not sensitive to δQ_N but is sensitive to δE_A and that, further decomposing the trends, δU_2 is more powerful in its effects on

δET_p than is δV_{dif} . *Ozdogan and Salvucci* [2004] suggest the following reasons to explain the strong correlation of δU_2 and δET_p : the oasis effect; increased regional surface roughness due to the growth of crops; local shielding of wind speed instrumentation; and regional climatological factors unrelated to local ET_a changes. They will further report on the large degree to which the complementarity of ET rates depends on changes in wind speed, and further on a high pressure anomaly that significantly slows the prevailing winds over the study area [*Salvucci*, personal communication, 2004].

The broad negative δU_2 displayed in Figure 4.13 has broad implications for predicting trends in ET_a : the direct physical effect of U_2 is to modify eddy diffusivity, with increasing U_2 leading to increasing eddy diffusivity, and increasing turbulence, both of which increase ET_p ; in terms of modeling ET_a , holding all else equal and assuming an $f(U_2)$ with a positive slope (i.e., that the wind function increases with increasing wind speed), a reduced U_2 will reduce $f(U_2)$ reflecting a reduced E_A and an increased ET_a . That the decrease is continent-wide provokes interest in examination of large-scale atmospheric pressure changes found on the local scale by *Ozdogan and Salvucci* [*Salvucci*, personal communication, 2004].

Figure 4.14 displays the distributed trends in humidity as measured by the annual average vapor pressure deficit, V_{dif} , across the 42-year time-series. Broadly, the central and eastern parts of the conterminous US—the southern High Plains, the Central Lowland plains, the South, the Great Lakes region, and most of the mid- and northern-Atlantic states—indicate decreasing V_{dif} , or increasing humidity, while much of the far-western coastal states, the Southwest, the western northern-tier states, and pockets along the southern Atlantic coast show increasing V_{dif} , or decreasing humidity. By area, across

74.7% of the conterminous US V_{dif} is decreasing (becoming more humid) (30.0% significant at the 95% level, 44.8% not significant), while the remaining 25.3% is increasing, or becoming less humid (6.1% significant at the 95% level, 19.2% not significant). Across the conterminous US, the trend of the spatial mean annual V_{dif} is a decrease of 0.012 hPa/year, for a 42-year decrease of 0.504 hPa or 7.8% of the mean (a downward trend of -0.009 mmHg/year, or of -0.390 mmHg over the 42-year period of study). Given that 36.1% of the conterminous US indicates significant trends in either direction, and that annually averaged V_{dif} spatially averaged across the conterminous US has decreased by 7.80% of the long-term mean, calls into question the central assumption of *Roderick and Farquhar* [2002]: that V_{dif} across the conterminous US has been stationary over the last 50 years.

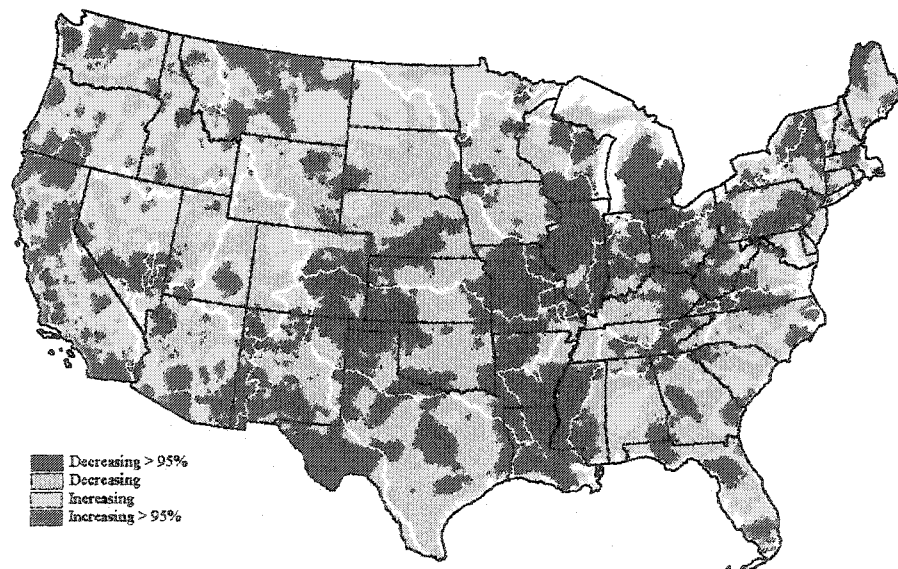


Figure 4.14: Distributed trends in annual V_{dif} across the conterminous US, as measured by the Mann-Kendall test statistic $Z(V_{dif})$ of the 42-year time-series. Dark colors indicate statistically significant trends at the 95% confidence level: red increasing, blue decreasing. Also shown are state- and WRR-boundaries.

In order to examine more closely the implications of these findings, it must first be re-emphasized that, on its own, V_{dif} informs only as to the capacity for over-passing air to hold more moisture; nothing about how fast the over-passing air is moving, or the rate at which this deficit, whatever its magnitude, can move moisture away from an evaporating surface. In order for V_{dif} to reveal anything at all about the origins of trends in ET_{pan} (as supposed by *Roderick and Farquhar* [2002]) or ET_a , it must be multiplied by $f(U_2)$, as shown in Equation (4.5), and thereby reveal E_A , the advective component of the evaporative process. Treating the conterminous US as a whole, in the manner of *Roderick and Farquhar* [2002], when both V_{dif} and $f(U_2)$ are combined in E_A and the constants in the difference equation for δET_a are included as their long-term mean, spatially averaged values, again in the manner of *Roderick and Farquhar* [2002], it is shown that, in fact, the trend in E_A accounts for over 50% of the trend in ET_a , contrary to the finding of *Roderick and Farquhar* [2002] (3.0 mm/year² for the vapor transfer function and 1.8 mm/year² for the radiative flux). This last statistic accounts for the other terms in the difference equation for ET_a : those in γ , Δ , and α . Thus, their consequent assertion that the complementary relationship plays little part in determining trends in ET_{pan} , that such trends are due solely to trends in R_7 , and that therefore the complementary relationship is an unsatisfactory explanation for the “Pan Evaporation Paradox” is deeply flawed. Indeed, this new result demonstrates that any resolution of this so-called paradox must account for the *non-stationarity* of humidity.

4.6 Modeling ET_a

Here the complementary relationship model of ET_a described in Section 4.4.2 and whose calibration is described in Section 4.4.4 is used to model ET_a distributed across the conterminous US. At a sequence of spatial scales and following the same procedures described in Section 4.5, trends in the components of modeled ET_a are analyzed to examine the effect of spatial scales on trend analysis. The input variables to the Advection-Aridity model used to generate the following results are discussed in Section 4.5.1. Both ET_a^* - and ET_{pan} -based parameterizations of $f(U_2)$ are used, in two separate modeling runs, and their assumptions and differences are highlighted, both in terms of the mean annual surfaces and of the trends. Both calibrations depend on assumptions that are either explicit, in the case of the ET_a^* -based calibration, or implicit, in the case of the ET_{pan} -based calibration. The different drawbacks for each calibration are discussed in Section 4.4.4.

4.6.1 Mean Annual ET_a

The results discussed herein were generated at a monthly time-step over the period WY 1953-1994, at a 5-km resolution, using a topographically corrected solar radiation input (whose derivation is explained in Chapter 2) in the derivation of Q_N , ET_a^* - and ET_{pan} -based wind functions, and a land-surface value for α of 1.3177.

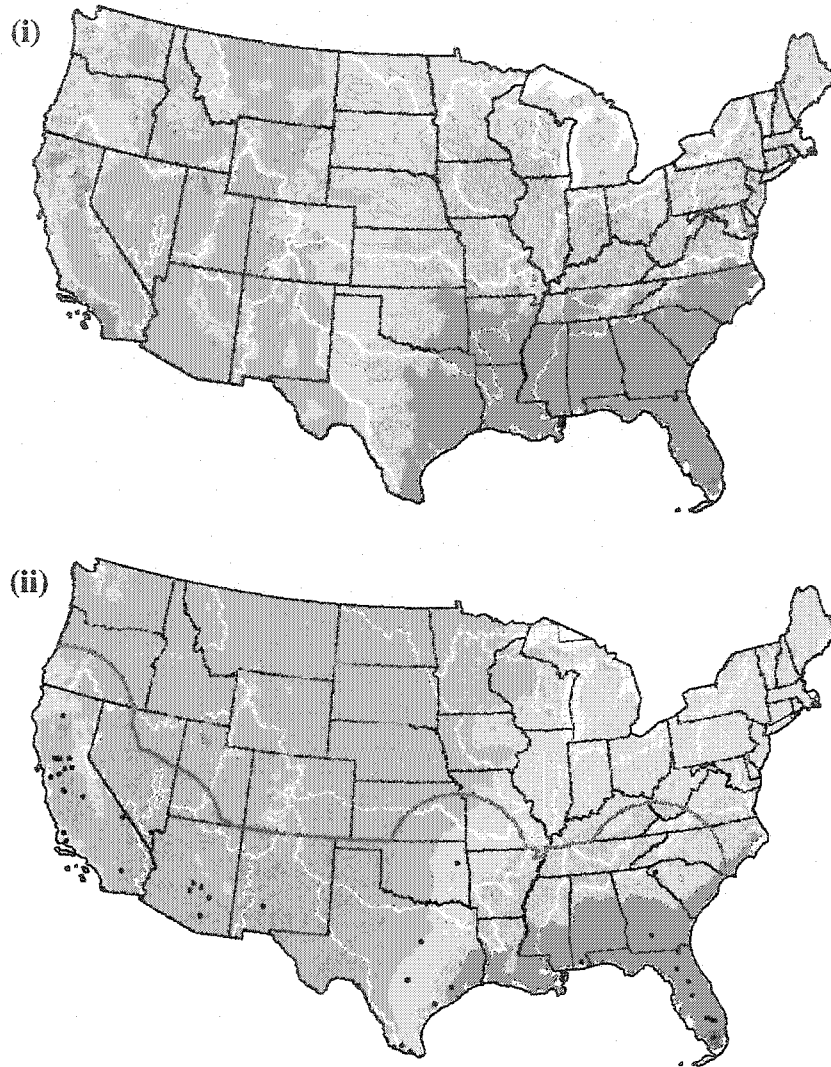


Figure 4.15: Distributed mean annual ET_a generated across the conterminous US over 42 years by the regional, seasonal Advection-Aridity model applied with $f(U_2)$ calibrated to (i) ET_a^* ; (ii) annual ET_{pan} ; and (iii) warm-season ET_{pan} . Also shown are the state- and WRR-boundaries and in (i) the 655 test-basins, in (ii) the 43 annual pans and the boundaries of the southern region, and in (iii) the 228 warm-season pans used to calibrate the respective models.

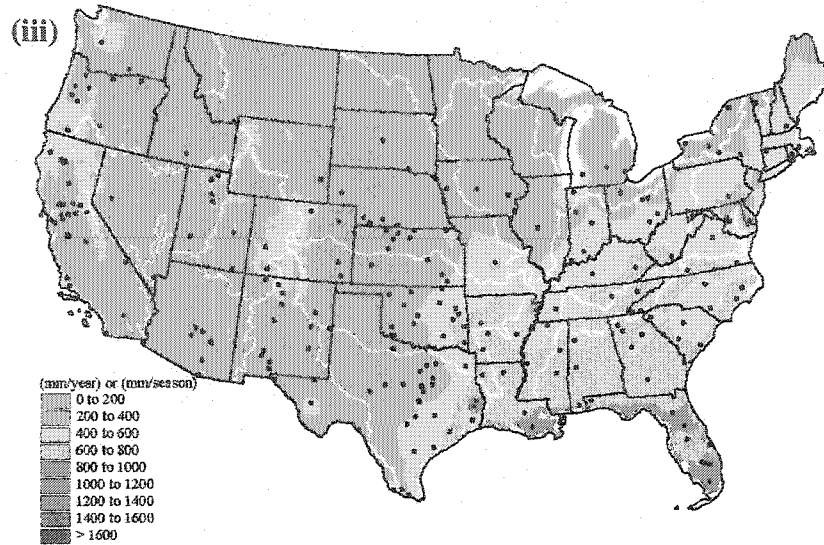


Figure 4.15 (cont.): Distributed mean annual ET_a generated across the conterminous US over 42 years by the regional, seasonal Advection-Aridity model applied with $f(U_2)$ calibrated to (i) ET_a^* ; (ii) annual ET_{pan} ; and (iii) warm-season ET_{pan}^{ws} . Also shown are the state- and WRR-boundaries and in (i) the 655 test-basins, in (ii) the 43 annual pans and the boundaries of the southern region, and in (iii) the 228 warm-season pans used to calibrate the respective models.

Figures 4.15(i) and (ii) present the spatial distribution of the mean annual ET_a depths as modeled by the ET_a^* -based calibration and the ET_{pan} -based calibration, respectively. Figure 4.15(iii) presents the mean warm-season ET_a -depth based on the ET_{pan}^{ws} -based calibration. The ET_a^* -based calibration predicts ET_a with a distinct positive latitudinal gradient in the eastern, homogenous US, with mean annual ET_a decreasing northwards away from the Gulf of Mexico, and a spatial distribution in the western US complicated by the effects of a longitudinal gradient that parallels precipitation with ET_a decreasing in a westward direction until the West Coast region is reached, and a positive elevational gradient with ET_a increasing with the increased precipitation at higher elevations. Across the conterminous US, the ET_{pan} -based calibration shows similar patterns. However,

across the southern region, away from the immediate environs of the Gulf of Mexico, the ET_a^* -based calibration over-predicts ET_a when compared with the ET_{pan} -based calibration. Over the entire conterminous US, the mean annual ET_a predicted by the ET_a^* -based calibration is 568 mm/year. Across the southern region, mean annual ET_a estimated by the ET_a^* -based calibration is 630 mm/year, but only 417 mm/year as estimated by the ET_{pan} -based calibration. The calibration based on warm-season ET_{pan} predicts mean seasonal ET_a of 345 mm/season across the conterminous US, following roughly the same spatial distribution as the (annual) ET_{pan} -based calibration.

4.6.2 Model Performance

Figure 4.16 describes the performance of both models as measured against both sets of calibrating data: it describes the replication of the ET_a data used to calibrate the ET_a^* -based calibration by both the ET_a^* -based calibration and the ET_{pan} -based calibration; and the replication of ET_{pan} data used to calibrate the ET_{pan} -based calibration estimated by ET_p as modeled by both the ET_{pan} -based calibration and the ET_a^* -based calibration. Ideally, all points would lie on the 1:1 relation indicated on the graph, or, more realistically, be normally distributed around it with a low variance. As should be expected, both models perform better at replicating their own calibration data than they do other data: the ET_a^* -based calibration predicts ET_a with a slope of 0.8404 ($R^2 = 0.9194$, p -value < 0.05) but predicts ET_p with a slope of only 0.4313 ($R^2 = 0.5174$, p -value < 0.05); the ET_{pan} -based predicts ET_p with a slope of 0.9952 ($R^2 = 0.9973$, p -value < 0.05) but predicts ET_a with a slope of 0.8074 ($R^2 = 0.5153$, p -value < 0.05). These less-

than-unity slopes indicate that, at the higher reaches of the respective ranges, both models tend to under-predict the data not used to calibrate them.

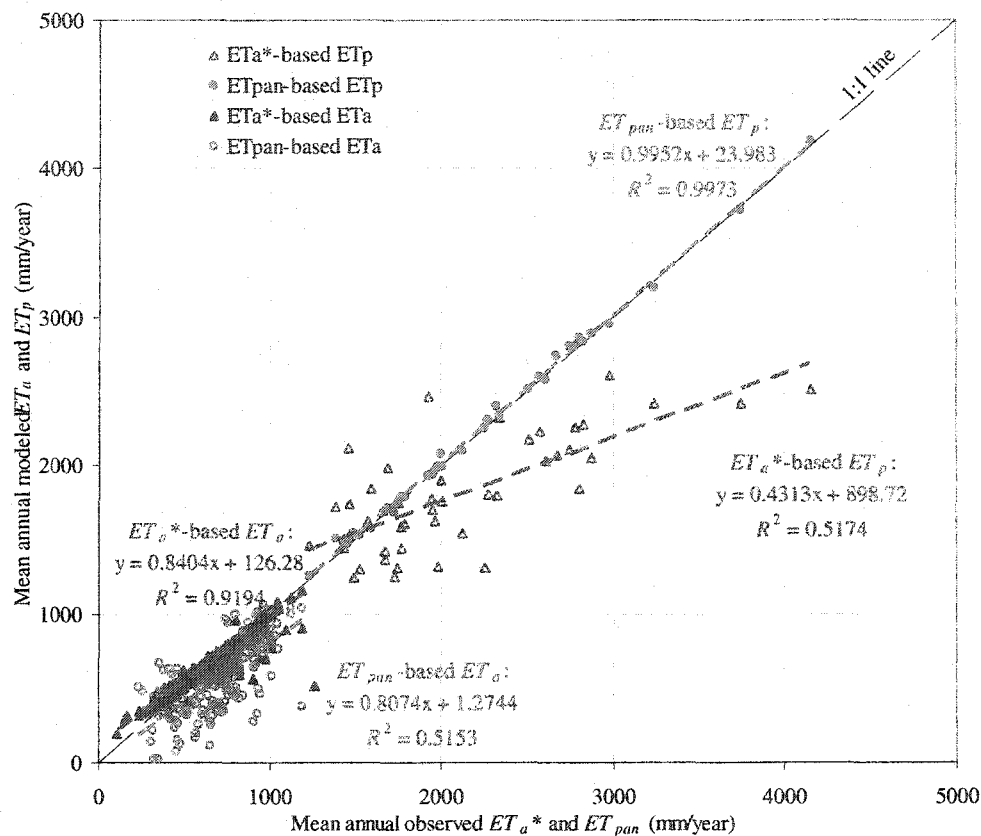


Figure 4.16: Modeled estimates of ET_a and ET_p versus observed estimates of ET_a^* and ET_{pan} , respectively, derived from the ET_a^* -based calibration (shown as Δ and $\blacktriangle$) and the ET_{pan} -based calibration (shown as $\circ$ and $\bullet$). Solid shapes represent the data used for calibration in each model as replicated by that model, and the ET_{pan} -based calibration in 207 test-basins in the southern region.

In order to gain some measure of the performance of the re-parameterized Advection-Aridity model, the average annual water balance closure error, or “closure error,” is derived by comparing the modeled ET_a to the independent evapotranspiration estimate

ET_a^* . The closure error ε for the model is calculated for each basin, as a percentage of average annual precipitation, from Equation (4.42):

$$\varepsilon = \frac{\sum_{i=1}^{42} \sum_{j=1}^{12} (ET_{a(i,j)}^* - ET_{a(i,j)})}{\sum_{i=1}^{27} \sum_{j=1}^{12} P_{(i,j)}} * 100\% \quad (4.42)$$

where ET_a is the ET_a^* -based estimate of ET_a or the ET_{pan} -based estimate of ET_a , and i and j here represent the water year and water month, respectively.

Table 4.2: Summary statistics for water balance closure errors for the population of closure errors in either the 655 test-basins across the conterminous US or the the 207 test-basins across the southern region, or both.

Statistic	Models		
	ET_a^* -based		ET_{pan} -based
	All 655	Southern 207	Southern 207
Mean (% prcp)	-3.63%	-2.87%	14.52%
Median (% prcp)	-2.88%	-2.07%	10.28%
Minimum (% prcp)	-29.72%	-23.12%	-31.62%
Maximum (% prcp)	35.03%	18.59%	94.03%
St. Dev. (% prcp)	5.17%	4.35%	19.05%
Skewness	-0.3428	-0.3499	1.3696

Non-zero closure errors must first be considered to be either an over-prediction (negative closure error) or under-prediction (positive closure error) of ET_a by the models. Other possible explanations—not quantified in this study—are: (i) violations of the assumptions inherent in Equations (4.13) and (4.8) used to develop the ET_a^* estimates,

perhaps through the effects of groundwater pumping, surface-water diversions, or violations of the assumption of negligible net groundwater flow out of the basin; (ii) violations of the assumption of stationarity in climatological forcing; (iii) errors in the hydroclimatological record; and (iv) errors induced by spatial interpolation of the climatic variables.

In the case of modeled ET_a data, by far the best model is that based on ET_a^* . Support for this conclusion is indicated in Figure 4.16, where all the ET_a data predicted by the ET_a^* -based calibration lie near the 1:1 line, and supported in Table 4.2, which shows the summary statistics for the analysis of closure errors, whose derivation is described in Section 4.5.1: the mean and the median are both near-zero (-3.63% and -2.88%, respectively), and the skewness of the population is -0.3428, indicating a non-normal distribution. As regards the ET_{pan} -based calibration, that most of the ET_a data lie below the 1:1 line indicates that this model under-predicts ET_a . This is borne out by the significant negative bias evident in the summary statistics in Table 4.2: ϵ for the ET_{pan} -based calibration is 14.52%. This latter statistic, along with the high positive median and high positive skewness indicates that the ET_{pan} -based calibration under-predicts ET_a across the population of 207 test-basins in the southern region. These observations are further supported by the distribution of closure errors shown in Figure 4.17, where the majority of the distribution lies to the right of zero, with a skewness of +1.3696, indicating a non-normal distribution. The standard deviation of the ET_{pan} -based calibration compares poorly with that of the ET_a^* -based calibrations: 19.07% for the former versus 5.17% for the latter. That the relative poor performance of the ET_{pan} -based calibration is not due to a geographical bias induced by the difference in test-basin

populations used is borne out by comparing the summary statistics for each model across both regions in Table 4.2 below: neither model shows a difference between its two regional performances.

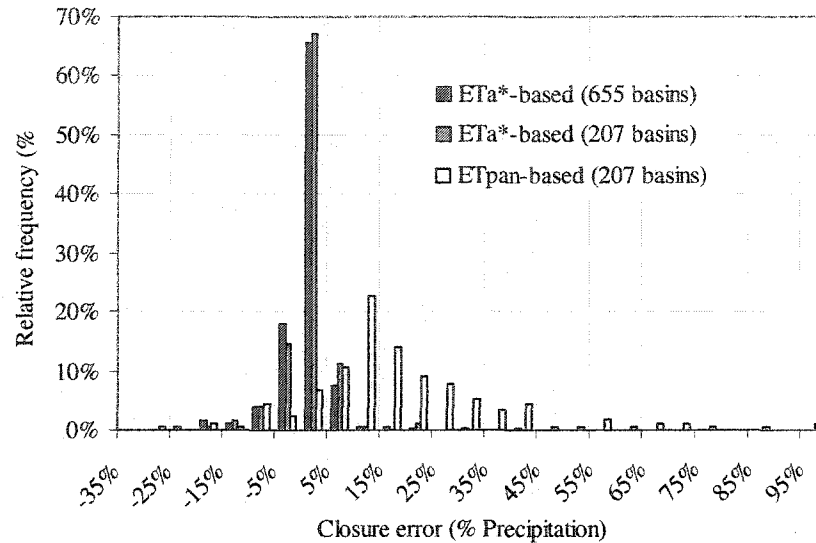


Figure 4.17: Distributions of mean annual closure errors (expressed as percentages of mean annual basin-wide precipitation) at the 655 test-basins, derived using (i) the ET_a^* -based calibration (shown in blue) and (ii) the ET_{pan} -based calibration (shown in red).

It is interesting to note that the ET_{pan} -based calibration replicates both its calibration data and that of the other ET rate— ET_{pan} for the former, and ET_a for the latter—better than does the ET_a^* -based calibration. While this last finding may be a function of the ET_{pan} model simply performing better, perhaps due to its capturing the monthly variability in the wind function $f(U_2)$, it may also result from the methodology used to generate Figure 4.16: in the case of the ET_{pan} -based calibration, the output ET_p and ET_a data sets were queried at points representing the input pans, whereas for the ET_a^* -based calibration, spatial averages of the output ET_p and ET_a data sets were generated across the extent of each of the individual basins.

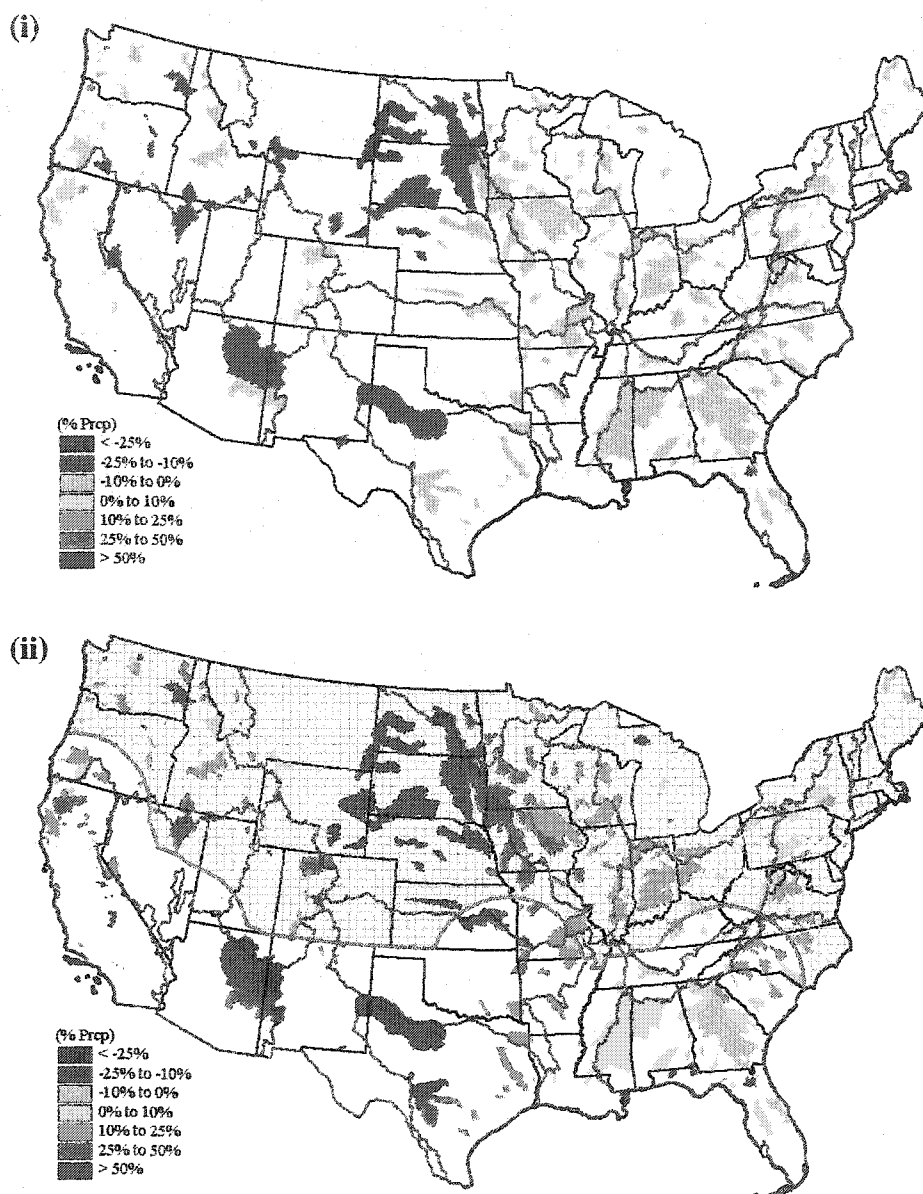


Figure 4.18: Spatial distribution of mean annual closure errors (expressed as percentages of mean annual basin-wide precipitation) at the 655 test-basins, derived using (i) the ET_a^* -based calibration, and (ii) the ET_{pan} -based calibration. Also shown are the state- and WRR-boundaries and, in (ii), the boundaries of the southern region.

Figure 4.18 indicates the spatial distribution of the closure errors generated by (i) the ET_a^* -based calibration, and (ii) the ET_{pan} -based calibration across the test-basins used to generate the ET_a^* data. In the case of the ET_a^* -based calibration and across all 655 test-

basins in the conterminous US, the mean bias towards over-estimation of ET_a by the model (negative ϵ) is evident across the entire country, with the High Plains (particularly in their northern reaches) and other areas of the inland West showing the greatest over-estimation by the model. The basins where ET_a (positive ϵ) has been under-estimated are distributed at random throughout the eastern and western thirds of the country; there are no basins in the central third where ET_a has been under-estimated. Limiting discussion of the ET_{pan} -based calibration to the southern region where the model can be said to be calibrated, the central third of the southern region shows the worst results for the ET_{pan} -based calibration—in this case, under-estimation of ET_a (positive ϵ). With the exceptions of a few basins in California, the ET_{pan} -based calibration overwhelmingly under-estimates ET_a across the rest of the western southern region, though not to the extent as those in the central third of the region. In the east, the under-estimation is less pronounced, and the majority of basins in Georgia and Florida show over-estimated ET_a (negative ϵ). It is also interesting to note that the basins which show the worst results in one model show similarly, but oppositely, poor results in the other.

Figure 4.19 displays the variations of closure errors with mean annual basin-wide precipitation (P) measured at each of the 655 test-basins across the conterminous US in the case of the ET_a^* -based calibration and 207 southern test-basins in the case of the ET_{pan} -based calibration. Although the lines of best-fit shown appear to be somewhat arbitrary, they indicate that the two models display broadly opposite results: in arid basins (low P), the ET_a^* -based calibration tends to under-estimate ET_a , while the ET_{pan} -based calibration grossly over-estimates ET_a in low- P basins. Both models do increasingly well with increasing P . The relationship of ϵ to P is somewhat stronger for the ET_{pan} -based

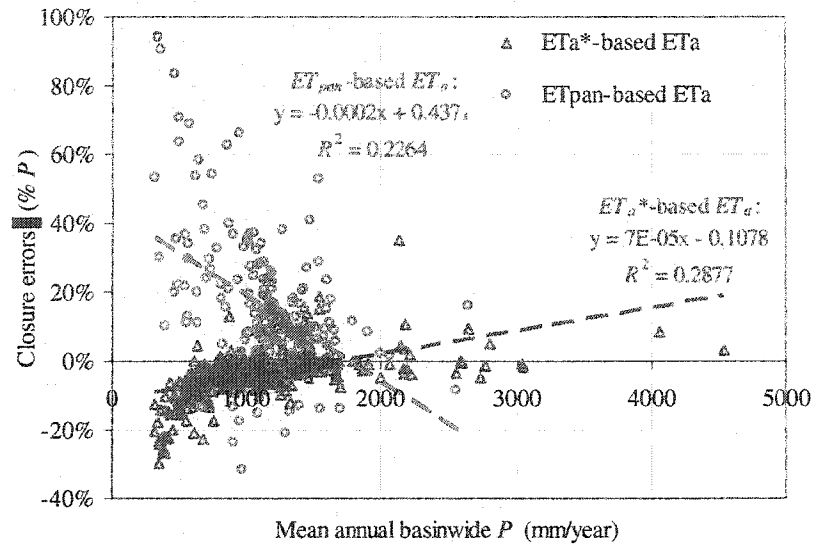


Figure 4.19: Mean annual closure errors versus mean annual basin-wide precipitation depth for ET_a derived from the ET_a^* -based calibration in 655 test-basins across the conterminous US (shown as Δ), and the ET_{pan} -based calibration in 207 test-basins in the southern region (shown as $\circ$).

calibration (slope = -2×10^{-4} , $R^2 = 0.226$, p -value < 0.05) than for the ET_a^* -based calibration (slope = 7×10^{-5} , $R^2 = 0.288$, p -value < 0.05), which should be expected, considering that the ET_a^* estimates to which the model was calibrated are a function of P , also, as shown in Equation (4.13), whereas the ET_{pan} -based calibration is calibrated to observations of ET_{pan} that are effectively independent of observations of P .

Figure 4.20 displays the variations of closure errors with mean annual (WY 1953-1994) basin-wide ET_a^* , measured at each of the 655 test-basins across the conterminous US in the case of the ET_a^* -based calibration and 207 southern test-basins in the case of the ET_{pan} -based calibration. This is an interesting result: the ET_a^* -based calibration, calibrated on the very observations of ET_a^* used on the y-axis of this plot, displays a stronger relationship to ET_a^* (slope = 2×10^{-4} , $R^2 = 0.390$, p -value < 0.05) than does the

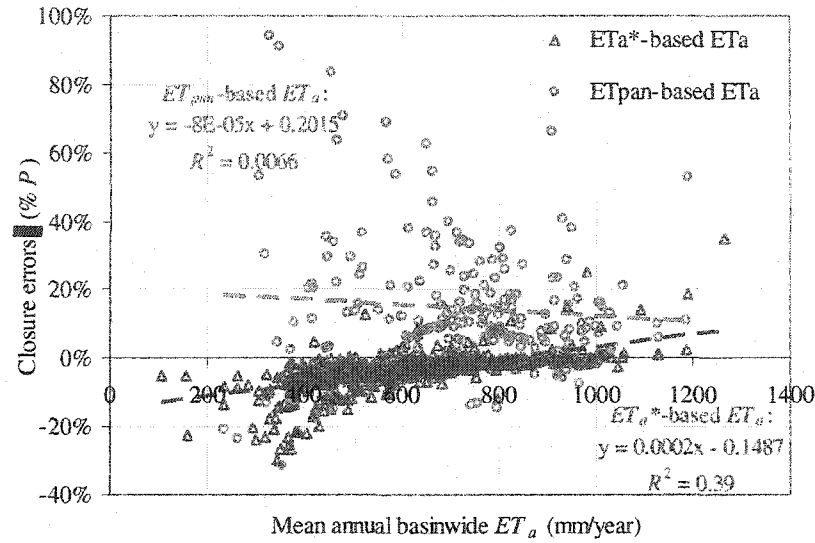


Figure 4.20: Mean annual closure errors versus mean annual basin-wide ET_a^* depth for ET_a derived from the ET_a^* -based calibration in 655 test-basins across the conterminous US (shown as Δ), and the ET_{pan} -based calibration in 207 test-basins in the southern region (shown as $\circ$).

ET_{pan} -based calibration, which, while its bias towards under-predicting ET_a is clear, appears to bear little or no functional relationship to ET_a^* (slope = -8×10^{-5} , $R^2 = 0.007$, p -value = 0.244). The ϵ populations of both calibrations—the ET_a^* -based calibration in particular, but to some extent the ET_{pan} -based calibration—are most variable in basins with low ET_a^* and converge with increasing ET_a^* .

Figure 4.21 displays the variations of closure errors with mean annual basin-wide U_2 , measured at each of the 655 test-basins across the conterminous US in the case of the ET_a^* -based calibration and 207 southern test-basins in the case of the ET_{pan} -based calibration. The figure demonstrates the effects of the different calibrations of the advective component. The ET_{pan} -based ϵ population is strongly correlated with U_2 (slope = 0.221, $R^2 = 0.3124$, p -value < 0.05), with ET_a being increasingly under-estimated with

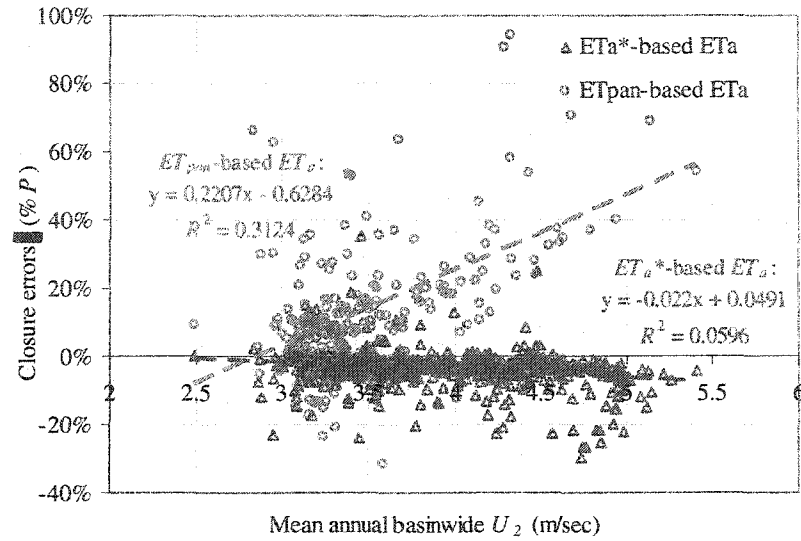


Figure 4.21: Mean annual closure errors versus mean annual basin-wide U_2 for ET_a derived from the ET_a^* -based calibration in 655 test-basins across the conterminous US (shown as Δ), and the ET_{pan} -based calibration in 207 test-basins in the southern region (shown as $\circ$).

increasing U_2 (slope = -0.022, $R^2 = 0.0596$, p -value < 0.05). The ET_a^* -based ϵ population appears to bear little or no functional relationship to U_2 . The U_2 -related bias of the ET_{pan} -based calibration—obvious especially in comparison to the ET_a^* -based calibration—is another interesting result: although neither model was calibrated explicitly to observations of U_2 , not only does the ET_{pan} -based calibration come closest, but there are fewer sources of uncertainty than in the ET_a^* -based calibration's use of $P - R$ to model ET_a . The relationships displayed in Figure 4.21 are a function of the shapes of the $f(U_2)$ relationships, samples of which are shown in Figures 4.4(iii) and 4.4(iv). All else equal, the $f(U_2)$ relationships with the steeper positive slopes (highest values of b in Equation 4.11) tend to suppress modeled ET_a (as shown in Equation 4.6) with increasing U_2 , and therefore lead to lower over-estimations (or a greater under-estimations) of ET_a . It is the

wide variety of slopes in their $f(U_2)$ relationships (parameter b in Equation 4.11) that results in the lack of functional relationship between the ET_a^* -based ϵ population and U_2 . In order to eliminate the strong positive relationship of the ET_{pan} -based ϵ population with U_2 , less steep $f(U_2)$ relationships are indicated. This is then a trade-off: on the one hand, the ET_{pan} -based calibration results in physically sensible $f(U_2)$ relationships that are similar to those reported in the literature but result in a model poorly calibrated with respect to U_2 ; on the other hand, the ET_a^* -based calibration, which has a degree of freedom in the estimation of its $f(U_2)$ parameters that result in physically less sensible $f(U_2)$ relationships, nevertheless yields a model that is well-calibrated with respect to U_2 .

4.6.3 Trends in ET_a at Different Spatial Scales

Temporal trends in hydrologic variables may occur and—given the spatially distributed set summarized in Figure 4.15—may be studied at various spatial scales. For example, at the global or continental scale, warming as a result of the greenhouse effect may affect all aspects of the hydrologic cycle, with the primary effect being that of the rising mean temperature resulting in a more energetic hydrologic cycle. At the WRR-scale, effects on the hydrologic cycle may run from modifications of weather patterns, such as deviation of storm tracks, to the effects of land-use changes, such as increased latent heat flux and humidity from large-scale irrigation. These effects may be manifested in the short term—in anthropogenic migrations of agriculture, for example—and in the long term—as natural migrations of vegetative species in response to changes in moisture availability that result from changes in precipitation intensity, totals, and seasonality, and temperature effects on ET_a . At the basin-scale, the effects on trends in the water yield

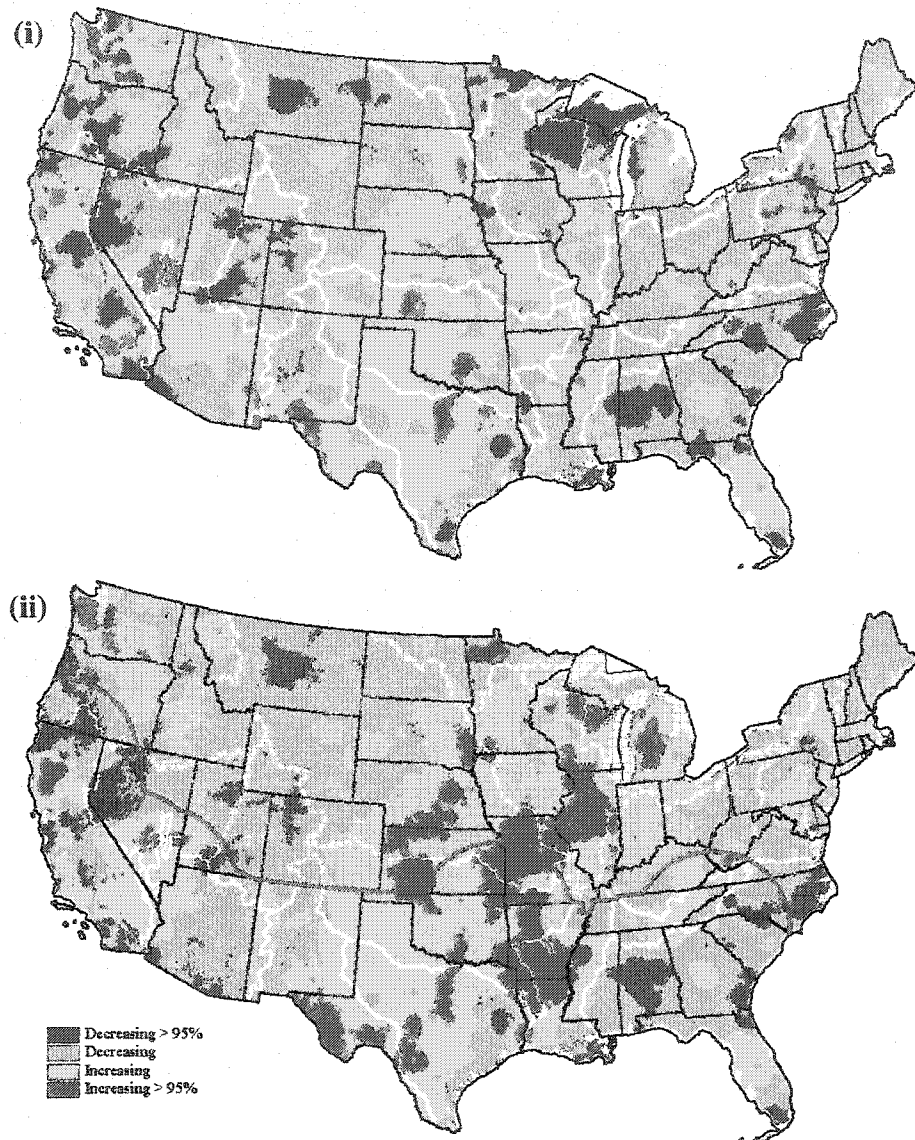


Figure 4.22: Distributed trends in annual ET_a across the conterminous US, as measured by the Mann-Kendall test statistic ($Z(ET_a)$) of a 42-year time-series generated by the regional, seasonal Advection-Aridity model with $f(U_2)$ calibrated to (i) ET_a^* , and (ii) annual ET_{pan} . Dark colors indicate statistically significant trends at the 95% confidence level: red increasing, blue decreasing. Also shown are the state- and WRR-boundaries and, in (ii), the boundaries of the southern region.

function may be difficult to detect, as the integrative dynamics of the component basin processes may average such effects out. Analyses of the components themselves—

precipitation and ET_a —may therefore be more instructive. At this scale, these include the direct effects of temperature on ET_a , which may be readily modeled by use of regional ET models, and by the local variations in the dynamics of the hydrologic cycle, which may include changes in storages, the seasonality of precipitation, and in vegetation type and cover. With the variety of possible scales of responses in mind, results are presented here at a variety of spatial scales.

The overall picture of trends in ET_a across the conterminous US over the period 1953-1994 is presented first, then the trends of the two components of ET_a —the radiative flux Q_N and the regional advective flux E_A —are examined in the context of the complementary relationship at a succession of nested spatial scales. They are presented spatially across the extent of the conterminous US, then for each of the 18 WRRs that constitute that region, then for each of the 334 AUs that comprise the 18 WRRs.

4.6.3.1 Continental-scale Analysis

Figure 4.22 presents the larger picture: that of distribution of ET_a trends across the conterminous US, estimated by the Mann-Kendall test-statistic for the long-term time-series in ET_a estimated at each 5-km pixel by the Advection-Aridity model using: (i) the ET_a^* -based calibration of $f(U_2)$; and (ii) the ET_{pan} -based calibration. Quantifying these trends using linear regression on the spatial mean annual ET_a across the conterminous US, ET_a^* -based ET_a is decreasing by 0.565 mm/year^2 ($p\text{-value} < 0.05$). Across the southern US, ET_{pan} -based ET_a is decreasing at 0.208 mm/year^2 ($p\text{-value} = 0.4572$), while across the same region, ET_a^* -based ET_a is decreasing at 0.470 mm/year^2 ($p\text{-value} = 0.1812$).

These results bear comparison to those of Szilagyi [2001], who reported a 2.5% increase in annual ET_a over the period 1961-1990, and who, in a follow-up paper [Szilagyi *et al.*, 2001] conclude that use of the complementary relationship over-estimates trends in ET_a . Over this shorter intermediate period, this study supports their findings: averaged across the conterminous US, ET_a^* -based mean annual ET_a has increased by 5.49% from 1961-1990. Differences in the results may relate to the difference in methodology: results here were derived from a model that is both spatially distributed and—at least in the case of the ET_a^* -based calibration—well-calibrated; they did not rely on continental-scale spatial averaging from station-values of ET_a , as did Szilagyi [2001] and Szilagyi *et al.* [2001], who used 210 and 132 stations, respectively.

A preliminary inspection of spatial distributions reveals complex results from both models, with few continental-scale patterns emerging. In the southern US, where both models estimate trends, the exceptions to this appear to be the Central Lowland Plains, the southern High Plains, northern California, parts of the desert Southwest, and central Florida, where both models estimate increasing ET_a ; and the South, where the trend is to decreasing ET_a . In the northern US, as estimated by the ET_a^* -based calibration alone, the only other regional-scale results are increasing ET_a in parts of the inland Pacific Northwest, and decreasing ET_a in the northern High Plains, the northern and central Rocky Mountains, and the Mid-Atlantic states. The rest of both models' study areas present complex, heterogeneous pictures from which no commonalities and few other generalities can be drawn. Across the conterminous US, the ET_a^* -based calibration shows increasing ET_a across 33.6% (2.1% significant at the 95% level, 31.5% not significant); decreasing in the remaining 66.4% (8.7% significant at the 95% level, 57.7%

not significant). Across the southern US, the ET_{pan} -based calibration shows increasing ET_a across 51.1% (10.7% significant at the 95% level, 40.4% not significant), and the ET_a^* -based calibration across 43.0% (3.3% significant at the 95% level, 39.8% not significant); ET_{pan} -based calibration shows decreasing ET_a across its remaining 48.9% (8.8% significant at the 95% level, 40.1% not significant), and the ET_a^* -based calibration across its remaining 57.0% (9.4% significant at the 95% level, 47.6% not significant).

4.6.3.2 WRR-scale Analysis

Examining the trends in ET_a displayed in Figure 4.22 on the basis of WRRs, few show consistent results, particularly and perplexingly so for the ET_a^* -based calibration, where only WRRs 2 (Mid-Atlantic), 5 (Ohio), 6 (Tennessee), and 9 (Souris-Red-Rainy) can be said to be predominantly decreasing, and no WRRs are predominantly increasing. All other WRRs are combinations of decreasing and increasing ET_a , and contain few obvious WRR-wide trends. In the ET_{pan} -based calibration applied across the southern US, WRR-wide trends are more obvious: WRRs 11 (Arkansas-White-Red) and 12 (Texas-Gulf) show predominantly increasing ET_a , while WRRs 3 (South Atlantic-Gulf) and 15 (Lower Colorado) show predominantly decreasing ET_a . Again, the remaining WRRs combine both decreasing and increasing ET_a , and contain few obvious WRR-wide trends. Comparing the two calibrations on the WRR-scale, it is somewhat surprising that the ET_{pan} -based calibration should show such spatially more coherent results than the ET_a^* -based calibration, given that the $f(U_2)$ -values for the latter were lumped across the WRRs and their component Accounting Units (AUs), whereas the $f(U_2)$ values for the former were distributed by a simple IDW spatial interpolation.

The non-homogeneity of these trends at the continental scale and even within specific WRRs is in part the result of the fact that neither the conterminous US nor its constituent WRRs are climatologically homogeneous regions. For instance, WRR 10 (Missouri) includes both the Rocky Mountains at the Continental Divide on the Idaho-Montana border and vast tracts of the High Plains, extending as far southeast as the Mississippi River on the Missouri-Illinois border. Examining results from such a large and hydrologically diverse single region may not be a useful tool and may instead have the effect of rendering useful data into mere noise. In a study of regional streamflow patterns and hydroclimatology, *Lins* [1997] concluded that although the division of the conterminous US into the 18 WRRs is based purely on surface watersheds, the WRRs do not correspond to observed hydroclimatology, as many of the hydrological driving forces are not constrained by the drainage divides that define the WRRs. An examination of the results at the WRR-scale is somewhat dissatisfying and indicates that this scale may not be optimal for such a discussion.

Next, trends in ET_a and in the component dynamics Q_N and E_A lumped across at a sequence of finer, nested spatial breakdowns are examined: the 18 WRRs that constitute the lower-48 states; and then the 334 AUs into which these WRRs are divided. This allows conclusions to be drawn as to the efficacy of spatial averaging and the appropriate scale of analysis. As the desire here is to examine trends for all regions in the conterminous US, and as there is less interest in the different effects of each calibration than in the effects of spatial scale, the model choice is restricted to the ET_a^* -based calibration.

4.6.3.3 Spatial Breakdown of Component Trends

Figure 4.23 indicates, for the entire lower-48 states taken as a whole and at two finer spatial breakdowns, the relative trends in the driving factors behind trends in components of ET_a^* -based ET_a . The figure is presented in an identical fashion to Figure 4.10. The y-axis, $Z(Q_N)$, represents trends in the net available energy; increasing above the x-axis and decreasing below. The x-axis, $Z(E_A)$, represents trends in the regional drying power of the air; increasing E_A and hence, all other components remaining constant, tending to decrease ET_a to the left of the y-axis, and decreasing E_A and hence, all other components remaining constant, tending to increase ET_a to the right. The axes are shown in this manner in order to correspond to the trends indicated in Figure 4.9, wherein the first cause for a trend in ET_a —a trend in the available energy—moves a cell horizontally, and the second cause—a trend in wetness or regional drying power of the air—moves a cell in the vertical direction. Thus, each quadrant of Figure 4.23 represents a different combination of influences driving trends in ET_a as indicated by the labeled arrows in each quadrant.

As regards the trends in the components spatially averaged across the entire conterminous US as a whole, indicated by the solid blue circle, decreasing trends are observed in both E_A ($Z(E_A) = -3.696$) and in Q_N ($Z(Q_N) = -3.750$). That the resulting trend in nationwide ET_a is decreasing ($Z(ET_a) = -1.799$, significance = 69%, at a rate of 0.565 mm/year^2) indicates that of these conflicting effects on trends in ET_a , the decreasing trend in Q_N is more powerful than that in E_A . In physical terms, the decrease in ET_a due to a long-term decrease in Q_N more than counteracts the decrease in E_A observed as a long-

term reduction in either vapor pressure deficit (due to wetting of the surrounding region) or wind speeds, or both.

With regard to the results for the spatial breakdown into the 18 WRRs that comprise the conterminous US, every WRR, indicated by the red triangles, reports trends that are similar to that of the spatial mean for the lower-48—decreasing Q_N and decreasing E_A . However, the following three points must be made. First, the lower-48 states datum and the WRR data are all in the same quadrant with the latter data scattered around the former: their component trends lead to decreasing ET_{pan} but mixed effects on ET_a . Second, they are widely distributed about the results for an area-weighted mean of the 18 constituent WRRs (indicated by the hollow blue circle), for example, WRR 9 (Souris-Red-Rainy) reports little trend in Q_N ($Z(Q_N) = -1.127$, significance = 73.8%) but a significant trend in E_A ($Z(E_A) = -2.547$, significance = 97.4%), whereas WRR 13 (Rio Grande) reports the most significant trend in Q_N ($Z(Q_N) = -4.812$, significance = 97.2%) but the least significant trend in E_A ($Z(E_A) = -0.499$, significance = 43.8%). Third, when examining trends at the spatial mean of the conterminous US, that is the aggregate of all areas covered by the individual WRRs, a significant bias in the results becomes obvious. The trend statistics of the conterminous US taken as a single lumped spatial unit (solid blue circle) exceed those of the area-weighted mean of the 18 WRRs: $Z(E_A) = -3.696$ and $Z(Q_N) = -3.750$ for the former, versus $Z(E_A) = -2.687$ and $Z(Q_N) = -3.010$ for the latter. These differing trend results underscore the point that analyses at different scales may result in different (and erroneous) trend results; clearly, it is preferable to examine trend results at as close a scale to that at which the physical dynamics operate as is possible.

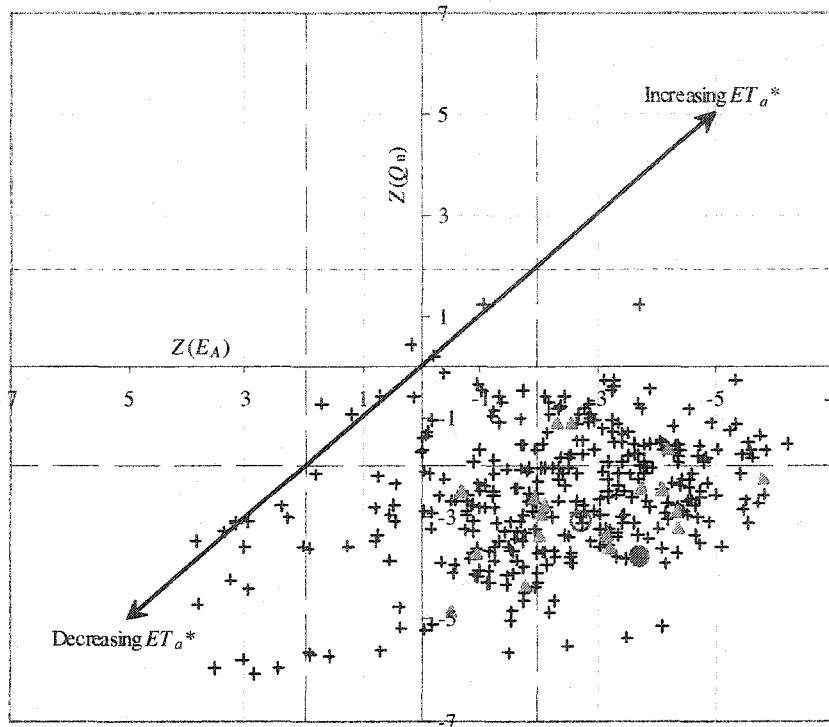


Figure 4.23: Orthogonal plot of annual Mann-Kendall test statistics for the Q_N and E_A components of ET_a^* -based ET_a , spatially averaged over the following nested range of spatial extents: the conterminous US, indicated by a blue circle; the 18 Water Resource Regions, indicated by red triangles; and the 334 6-digit Accounting Units, indicated by black crosses. The hollow blue circle represents the spatially weighted trend statistic for the aggregate of the 18 WRRs. In each case, the $Z(E_A)$ term is calculated according to the appropriate $f(U_2)$ and plotted in reverse—positive left, negative right—to coincide with the effects shown in Figure 4.9. Dashed lines indicate the 95% confidence limits for uncorrelated time-series.

At the finest scale shown in Figure 4.23—that of the 334 AUs that comprise the 18 WRRs—much more scatter is evident. Again, a visual inspection of their distribution shows that they are, as expected, scattered around the spatially weighted mean conterminous US datum (hollow blue circle) and the 18 WRR data. Many AUs now appear in different quadrants than the data for their parent WRRs. Of the 334 AUs, 289

appear in the original quadrant, where decreasing E_A and decreasing Q_N predict mixed effects on ET_a ; 41 now appear in the lower-left quadrant, where decreasing Q_N is matched with increasing E_A to predict decreasing ET_a ; three AUs appear in the upper-right quadrant, where increasing Q_N and decreasing E_A , predicting increasing ET_a ; and the remaining single AU reports increasing E_A and increasing Q_N , predicting mixed effects on ET_a . This figure also shows evidence of the so-called “Pan Evaporation Paradox,” in that some AUs now have a very strong positive E_A trend but a relatively weak negative Q_N trend, thereby certainly reducing ET_{pan} but also reducing ET_a : such behavior is, of course, now explicable in context of the complementary relationship.

The near-continental scale of analysis is at a spatial scale similar to that of *Szilagyi* [2001], *Szilagyi et al.* [2001], and *Roderick and Farquhar* [2002]. Taking the conterminous US as a whole and relating these trends to ET_{pan} as examined by *Roderick and Farquhar* [2002], it is clear that the downward trend they observed in ET_{pan} may be explained by either the trend in the solar radiation component or in the advective component, or both; both negative component trends act to decrease ET_{pan} , without conflict.

In relating the trends in ET_a in the context of the complementary relationship, it is important to remember that a decreasing trend in Q_N will tend to reduce ET_a , while a decreasing trend in E_A will tend to be associated with increasing ET_a . Simply, this latter relationship reflects the increase in humidity due to a regional increase in ET_a . Thus, the continental-scale results indicate that the trend observed in ET_a is a result of conflicting trends in its two components, with the downward trend in Q_N counteracting the negative E_A trend.

Examining the observed trends in ET_a at the near-continental scale is unsatisfying as the gross spatial averaging obscures the dynamics at work on the minimum scales at which regional ET_a is determined. In fact, from the continental-scale result alone, one may be led erroneously to conclude that the complementary relationship does not operate, or that, in the manner of *Roderick and Farquhar* [2002], it is not a significant dynamic in determining long-term trends in evaporation rates. If one were to ignore the complementarity between potential and actual ET rates that results from the dependence of ET_p on ET_a , but were instead to predict ET_a based on observed (and presumed independent) ET_{pan} and some soil moisture measure, as is done in many basin-scale models, one may conclude that both component trends being negative leads directly to negative ET_a trends. However, when one examines the trends on smaller spatial scales, closer to the minimum, regional scale at which such complementarity is hypothesized to operate, one can see that drawing such a conclusion—that ET_a can be calculated as a monotonically increasing function of ET_{pan} —is physically indefensible.

4.7 Summary and Conclusions

In establishing a baseline for modeling the effects of climate change and variability on the hydrologic cycle, it is essential to combine trends in the driving dynamics of the hydrologic components under study in the correct manner. This study addresses this need as it relates to regional ET_a .

The recent literature on trends in ET_a is surveyed, providing motivation for much of the work that follows. Then the complementary relationship in general and the Advection-Aridity model of the complementary relationship are summarized, with

particular attention paid to the advective component, which is then calibrated in two manners: matching model ET_a to ET_a^* and matching model ET_p to ET_{pan} . Both calibrations rely on assumptions that constrain their applicability in the spatial and temporal domains. The parameter sets of both calibrations were compared and then both were used to generate long-term, spatially distributed estimates of ET_a . These ET_a -time-series were then verified against ET_a^* , and their respective performances examined in relation to the climatologies of the areas of application. A long-term trend-analysis on various evaporation rates—observed ET_{pan} and ET_a^* , and modeled ET_a —and in the driving dynamics of these evaporation rates—the available energy estimated by Q_N and the drying power of the air estimated by E_A —was performed. The different combinations of component trends were compared in the context of the traditional paradigm and in a manner pursuant to the hypothesis of a complementary relationship, and it was shown that the complementary relationship explains the observed ET_a^* -trends better. Then trends in the input and intermediate variables of the model ET_a were examined on a spatially distributed basis. The performance of the general model in estimating long-term trends in annual ET_a and its observed components is verified across the gamut of spatial scales: from the conterminous US as a whole for the ET_a^* -based calibration, and across the southern US for the ET_{pan} -based calibration, then at a succession of spatial scales: the nested component 18 Water Resource Regions, and the further nested 334 Accounting Units.

4.7.1 Complementarity of ET_a^* Trends

The examination of the trends in annual ET_a^* , Q_N , and E_A at 655 hydrologically undisturbed basins across the conterminous US at the spatial scales closer to the minimum scale at which the complementary relationship is hypothesized to operate, shows that, at the regional scale useful to water managers and climate modelers, making the familiar assumption that ET_a can be calculated as a function of some soil moisture measure constrained below an ET_p -estimate that is itself independent of ET_a —as is done in many traditional basin-scale models—is physically indefensible. While there are a few basins (8.1% of the conterminous 655, 10.6% of the southern 207) where observed trends confound an analysis within the context of the complementary relationship, any estimation procedure that ignores the complementary effects of regional advection is fundamentally flawed as it may fail to represent the physical processes that result in a trend in ET_a , and such anomalies may only be explained by reference to the complementary relationship. Again, this indicates that it is only by examining these component trends on a smaller scale that one teases out the importance of the complementary relationship. However, it is also potentially inaccurate to rely solely on the complementarity of ET_{pan} and ET_a to predict trends in ET_a : one must also make reference to the dynamics of the two components that constitute both ET rates *and how they combine within the complementary relationship* to draw complete conclusions, particularly in areas where the signal from trends in the regional advective component outweighs that from the local radiative component. These results serve to underscore the fact that any model that estimates ET_a on a regional scale must encode the complementarity between potential and actual ET rates.

4.7.2 Comparison with Others' Work

This study shows that significant trends in both Q_N and in E_A exist and that, counter to claims by *Roderick and Farquhar* [2002], they both affect trends in ET_a . From even the continental scale, the following three findings emerge: (i) there is a distinct negative δQ_N across the lower-48 states; (ii) δE_A is not equal to zero; and (iii) nor is δV_{dif} . These three findings call into question the efficacy of the simplifying assumption of zero-trend in one or other component [*Roderick and Farquhar*, 2002; *Szilagyi et al.*, 2001]. The first finding, while echoing the findings of *Roderick and Farquhar* [2002], refutes the contradictory assumption by *Szilagyi et al.* [2001] of temporal stationarity of the Q_N component; an assumption that would have left only long-term trends in E_A —through either V_{dif} or U_2 —to account for trends in ET_a . The second and third findings refute the findings of *Roderick and Farquhar* [2002], and serves to underscore a previous conclusion; that in using continental-scale values, as *Roderick and Farquhar* [2002] do, one ignores many areas that contradict any conclusions that may be drawn at such scales.

On a continentally averaged basis over the period WY 1961-1990, the results reported in this study—a 5.5% increase in ET_a^* -based mean annual ET_a and a 6.5% increase in ET_{pan} -based mean warm-season ET_a^{WS} —support those of *Szilagyi* [2001], who reports an increase in modeled annual ET_a over part of this shorter period, but estimates the increasing trend at twice that of *Szilagyi* [2001], although, another paper [*Szilagyi et al.*, 2001] concludes that the complementary relationship over-estimates trends in ET_a . However, as just noted above, the gross spatial averaging involved in examining trends at the near-continental scale of *Szilagyi et al.* [2001] and *Szilagyi et al.* [2001] obscures the dynamics at work on the minimum scales at which regional ET_a is determined. In fact,

from the continental-scale result alone, one may be led erroneously to conclude that the complementary relationship does not operate, or that, in the manner of *Roderick and Farquhar* [2002], it is not a significant dynamic in determining long-term trends in evaporation rates.

4.7.3 Advantages of Complementary Relationship Models

To hydrologists, one of the primary advantages of models of the complementary relationship is that they rely solely on routine climatological observations and allow the estimation of ET_a over large-scale land surfaces without *a priori* knowledge of the nature of the land surface, beyond that it satisfies the assumption of homogeneity at scale lengths conducive to establishment of a well-mixed boundary layer. Using such models, ET_a can then be estimated using data that describe the conditions of the over-passing air, thereby bypassing the complex and poorly understood soil-plant processes and obviating the need for locally optimized coefficients and surface parameterizations of soil moisture or stomatal resistance, or for observations of ET_{pan} , precipitation, or runoff.

4.7.4 The Development of a Complementary Relationship Model

A complementary relationship model, specifically the regional-seasonal Advection-Aridity model, was used to create an ET_a data set that is spatially distributed, long-term (42 years), and large-scale (continental). Recognizing the paramount importance of a proper calibration of the advective component of the model, two parameterizations of

$f(U_2)$ in the E_A term were prepared and compared, and each parameterization was checked across hundreds of climatically and topographically diverse basins.

The calibration of the advective component took two forms. First, matching model ET_a to ET_a^* yields annual surfaces of $f(U_2)$ parameters over the entire conterminous US, subject to the assumptions that long-term estimates of P , R , and ET_a represent the only fluxes into or from the basin, and that all in-basin storages are stationary, and to the limitations of useful time-periods that such an approach invokes. The second calibration matched model ET_p to ET_{pan} , yielding monthly wind function surfaces over the southern US for the whole year, and over the entire conterminous US for the warm season. This calibration invokes the assumption that ET_{pan} represents the integration of a well-mixed boundary layer over a regional-scale surface that is homogenous with respect to topography and water availability, and subject, too, to the spatio-temporal limitations on the availability of data.

Section 4.2 alludes to difficulties in the use of ET_{pan} data as direct estimators of ET_p : such an assumed equivalence is prone to misinterpretation and error. Here ET_{pan} data are used as estimators of ET_p properly, first to observe its complementarity with estimates of ET_a^* , and then within the context of a model that makes use of this complementary relationship to estimate ET_a . In doing so, one proceeds from the knowledge familiar to users of traditional paradigms—that pans measure the potential of an air body to evaporate free water—but then further dictates that this potential rate is not independent of the limiting effects of actual evaporation from the region surrounding the point but that, through the integrative effects of turbulent mixing in the boundary layer, this point estimate represents the potential rate of evaporation into an air body that is already

affected by regional evaporation. This proper treatment of the predictive powers of ET_{pan} invokes assumptions inherent in the complementary relationship regarding the homogeneity of the region upwind of the pan and that the boundary layer in the region and including the pan is well mixed. Given that pans are often sited where they are hostage to the effects of land-use changes, affecting both the long-term time-series trends and the homogeneity of the land upwind, these assumptions—specific to the use of ET_{pan} as an estimator of regional ET_p , as in the complementary relationship—are prone to contravention.

Bearing in mind the limitations and assumptions mentioned above and further acknowledging the complications in producing accurate estimates of wind speed across heterogeneous topography from relatively few observation stations (relative to the extent of spatial interpolation), it is small surprise that the $f(U_2)$ s parameterized from both of these approaches should bear only a passing resemblance to those derived by other workers in this field and those predicted by intuition of the physics, both of which dictate that the drying power of the air takes a positive value that is then a positive function of wind speed.

While the two parameterizations examined in Section 4.4.4 do not share the same distribution as regards their parameter values (see Figures 4.4(i) and 4.4(ii)), they yield values that are of the same orders of magnitude across the range of observed wind speeds (see Figures 4.4(iii) and 4.4(iv): values range from -2×10^{-5} to 4.5×10^{-5} kg/m²/mb/sec in the case of the ET_a^* -based calibration, and 0.5×10^{-5} to 2.5×10^{-5} kg/m²/mb/sec in the case of the ET_{pan} -based calibration, both centered around 1×10^{-5} kg/m²/mb/sec). However, in the case of the ET_a^* -based calibration, the wind function values and shapes are widely

distributed and non-intuitive: some slopes are negative, while some values are negative for some ranges of wind speed. In the case of the ET_{pan} -based calibration, all values of the wind function are at least positive, although some slopes are (at least somewhat) negative. At least on the annualized basis shown in Figure 4.4(iv), in many cases in this sample of ET_{pan} -derived wind functions, there does not appear to be a functional relationship between wind speed and the back-calculated $f(U_2)$ value, which is to say that most relationships have near-zero slopes. This performance of the $f(U_2)$ -parameterization and their climatological variability as shown by Figures 4.19 through 4.21 further speaks to the importance of proper estimation of the $f(U_2)$. A better idea might be to follow Morton's lead and use a vapor transfer function in the advective component that is not an explicit function of wind speed: as an attempt to hew closely to the physical dynamics of ET_a , the inclusion of wind speed as an input variable may have biased the worth of the model in favor of its science over its applicability.

It remains therefore to answer the questions: which of these parameterizations is preferred, and how best can the applicability of any model so derived be improved?

Favoring the ET_{pan} -based calibration over the ET_a^* -based one is the fact that the former is the most physically defensible as it is calibrated to observations of an evaporative process (ET_{pan}), whereas the latter is derived from estimates of ET_a that represent the difference between two non-evaporative fluxes (P and R). Arguing for the ET_a^* -based calibration are two facts. First, the performance measure used to compare the two models (the mean annual water balance closure error, ε) indicate that the ET_a^* -based calibration out-performs the ET_{pan} -based calibration across the population of 207 southern basins (ET_a^* -based mean $\varepsilon = -2.87\%$ vs. ET_{pan} -based mean $\varepsilon = 14.52\%$).

Mitigating this apparent advantage, however, is the fact that the ET_a^* data used in the ET_a^* -based calibration is the same “ground truth” data to which both calibrations’ ET_a -estimates are compared by both models: it should be no surprise that the ET_a^* -based calibration replicates its own calibration data closer than does the ET_{pan} -based calibration. The second advantage of the ET_a^* -based calibration is that it yields wind functions over the entire conterminous US, whereas wind functions from the ET_{pan} -based calibration are available throughout the year over only southern portions of the conterminous US, or over the entire conterminous US but for the warm season only. Further complicating the issue of calibration-preference, the performances of both calibrations bear functional relationships to the climatologies in the areas of application.

In the final analysis, the choice of $f(U_2)$ -parameterization scheme depends to a large degree on the preference of the modeler, the availability of the calibrating data, and—as shown in the examination of the spatial distribution of the performance of the model and with regard to the spatio-temporal limitations of the availability of the ET_{pan} calibrating data—the region of interest.

If the choice made were to include wind speed data as an input to the model, best would be a model calibrated whose $f(U_2)$ s are calibrated on a spatially distributed basis by the best available information. This information would be a combination of estimates of ET_a^* across all available undisturbed basins and point estimates of ET_{pan} from a combined annual/warm-season data set. This latter ET_{pan} data set would eliminate the spatial restrictions of the annual ET_{pan} data set and the temporal restrictions of the warm-season ET_{pan} data set. A model so-calibrated could then be applied with a re-estimated Priestley-Taylor α_{PT} parameter in the formulation of ET_w (Equation 4.3) that eliminates

the apparent bias towards under-estimation of ET_a by the ET_{pan} -based calibration and that is supported by other researchers.

4.7.5 Spatial Breakdown of Trends in Modeled ET_a

Trend statistics of the two time-series were generated using both the Mann-Kendall test for each grid-cell in the conterminous US and simple linear regression analysis over larger spatial extents. Trends in ET_a and its component fluxes were examined at a variety of spatial resolutions (from continental through regional to that of AUs) and distributed surfaces of these trends were produced at the continental extent of the data set, and then over sub-regions within it. Further, long-term trends in the input climatic variables are examined.

With regard to the spatial characteristics and flexibility of the time-series, the complementary relationship is applied over as diverse a climatic and topographic extent as the conterminous US, breaking the mold of previous studies that have either been conducted at small spatial scales, or at single sites. The use of spatially distributed ET_a time-series—derived from spatial interpolation of point measurements of the input variables—as opposed to point estimates of ET_a , allows for the more-accurate generation of information in un-metered areas. Furthermore, the spatially distributed nature of the modeled ET_a time-series allows examination of regional sensitivities to climate change and variability at many scales and spatial breakdowns, including, in this case, the entire conterminous US, its 18 component WRRs, and their nested 334 AUs. Spatially averaging the distributed ET_a^* -based ET_a data set at the continental scale over this study's 42-year period, a 4.2% decrease is observed in annual ET_a (statistically

significant at the 69% confidence level). Thus, the primary advantage of the application of the complementary relationship on a distributed basis was highlighted: that useful results may be extracted from analyses conducted at scales limited at the smallest scale only by the spatial resolution of the model, and over extents that may range from the continental down to mere clusters of pixels.

The nested continental-WRR-AU breakdown indicates the importance of examining trends on a distributed basis. The potential for a significant bias in aggregating ET_a or its component dynamics spatially prior to conducting a trend analysis is demonstrated. This indicates that the utility of trend statistics derived at such coarse resolutions is limited, as the assumptions of normality inherent in their use as representative of nested, smaller-scale areas are unsound. Indeed, in examining trends in ET at the large (e.g., continental) scales that other researchers have used, one ignores areas that would otherwise contradict any conclusions that may be drawn, especially, as shown here with regard to the operation of the complementary relationship. This underscores the usefulness of this applying this trend analysis to a spatially distributed data set.

Examining and decomposing long-term trends in ET_a^* in the 655 test-basins into trends in the radiative and advective components showed that the complementary relationship hypothesis explains observed trends in ET_a^* better than does the traditional paradigm and demonstrates that, contrary to recent assumptions and assertions in the state of the science, trends in ET_a can be determined to originate in either its radiative component or its advective component, or both.

4.7.6 Conclusion

The regional-seasonal Advection-Aridity model is offered as a tool for studies of climate change and variability. Using the methodologies summarized in this chapter, it is possible to examine trends in ET_a and its components in any and all basins across the conterminous US, as the input data are distributed and reflect surface conditions regardless of the origins of the water and degree of anthropogenic disturbance. It may be concluded that dividing ET_a -trends up as to their origins serves as a useful tool to determine effects of climatological trends on ET_a . Regional or basin-scale trends can be determined to originate in either the energy flux or the water flux, or both. Thus, important information about a heretofore missing link in surface hydrology has been made available to water managers, climatologists, and ecologists, or to any student of the surface hydrological cycle.

5. Trends in Pan Evaporation and Actual Evapotranspiration across the Conterminous US: Paradoxical or Complementary?

5.1 Abstract

Using independent observations of pan evaporation (ET_{pan}) and water budget-derived actual evapotranspiration (ET_a^*), which represent potential evapotranspiration (ET_p) and actual evapotranspiration (ET_a), respectively, the first empirical evidence for the complementary relationship hypothesis is provided. Therefore, the complementary relationship between ET_a and ET_p is now an *observational fact* as opposed to merely a conjecture. ET_{pan} has decreased at 64% of pans in the conterminous US over the past half-century. Comparing trends in ET_{pan} and ET_a^* , the so-called “Pan Evaporation Paradox,” is observed and confirmed to be no more than a manifestation of the complementarity between actual and potential rates of evapotranspiration. Examining trends in the components of ET_a —the radiative energy and regional advective fluxes—it is shown that both components must be considered together to explain the relationship between ET_{pan} and ET_a^* .

5.2 Pan Evaporation “Paradox”

Trends in ET_a and ET_{pan} cannot be examined in isolation from each other: while ET_{pan} has long-provided agriculturalists and hydrologists a pulse for estimating ET_a , it is, in fact, a special, zero-dimensional case of ET_a and is a function of surrounding, regional-scale ET_a . It is this interaction that underlies the dynamic that has come to be known by the misnomer “Pan Evaporation Paradox,” wherein a decreasing trend in ET_{pan} observed

in several countries [e.g., *Chattopadhyay and Hulme*, 1997; *Peterson et al.*, 1995; *Golubev et al.*, 2001; *Lawrimore and Peterson*, 2000] appears contradictory to concurrent widespread increasing trends in basin-derived ET_a (hereafter referred to as ET_a^*) [*Szilagyi et al.*, 2001], GCM-derived ET_a [*Manabe*, 1997], temperature [*Folland and Karl*, 2001], and precipitation and cloudiness [*Karl et al.*, 1996]. All else equal, one expects evapotranspiration to increase with increases in temperature, and increasing evapotranspiration is necessary for increases in precipitation and cloudiness. The resolution of this “paradox,” has been cited as evidence of “climate alarmists’ illusionary world of ‘unprecedented’ global warming” [*Center for the Study of Carbon Dioxide and Global Change*, 2003].

As theorized by *Brutsaert and Parlange* [1998], the solution to the paradox turns on the relation of ET_{pan} to ET_a . Depending on moisture availability in the region around the pan, these two variables may be nearly identical or very different, but they are nevertheless related. To understand the changes in ET_{pan} , one must look at changes in ET_a , or at the variables influencing ET_a . As a recent editorial in the journal *Science* [*Ohmura and Wild*, 2002] stated, “...ultimately, what is important is the trend in actual evaporation. Pan evaporation matters insofar as it can offer a useful clue to the direction of the change in actual evaporation.” The editorial further called for an examination of ET_a in the context of its two driving components: the radiative flux and the advective flux. These fluxes have been addressed previously [*Szilagyi et al.*, 2001; *Roderick and Farquhar*, 2002; *Milly and Dunne*, 2001], but separately.

Trends are examined in both ET_{pan} and ET_a for the conterminous US, obtaining estimates of ET_a observationally as precipitation minus runoff (ET_a^*) for 655 relatively

undisturbed basins (Figure 5.1). These trends in ET_a^* are explained as functions of combinations of trends in the radiative and advective fluxes, and it is shown that both components must be considered together; neither in isolation explains the paradoxical-seeming behavior observed in ET_{pan} and ET_a^* .

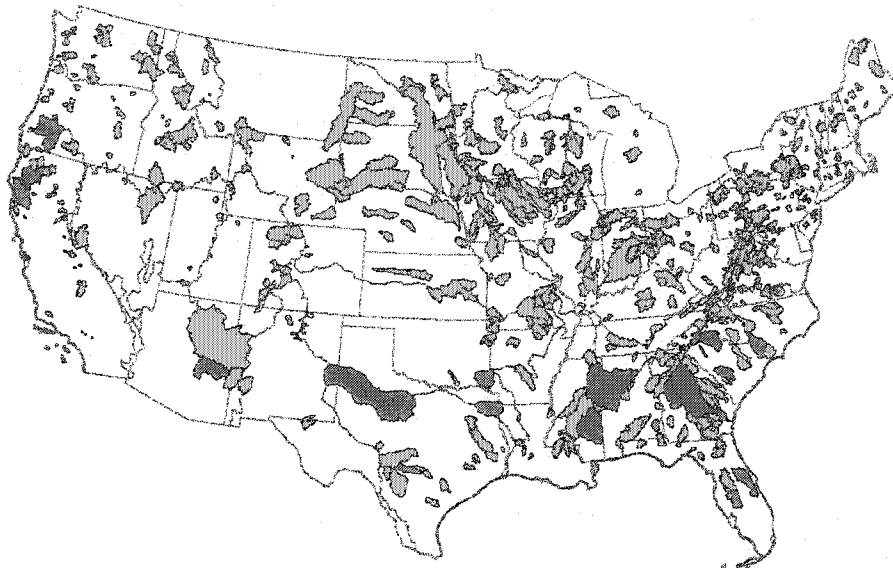


Figure 5.1: Locations of the 655 test-basins. The basins were selected from the Hydroclimatic data Network (HCDN) [Slack and Landwehr, 1992]. ET_{pan} and basin-derived ET_a^* from the basins shown in red were used to generate the comparison in Figure 5.3.

5.3 Trends in ET_{pan}

Limiting analyses to pans that reported at least 20 complete years or warm seasons (MJJASO) within the period 1950-2002 produces sets of 1248 data at 44 pans from which the annual trends were derived (Figure 5.2(i)); and of 7064 data from 228 pans for the warm-season trends (Figure 5.2(ii)), where a datum is a single year's or season's observation at a single pan. The data were homogenized to account for abrupt shifts in ET_{pan} measurements resulting from changes in pan-location or type, or other changes that

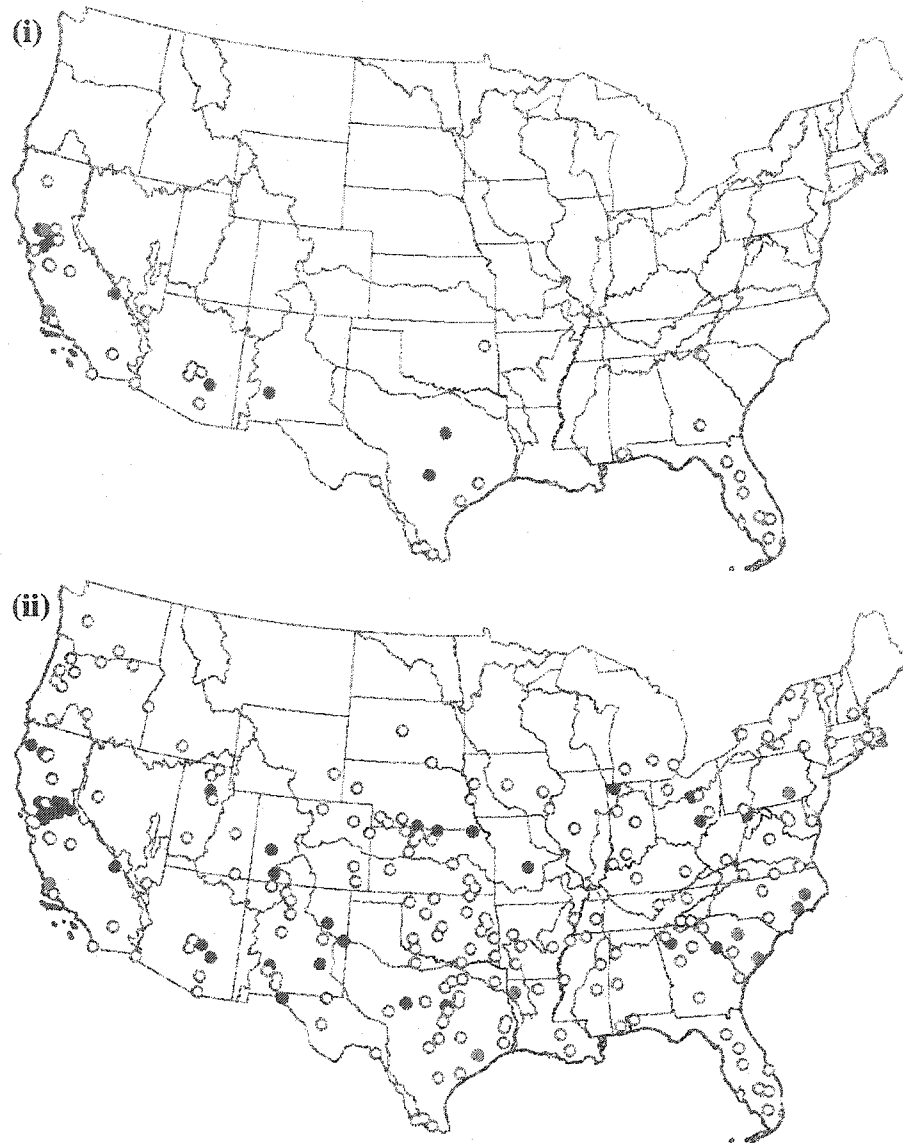


Figure 5.2: Trends in ET_{pan} across the conterminous US. (i) and (ii) show the annual pans over the period WY 1951-2002 and warm-season (MJJASO) pans over the period CY 1950-2001, respectively. Increasing trends are represented by red circles, decreasing trends by blue circles. Solid circles represent pans with trends significant at 90%. ET_{pan} data were drawn from NCDC Summary of the Day [EarthInfo, 1998a; NCDC, 2004a] and NCDC Summary of the Month [NCDC, 2004b].

could otherwise artificially bias trend results [Peterson *et al.*, 1998]. For each ET_{pan} time-series, a homogeneity analysis was performed to detect abrupt changes across the entire

period of record as indicated by the metadata [NCDC, 2004d] accompanying the raw data or by statistical tests (i.e, T-test and double-mass curve analyses) indicating statistically significant abrupt shifts at the 95% level. The time-series of 172 pans were homogenized around 326 abrupt data-shifts: 280 shifts due to changes in pan location and another 46 due to unspecified changes. In this manner 43% of the annual data and 55% of the warm-season data were homogenized.

Of the 44 annual pans, 64% show decreasing ET_{pan} ; of the 12 pans with significant trends (at the 90% level using the F -statistic of the trend slope), 75% are decreasing. Of the 228 warm season pans, 60% show the decreasing ET_{pan} trend reported widely in the literature [e.g., Chattopadhyay and Hulme, 1997; Peterson *et al.*, 1995; Brutsaert and Parlange, 1998; Roderick and Farquhar, 2002]; of the 43 pans with significant trends, 84% are decreasing. Warm-season ET_{pan} has decreased across most of the conterminous US, but there are significant exceptions: the Northwest, the Northeast, regions around the Gulf of Mexico, South Carolina, and southern Florida. Lumping ET_{pan} data spatially over a continental scale obscures these spatial differences, confusing examination of the driving dynamics of trends.

5.4 Complementary Relationship

The relationship between ET_{pan} and regional ET_a^* is apparent in Figure 5.3, which contains 192 data pairs, each consisting of an annual measure of ET_{pan} and an annual measure of ET_a^* from the test-basin (in red in Figure 5.1) containing the pan(s). For each year in the period WY 1953-1994 that an ET_{pan} measure was available, ET_a^* was computed for the surrounding basin, resulting in 192 paired annual observations of ET_a^*

and ET_{pan} . The highest values of ET_{pan} occur at the left of the graph, in water-limited environments, and are matched with the lowest values of ET_a^* . Moving to the right, precipitation increases, the water-limitation on the evaporative process gives way to an energy-limitation, and ET_{pan} decreases as ET_a^* increases. In general, ET_{pan} and ET_a^* rates converge in the wettest basins; the evaporation rate in purely energy-limited basins is referred to here as wet environment evaporation (ET_w).

The noise in the data may reflect the fact that ET_{pan} data are gathered at single points whereas ET_a^* data arise from hydrologic integrations over the basins containing the pans. The former therefore represent a limited sample of a population; the latter more closely represent its mean.

Figure 5.3 closely matches the theoretical shape of the complementary relationship between regional-scale ET_p and ET_a , and indicated in Figure 1.2. In this hypothesis [Bouchet, 1963], providing all the necessary assumptions hold—that the area upwind of the pan is homogenous as regards topography and moisture availability, that all available energy not taken up by ET_a goes to heat and dry the over-passing air, and that the radiative energy budget at the surface is otherwise unaffected by the feedback between ET_a and ET_p —then ET_p is driven above ET_w by the amount that ET_a falls below it. This relationship is expressed by:

$$ET_a = 2ET_w - ET_p \quad (5.1)$$

That the independent observations of ET_{pan} and ET_a^* in Figure 5.3, which represent ET_p and ET_a , respectively, so closely display complementarity provides strong evidence for the complementary relationship hypothesis. Therefore, the complementary

relationship between ET_a and ET_p is now an *observational fact* as opposed to merely a conjecture.

5.5 Trends in the Components of Evapotranspiration

Figure 5.3 depicts the behavior that has been characterized as paradoxical—wherein decreasing ET_{pan} is matched by increasing ET_a^* . While it would also be instructive to compare trends in ET_a^* with trends in ET_{pan} , too few pans lie within test-basins to make any such comparison meaningful. Instead the annual depths presented in Figure 5.3 may be re-interpreted as an ergodic-type approximation of such trends, with the relationship of ET rates to variations in precipitation presented as a surrogate for actual temporal trends in the ET rates themselves. In this ergodic substitution, each datum pair shown in Figure 5.3 may be conceived as the paired ET_{pan} and ET_a^* rates for a single time-instance of a single basin with a given moisture availability and energy input. The effects of trends in the driving components of ET_a^* (or ET_a) and ET_{pan} (or ET_p) are indicated in Figure 5.3 by the arrows. In theory, a decreasing radiative budget (Q_N)—due to increasing cloudiness, for example—lowers the dashed lines representing both ET_a^* and ET_{pan} , while increasing Q_N raises them; a decreasing advective flux (indicated by the drying power of the air, E_A)—due to increasing precipitation, for example—moves a datum pair convergently to the right along their respective dashed lines, upwards for ET_a and downwards for ET_{pan} , whereas increasing E_A moves a datum pair divergently to the left, downwards for ET_a and upwards for ET_{pan} .

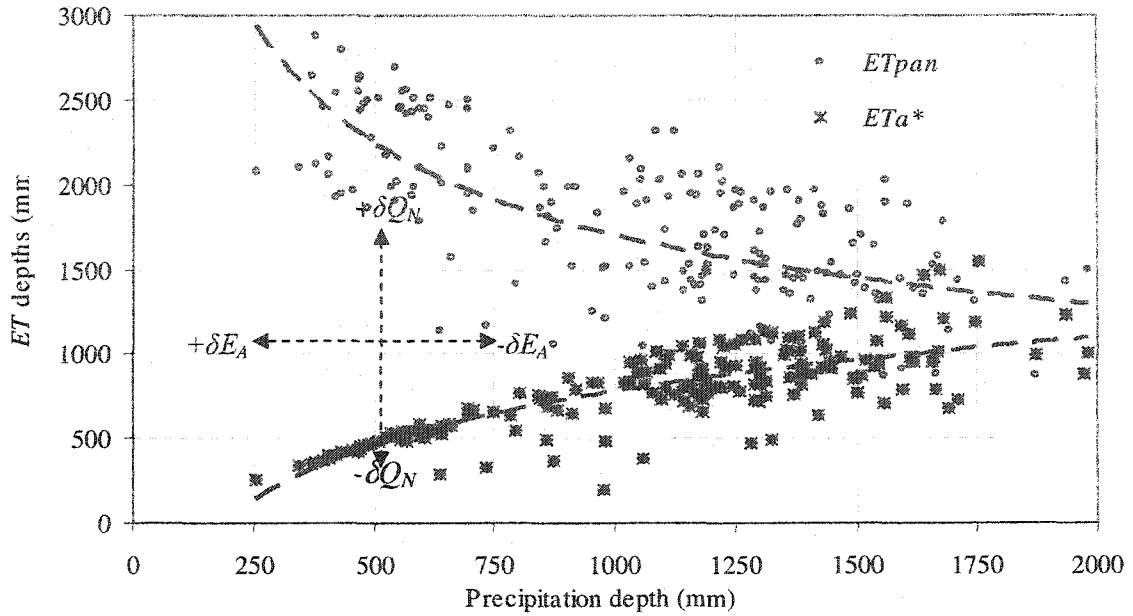


Figure 5.3: Point annual depths of ET_{pan} and basin-wide annual depths of ET_a^* . Data for a single basin-pan pair line up vertically. Arrows marked “ δE_A ” and “ δQ_N ” indicate the effects on ET_a^* and ET_{pan} of trends of the indicated signs in their vapor transfer (E_A) and energy flux (Q_N) components, respectively. ET_a^* is calculated for each basin as the difference between precipitation and runoff, the former data being predicted by the Parameter-elevation Regressions on Independent Slopes Model (PRISM) [Daly *et al.*, 1994] and the latter extracted for USGS gages listed in the Hydroclimatic Data Network (HCDN) [Hydrosphere, 1996; Slack and Landwehr, 1992].

To understand trends in ET_{pan} , one would ideally observe trends in Q_N and E_A estimated from measurements taken at the locations of the pans. However, measurements for these variables are rarely coincident with the pans. Instead, to understand trends in ET_{pan} trends in ET_a^* (the complement to ET_{pan} , as indicated in Figure 5.3) are examined in terms of trends in both Q_N and E_A , mindful that ET_a is the hydrologic flux of primary interest [Ohmura and Wild, 2002].

ET_w and ET_{pan} may be expressed as functions of Q_N and E_A as:

$$ET_w = f(Q_N) \text{ and } ET_{pan} \equiv ET_p = f(Q_N, E_A). \quad (5.2)$$

The temporal trend in ET_a (denoted by δET_a) can then be expressed as a combination of trends in its component fluxes— δQ_N representing the time-rate of change in the radiative energy flux; δE_A that in the advective or vapor transfer flux (i.e., in the regional drying power of the air)—as follows:

$$\delta ET_a = \left(2 \frac{\partial ET_w}{\partial Q_N} - \frac{\partial ET_p}{\partial Q_N} \right) \delta Q_N - \frac{\partial ET_p}{\partial E_A} \delta E_A. \quad (5.3)$$

In Equation (5.3) all ordinary differentials are observable; the partial derivatives depend on the equations used for ET_w and ET_p —typically, some variation of the Priestley-Taylor equation (1.12) and Penman equation (1.7) [e.g., *Brutsaert and Stricker*, 1979], respectively. In traditional paradigms, ET_a is estimated as a monotonically increasing function of ET_p or of ET_{pan} and moisture availability, implying that trends in ET_a are a positive function of trends in ET_p , and therefore similarly in the drying power of the air E_A . However, as shown in Equation (5.3), this is not the case. The E_A term not only drives ET_a (wherein more moisture potentially evaporates into the air as a result of the air being drier), but also reflects the effects of ET_a on regional advection (the regional drying power of the air increases when there has been less evaporation). ET_{pan} represents a special case of ET , in that while it is observed, it is only “actual” in the sense that it is the rate at which a wet surface of no spatial dimension evaporates into an air-volume that represents regional, often water-limited ET_a . It follows that trends in ET_{pan} are positive functions of trends in E_A .

Incident solar radiation (R_G) provides the major energy input to any evaporative process, and is an excellent estimator of Q_N . Averaged across the conterminous US for

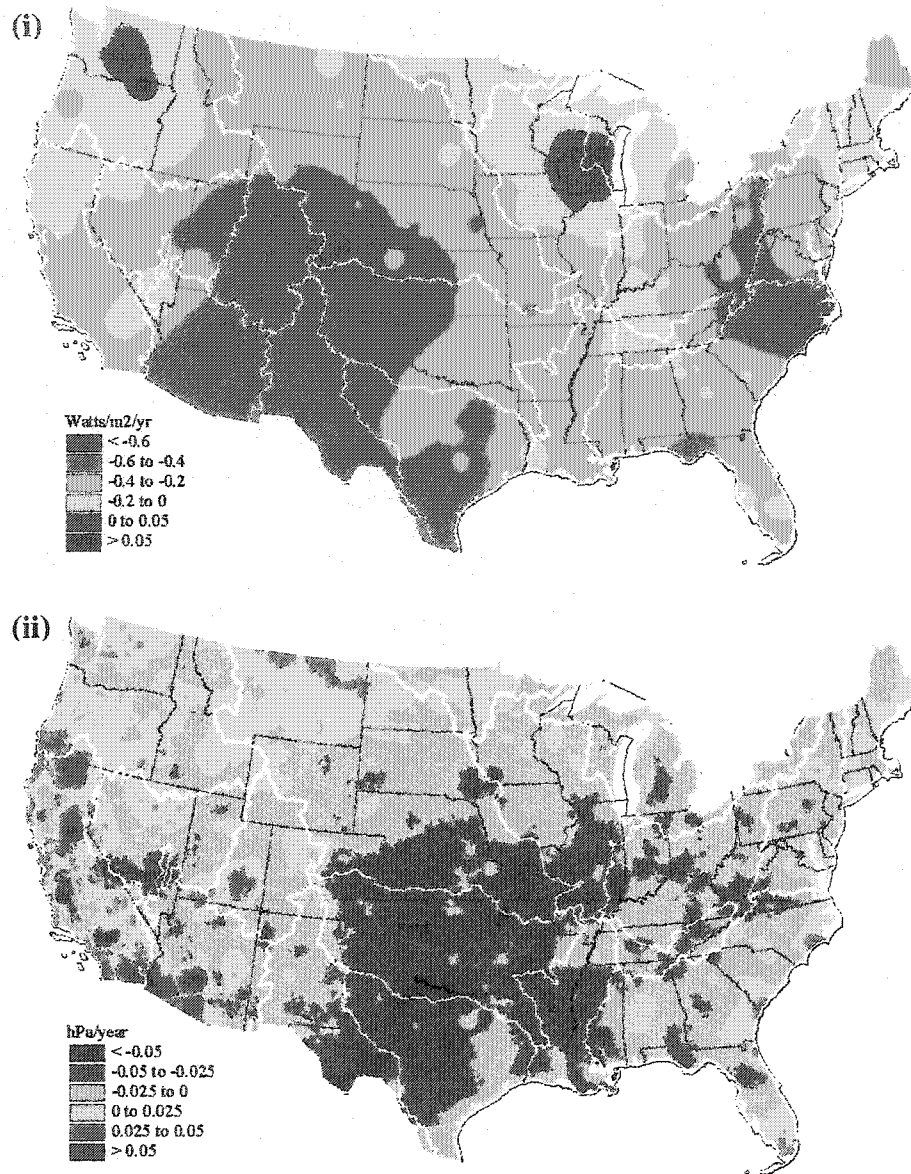


Figure 5.4: Trends in mean annual incident solar radiation R_G (i) and vapor pressure deficit V_{dif} (ii), spatially interpolated from monthly time-series (WY 1953-1994) of observations and expressed in (i) watts/m²/year and (ii) hPa/year, as the slope of a linear fit to the annual time-series at each 25 km² pixel. R_G data were drawn from the SOLMET [NCDC, 2001], SAMSON [NOAA, 1993], and NCDC Airways Solar Radiation [EarthInfo, 1998b] data sets and are corrected for local topographic effects. V_{dif} data were derived from air temperature data extracted from NCDC Summary of the Day [EarthInfo, 1998a; NCDC, 2004a] and dew-point temperature data from NCDC Surface Airways [EarthInfo, 1998b; NCDC, 2004c] and SAMSON [NOAA, 1993] data sets.

WY 1953-1994, a decrease in R_G of 0.298 watts/m²/year is observed, for a 42-year decrease of 12.52 watts/m² or 14.4% of the mean, lending indirect support to the findings of *Roderick and Farquhar* [2002] and *Gilgen et al.* [1998]. On a distributed basis (Figure 5.4(i)), R_G decreased over 98% of the conterminous US. The western Great Lakes region and the inland Pacific Northwest are exceptions to this general decrease.

Humidity is a key factor in E_A . As measured by the vapor pressure deficit (V_{dif}), humidity decreased over most of the eastern US, but across the West the pattern is heterogeneous (Figure 5.4(ii)). V_{dif} decreased over 75% of the conterminous US; the mean trend is a decrease of 0.012 hPa/year, for a 42-year decrease of 0.504 hPa or 10.1% of the mean. However, in order for V_{dif} to reveal anything about ET_{pan} or ET_a it must be multiplied by a functional measure of the speed of the over-passing air, generally in the form of an empirical function of wind speed $f(U_2)$, revealing E_A , the advective flux. Thus, trends in E_A can be due to trends in wind speed U_2 , V_{dif} , or some combination of both.

To show how the trends in ET_a and its component fluxes are related, trends in annual ET_a^* , Q_N , and E_A are examined at the 655 test-basins with data for 1953-1994 (Figure 5.5). The distribution of negative and positive ET_a^* trends across the quadrants of Figure 5.5 reflects the spatial distribution and direction of trends in R_G and V_{dif} (Figure 5.4). Overall, 92% of basins lie below the x-axis, reflecting the predominantly decreasing R_G (and hence decreasing Q_N); and 89% of the basins lie to the right of the y-axis, reflecting the fact that most test-basins are located in the central and eastern US where decreasing V_{dif} (and hence decreasing E_A , all else equal) predominates.

In the lower-right quadrant, where 528 of the basins fall, the directions of the component trends conflict in their effects on trends in ET_a^* : the decrease in E_A tends to

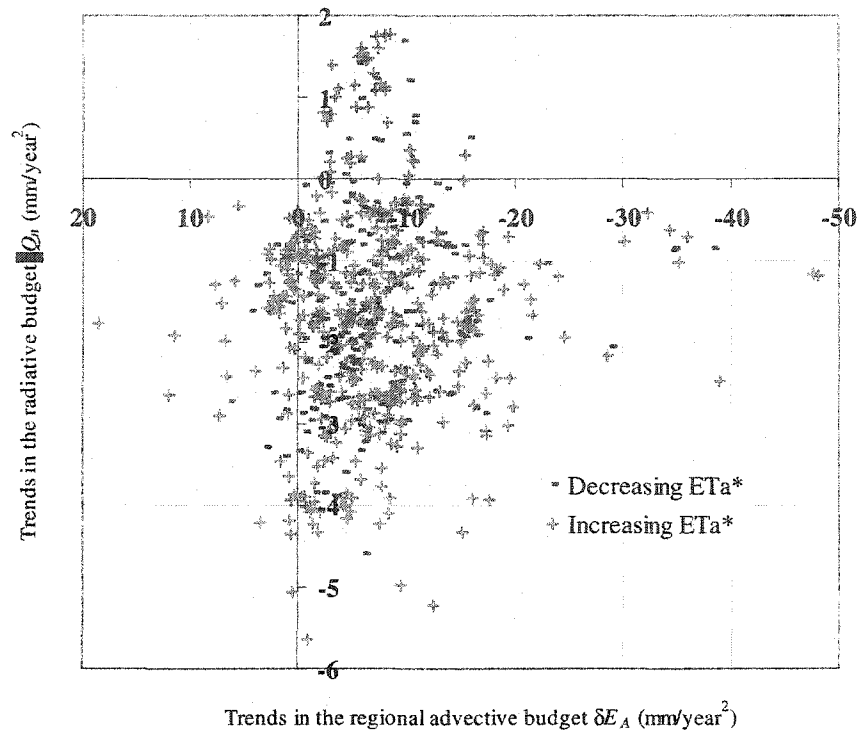


Figure 5.5: Slope parameters for the Q_N and E_A components of trends in annual ET_a^* over the period WY 1953-1994 for the test-basins indicated in red in Figure 5.1. Red “+” symbols indicate increasing ET_a^* rates, blue “-” symbols decreasing ET_a^* rates. Trends are plotted orthogonally, with δE_A plotted in reverse (positive left, negative right). Values for Q_N and E_A were computed by spatially averaging across all 25 km² pixels in a basin.

reflect increasing regional ET_a^* , whereas the decrease in Q_N tends to decrease local ET_a^* . Consider a test-basin from the far right of the graph, representing USGS gage 10263500 located in the northern Mojave Desert of Southern California, which exhibits a decrease in depth-equivalent Q_N of 1.168 mm/year² and a decrease in depth-equivalent E_A of 47.685 mm/year². These component trends have opposing effects on ET_a . Taking into account the relative difference in trend magnitudes between the two (the trend in E_A far exceeds that in Q_N), one would expect ET_a to increase and, indeed, this is the case: annual ET_a^* increased at 0.262 mm/year².

Figure 5.5 also helps explain the relation of ET_{pan} to ET_a^* . ET_{pan} should be decreasing in basins in the lower-right quadrant of Figure 5.5, where both Q_N and E_A decreased. Because ET_a^* increased in about half (276) of the basins of this quadrant, decreasing ET_{pan} is clearly not an indication of decreasing ET_a^* . To the contrary, decreasing ET_{pan} is often associated with increasing ET_a^* . That ET_a^* increased in these 276 basins, where the effect of decreasing E_A outweighs the effect of decreasing Q_N , can only be explained in the context of the complementary relationship. This finding stands in opposition to those of *Roderick and Farquhar* [2002], who claimed that V_{dif} has not changed across the conterminous US, and asserted instead that the complementary relationship plays little part in determining trends in ET_{pan} and that such trends are due solely to trends in R_G . However, accounting spatially for changes in V_{dif} (Figure 5.4(ii)), combining V_{dif} with the wind function in a formulation of E_A , and using E_A with Q_N in a common model for ET_a [*Hobbins et al.*, 2001], it is found that the portion of the conterminous US-wide trend in ET_a attributable to trends in E_A amounts to an increase of 3.0 mm/year², whereas that attributable to the trend in Q_N amounts to a decrease of 1.8 mm/year².

Conclusions drawn from trends in ET_{pan} about corresponding trends in ET_a without reference to the dynamics of the two components that constitute both ET rates and how they combine within the complementary relationship will be incomplete and often incorrect. Thus, any estimation procedure that ignores the complementary effects of regional advection will fail to represent the physical processes involved in a trend in ET_a , and potentially misdiagnose the cause of the trend, particularly in areas where the signal from trends in the regional advective component outweighs that from the local radiative

component. Although ET_{pan} is a very useful concept, it can be misleading if used by itself to indicate climatic trends.

5.6 Summary and Conclusions

Using independent observations of ET_{pan} and ET_a^* , which represent ET_p and ET_a , respectively, the first time evidence for the complementary relationship hypothesis is provided. Therefore, the complementary relationship between ET_a and ET_p is now an *observational fact* as opposed to merely a conjecture.

ET_{pan} has decreased at 64% of pans in the conterminous US over the past half-century. Comparing trends in ET_{pan} and ET_a^* , the so-called “Pan Evaporation Paradox,” is observed and confirmed to be no more than a manifestation of the complementarity between actual and potential rates of evapotranspiration. Examining trends in the components of ET_a —the radiative energy and regional advective fluxes—it is shown that both components must be considered together to explain the relationship between ET_{pan} and ET_a^* .

6. Summary and Conclusions

6.1 Summary of Work

Models of regional evapotranspiration that consider the land surface-atmosphere interface as an integrated whole and that are well-calibrated and spatially distributed must be developed. The research described in this dissertation has addressed this need by examining the complementarity between ET_p and ET_a that is predicated on a holistic approach to the evaporative process, then proposing a complementary relationship model, specifically an improved regional-seasonal Advection-Aridity model, as a tool for climate change studies, and presenting the findings of a study of trends in ET_a across the conterminous US. This has addressed questions that had, in the absence of such a data set, heretofore been moot; in the context of this study, these are questions about direct observations of the effect of change and variability of climate on the land surfaces-atmosphere interface. More specifically, this dissertation addresses the thesis first stated in Section 1.1.5, to wit:

that at a regional scale, ET_a and ET_p are mutually complementary; that this is supported by independent observations of ET_a^ and properly adjusted ET_{pan} and via trend analyses of the radiative and advective component dynamics of the evaporative process*

The complementarity of ET_a and ET_p was demonstrated using a spatially coincident subset of homogenized observations from 43 annual pans across the US and 655 basin-derived estimates of ET_a . These two rates were not independent of each other or of the

moisture availability of the region of estimation, diverging in arid regions and converging in wet regions, as predicted by the complementary relationship hypothesis [Bouchet, 1965].

that by using the complementary relationship, ET_a and therefore trends in ET_a are estimated better than by traditional paradigms over a wide variety of terrains and climatic regimes

Trends in the driving dynamics of the evaporative process—the radiative and advective fluxes—were shown to combine in the context of the complementary relationship, as in this manner, they explained the observed long-term trends in basin-derived ET_a^* at 655 hydrologically undisturbed test-basins across the conterminous US better than in the traditional paradigm: 89-92% (depending on the specifics of the advective component calibration) of the basin-wide trends were explained by the complementary relationship as opposed to only 43-44% by the traditional paradigm.

that a model of the complementary relationship can be formulated whose component dynamics are parameterized with reference to topographically corrected solar radiation, in the case of the radiative input, and properly calibrated with reference to homogeneous observations of ET_{pan} , in the case of the advective dynamic

In the generation of an ET_a model based on the complementary relationship, both the radiative and advective components were re-formulated and improved. The solar radiation input was divided into direct normal and diffuse radiation, with a new time-

integrated, topographic correction factor that accounted for the temporal and spatial variations of the angle of the sun in heterogeneous terrain applied to the former. The reformulation of the advective dynamic took the form of two calibrations of the wind function: first, an ET_{pan} data set that had been homogenized was used to match ET_p ; second, an ET_a^* data set drawn from the 655 hydrologically undisturbed test-basins was used to match ET_a directly. The two calibrations were compared qualitatively as to their parameter-values, primary assumptions, and drawbacks, and quantitatively as to their ability to predict ET_a^* . The ET_{pan} -based calibration, although more physically based than the ET_a^* -based calibration, under-predicts ET_a to a far greater degree. Both models' performances are affected by the climatology of the region of estimation, implying both that further calibration of the other advective parameter, the Priestley-Taylor constant α_{PT} (Equation 4.3), and a combination approach that uses information yielded by both the ET_{pan} and ET_a^* calibration data, is indicated.

that this model can then be a useful tool for estimating regional-scale, spatially distributed ET_a and, more importantly, as a baseline for trend analyses at a variety of scales

Both the ET_a^* -based and ET_{pan} -based calibrations of the Advection-Aridity model were used to create monthly time-series of ET_a for a 42-year period at a 5-km resolution over the conterminous US. Trend statistics of time-series of ET_a and E_A from both calibrations of $f(U_2)$ and of the single time-series of Q_N , U_2 , and V_{dif} were then generated for each grid-cell to establish the spatial distributions of long-term trends of all components of ET_a and of ET_a itself. Trend statistics of spatially averaged time-series of

ET_a^* -based ET_a , ET_a^* -based E_A , and Q_N examined over nested spatial extents at a successive series of spatial scales—from the continental-scale to that of the individual test-basins—showed that a spatially distributed analysis of trends leads to conclusions that spatial averaging glosses over. This analysis verified the conclusions of other workers in the field—confirming some and refuting others—but primarily concluding that regional- or basin-scale trends in ET_a originate in the energy flux or the water flux, or both. The regional-seasonal Advection-Aridity model of the complementary relationship in regional ET_a is shown to perform well in diagnostic studies of past, or hydrologic record-length, climate change and variability.

6.2 Unique Contributions

The primary new contributions of the study described in this dissertation are three-fold:

(1) Direct observational confirmation of the complementary relationship: this study provides the first direct observational evidence in support of the hypothesis of a complementary relationship between ET_p (measured here using observations of ET_{pan}) and ET_a (estimated here using ET_a^*) gathered on a simultaneous and spatially coincident basis, from a range of pans and basins spanning many climatic regimes in the conterminous US. In the first study that examined trends in the evaporative process as a function of both the radiative and advective components, the complementarity was confirmed with respect to these driving dynamics: they were shown to combine to produce trends in ET_a that can better be explained by the complementary relationship than by traditional paradigms. Trends in all ET rates and their component dynamics were examined as to their direction and significance on a spatially distributed basis and on

bases that confirmed or refuted the results and conclusions of others, whose methodologies were here improved upon by examining trends at a variety of smaller spatial scales.

While the complementary relationship has been hypothesized on a heuristic basis [Bouchet, 1963] and shown to work well as a guiding principle in ET_a -modeling [Brutsaert and Stricker, 1979; Morton, 1983; Hobbins *et al.*, 2001a, 2001b], this study has now changed the hypothesis from a conjecture to an observational fact. In doing so, this study also lays to rest the oft-mentioned “Pan Evaporation Paradox”—generally described as a contradiction of observed decreasing ET_{pan} when it is compared to rises in global temperature [Roderick and Farquhar, 2002], precipitation and cloudiness and GCM-predicted ET_a [Brutsaert and Parlange, 1998]. This “paradox” has been used by climate-change nay-sayers to cast doubt on “climate alarmists’ illusionary world of ‘unprecedented’ global warming” [Center for the Study of Carbon Dioxide and Global Change, 2003], but it is here shown to be no more than the consequence of the dependence of ET_p on ET_a that lies at the heart of the complementary relationship.

(2) The development of a new ET_a data set—one that is spatially distributed, long-term (~50 years), over a large spatial extent (continental), and accurate—was developed using two calibrations of its advective component, and tested across hundreds of climatically and topographically diverse basins in order to maximize its climatological robustness. Such data are available for anywhere in the conterminous US and at any scale and spatial breakdown so desired: from the entire conterminous US; into WRRs, states, climatic divisions, specific watersheds or physiographic regions; and on down to that of a single 5-km pixel. This represents a significant leap forward from the previous best

study—that of Szilagyi *et al.* [2001], who generated continental-scale averages from point values—both in that a spatially distributed technique permits the examination of regional sensitivities to climate change and variability and in that examining long-term trends in the input climatic variables obviates assumptions of stationarity in any component, specifically Q_N (see Section 5.2).

(3) A comparison of wind function calibrations in the formulation of the ET_p rate in the complementary relationship model. Many researchers have developed wind functions—empirical and theoretical—in the past, but this study distributed them over a continental extent, and compared two distinct methodologies: one based on optimizing the match between mean annual modeled ET_a and ET_a^* , the other more directly matching ET_p to ET_{pan} . The variety of wind function parameter-values derived by other researchers was reflected in the parameter values here derived across the conterminous US, both within the population of each calibration and between the two. The ET_{pan} -based population of parameter values was less noisy than that of the ET_a^* -based population but bore, on the whole, a less-significant functional relationship to wind speed. While the ET_a^* -based calibration performed best in predicting ET_a when tested in an admittedly biased process, the ET_{pan} -based calibration was more physically based on observations of the evaporative process. In this context, a further methodological contribution would be the development of a spatially distributed, seasonal wind function parameter set that combines calibration information from the ET_a^* and warm-season ET_{pan} data sets across the entire conterminous US and the annual ET_{pan} data set in the southern US. A concurrent re-estimation of the value of the Priestley-Taylor α_{PT} parameter in the formulation of ET_w could then eliminate any bias towards under-estimation of ET_a .

Further contributions included work to address various data and methodological problems in the applicability of the regional-seasonal Advection-Aridity model of the complementary relationship, specifically, and, in general, the applicability of any model that requires knowledge of the energy budget at the surface in topographically heterogeneous and climatically challenging terrain. With respect to input variables to the models, improvements were made to the solar radiation input field, while improvements to the estimate of the independent evapotranspiration ET_a^* used in model calibration and validation were attempted through the precipitation input.

- A long-term, spatially distributed, topographically corrected, monthly weighted solar radiation Q_N data set across the conterminous US was generated. The solar radiation input to the model was divided into its direct normal and diffuse components and the former was corrected for the temporally variable effects of topography.
- Missing diffuse radiation data from SOLMET data were reproduced. This was the most significant work in the generation of a gap-free record of all variables and model output: complete records for all of the climatologic and hydrologic variables for the ET_a model are available from WY 1953–1994.
- A regional-specific re-parameterization of the wind function factor in the advective portion of ET_p was performed.
- Use of data from the PRISM model—developed specifically [Daly *et al.*, 1994] for estimating precipitation in mountainous areas—increased the reliability of the estimate of ET_a^* , which is used as a ground truth for the estimate ET_a .

- A long-term, spatially diverse ET_{pan} set was homogenized across the conterminous US for warm-season ET_{pan} , and the lower conterminous US for annual ET_{pan} .

6.3 Conclusions

As the primary conclusions of this dissertation are described in detail at the end of each of the four previous chapters, they are only summarized here.

First and most significantly, the complementary relationship in regional rates of ET_a and ET_p holds over the gamut of climatic regimes represented in the conterminous US. Thus, the complementary relationship hypothesis appears to be verified by observational evidence, and must now be considered an “observational fact” as a result of this work. In addition to the direct observational evidence provided by ET_{pan} and ET_a^* , modeling evidence supports this conclusion indirectly. As a corollary of having verified the complementary relationship hypothesis, the so-called “Pan Evaporation Paradox” is observed to be nothing more than the result of the physical relationship between ET_a and ET_p acting over regional scales. This relationship mirrors that predicted by the hypothesis of a complementary relationship in regional ET_a .

For predicting ET_a in large-scale, homogenous areas, complementary relationship models that predict ET_a directly are preferred over traditional models for the following reasons: they implicitly account for the soil moisture-dependence of ET_p ; there need be no direct dependence on ET_{pan} ; the input data are distributed and reflect surface conditions regardless of the origins of the water and degree of anthropogenic disturbance; and they can predict ET_a over regional extents and a variety of climatic regimes to within

3.63% of mean annual precipitation (in the case of the ET_a^* -based model applied on an annual basis in 655 basins).

Using geographically diverse ET_{pan} and ET_a^* data and spatially distributed modeling input fields, spatially distributed, long-term, large-scale trends in ET_a and in all of its components—net available energy Q_N in its radiative component and vapor pressure deficit V_{dif} , wind speed U_2 , and drying power of the air E_A , in its advective component—have been examined and enumerated for the first time. However, significant difficulties remain in the use of both sets of calibration data. In the use ET_{pan} observations to calibrate estimates of ET_p , issues relating to the functioning of the pans themselves may be resolved merely by homogenizing the time-series, but the inherent assumptions of regional homogeneity of topography and water availability around the pan are crucial but easily violated. In the use of ET_a^* to calibrate ET_a , the zero-flux and stationary-storage assumptions inherent in the derivation of ET_a^* are easily contravened, limiting the utility of this estimate in some regions.

Parameterizing the advective component of the complementary relationship model with an explicit function of wind speed requires wind functions that are spatially distributed and calibrated to the best available information. Based on this study, these would be both ET_a^* data from all available undisturbed basins and ET_{pan} data combined in such a manner as to eliminate the spatial restrictions of the annual ET_{pan} data and the temporal restrictions of the warm-season ET_{pan} data. Concurrently, a re-estimation of the Priestley-Taylor α_{PT} parameter in the ET_w formulation would eliminate the apparent bias towards under-estimation of ET_a by ET_{pan} -based calibrations. While such a parameterization would hew more closely to the physical dynamics of ET_a , an alternative

technique without an explicit function of wind speed (e.g., the vapor transfer coefficient developed for the CRAE model by *Morton*, [1983]) would obviate the inclusion of a noisy wind speed data set. In general, the choice depends on the preference of the modeler, the availability of the calibrating data, the region of application, and the availability and quality of wind speed data.

In addressing the demand for analyses of trends in the advective and radiative components of ET_a [*Ohmura and Wild*, 2002], the findings of others are verified; some confirmed and others refuted. The widespread and significant decrease in Q_N across the lower-48 states supports one of the major findings of *Roderick and Farquhar* [2002]. However, in using continental-scale values, as *Roderick and Farquhar* [2002] do, one ignores many smaller-scale areas that contradict any conclusions that may be drawn from such analyses. That even at a continental scale neither E_A nor V_{dif} is stationary undermines their assertion that the complementary relationship does not play a role in resolving the Pan Evaporation Paradox. In fact, at all scales examined—over the whole conterminous US, for the WRRs, the AUs, and the 655 watersheds—neither the radiative or advective components can individually account for such behavior. Instead, this dissertation shows that the component trends operate together within the framework of the complementary relationship, proving that the complementary relationship is an important dynamic in resolving said paradox.

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LIST OF ABBREVIATIONS

AR(p)	Auto-regressive process of order p
AU	Accounting Unit
AVHRR	Advanced Very High Resolution Radiometer
CA	California
CBL	convective boundary layer
CD-ROM	Compact Disc-Read Only Memory
COOP	NWS Cooperative Observer Program
COOP ID	COOP station identifier
CRAE	Complementary Relationship Areal Evapotranspiration
CY	Calendar Year
DEM	Digital Elevation Model
DTR	Diurnal Temperature Range
GCM	General Circulation Model or Global Climate Model
GIS	Geographic Information System
HCDN	Hydro-Climatic Data Network
HTML	Hypertext Markup Language
HUC	Hydrologic Unit Code
IDW	Inverse-Distance Weighted
MJJASO	May through October
NCDC	National Climatic Data Center
NCEP	National Centers for Environmental Protection

ND	North Dakota
NGDC	National Geo-spatial Data Clearinghouse
NM	New Mexico
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service
OK	Oklahoma
OR	Oregon
PRISM	Parameter-elevation Regressions on Independent Slopes Model
SAMSON	Solar and Meteorological Surface Observation Network
TX	Texas
US	United States
USGS	United States Geological Survey
WBAN	Weather Bureau Army Navy
WMOID	World Meteorological Organization station identifier
WRR	Water Resource Region
WY	Water Year