THESIS

MODELING *CULEX TARSALIS* COQUILLETT ABUNDANCE ON THE NORTHERN COLORADO FRONT RANGE USING A LANDSCAPE-LEVEL APPROACH

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ABSTRACT

MODELING *CULEX TARSALIS* COQUILLETT ABUNDANCE ON THE NORTHERN COLORADO FRONT RANGE USING A LANDSCAPE-LEVEL APPROACH

Endemic and emerging vector-borne diseases are major health problems, and some of them are unlikely to be eliminated regardless of control efforts. The applications for remote sensing and Geographic Information System (GIS) data include the identification of larval mosquito habitats and forecasting of species distribution and abundance, thereby improving the ability to target control efforts to reduce the risk of transmission of vector-borne pathogens. The practicality for the incorporation of remotely sensed environmental data into a GIS has greatly enhanced the understanding for the spatial and temporal distribution patterns of vectors, thereby enabling improved vector control operations and disease management response.

Since the initial detection of West Nile virus (WNV) in Colorado in 2002, the northern part of the Colorado Front Range has come to be recognized as a high-risk area for WNV infections in humans, with 7.5% of the national cases of WNV being reported from Boulder, Weld and Larimer counties during 2003-2011 (http://diseasemaps.usgs.gov/wnv_historical.html). *Culex tarsalis* Coquillett is recognized as the primary species of concern in the transmission of WNV to humans along the northern Colorado Front Range.

Before implementing the tools needed to control the spread of a vector-borne disease, public health agencies and organization officials must consider the spatial and temporal factors which are driving the interactions between the pathogen, the vertebrate host(s), and the vector(s). A sound understanding of the vector biology will vastly improve the efficacy for its control. Previous research performed on the northern Colorado Front Range used National Land Cover Data (NLCD) and IKONOS satellite imagery to model adult mosquito abundance of *Cx. tarsalis*.

I applied a landscape-level approach to elucidate the effects of landscape-level environmental factors (independent or predictor variables) at multiple spatial extents on monthly adult *Cx. tarsalis* abundance (dependent variable) in Fort Collins, Loveland and Johnstown, Colorado using GIS technology. Multiple regression models provided empirical evidence for the seasonal variability in adult *Cx. tarsalis* populations. A more detailed representation for the importance of spatial extent for elevation, slope, distance to and area of irrigated lands and the distance to larval mosquito sites was obtained from this study. Multiple regression models developed using stepAIC were able to explain and forecast monthly adult mosquito abundance with accuracies ranging from 43%-73% in Fort Collins and 36%-68% in Loveland and Johnstown. The expression of environmental variables also differed by month and year. Mean elevation within a 500 m buffer of mosquito trap locations in Fort Collins were negatively correlated with mean monthly adult *Cx. tarsalis* abundance. A positive relationship existed between mean monthly adult *Cx. tarsalis* abundance in Fort Collins and the perimeter of larval mosquito habitats within a 1.0 km buffer of traps and the distance to irrigated lands at a spatial extent of 500 m around traps. Mean elevation, slope and distance to larval mosquito sites at a spatial extent of 500 m provided improved predictive power for mean monthly adult *Cx. tarsalis* abundance in Loveland and Johnstown.

My results indicate that landscape and topographic heterogeneity within the study area are interacting on a monthly basis in different ways, resulting in varying populations of adult *Cx. tarsalis* mosquitoes. I believe it is a combination of interactions between landscape variables identified in this study and weather variables which determines the seasonal spikes in mosquito abundance. The ability to understand the factors that drive vector abundance is critical in managing risk and will aid large scale Integrated Pest Management efforts.

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Larimer County is fortunate to have a wealth of resources in terms of academia and research professionals at both Colorado State University and the Centers for Disease Control Division of Vector Borne Infectious Diseases Branch located in Fort Collins, Colorado. In addition to this exceptional local knowledge, the capacity to monitor and study vector-borne diseases comes as a result of the specialized laboratories and equipment used to perform detailed experiments for which results can be transferred to the field for practical applications. These resources greatly improve the local and regional management of zoonoses.

I too am extremely fortunate to have selected a thesis which integrated this quality of local experience. These collaborative efforts aim to provide sound data from which a better understanding of how the local landscape may contribute to the West Nile virus transmission cycle in Larimer County. I express my sincere appreciation for the willingness of Dr. Chester Moore and Dr. Roger Nasci to provide me with specific local considerations about West Nile virus risk and mosquito abundance. I also am grateful to Dr. Lars Eisen for agreeing to assist me in the modeling efforts for *Culex tarsalis*, from which he brought suggestions to strengthen my models and reduce the biases that may not transfer to the field. To Dr. Boris Kondratieff, I express my respect for your love of systematics and your ability to continue to engage students in understanding the insect biology behind their life histories and survival. I also want to thank the Cities of Fort Collins and Loveland, the Town of Johnstown, the Northern Colorado Water Conservancy District (NCWCD) and Colorado Mosquito Control, Inc. for the use of mosquito abundance data, irrigated lands, local weather data and larval mosquito site layers. To the friends who suggested I step away from the laptop to do field work for a while, I thank you for knowing me all too well. Finally, I would like to expresses my gratitude to Dr. Sunil Kumar for the hours you spent working to guide me on geoprocessing and the encouragement you provided throughout this work.

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1. INTRODUCTION

1.1 West Nile Virus and A Sustained Presence Along the Northern Colorado Front Range

Endemic and emerging vector borne diseases are major health problems, and some of them are unlikely to be eliminated regardless of control efforts. These include West Nile virus (WNV) disease in North America and malaria in sub-Saharan Africa (Anderson et al. 2004, Mushinzimana et al. 2006, Kramer et al. 2008).

WNV belongs to the virus family Flaviviridae (Nash et al. 2001, Hayes et al. 2005, Gujral et al. 2007). WNV was initially isolated in Uganda in 1937 (Smithburn et al. 1940) and WNV transmission activity has since been documented in Africa, Europe, South America, West and Central Asia, India, and the Middle East (Hayes et al. 2005, Mattar et al. 2005). The virus made its first appearance in North America in 1999 when it was documented in New York City (Nash et al. 2001, Petersen and Hayes 2004). Starting in the northeastern portion of the United States, the virus steadily expanded westward and also moved south into Central America and northward into Canada in the years that followed (Hayes et al. 2005). Birds were initially believed to serve as a critical bridge in mediating arbovirus transmission (Reeves 1974) and have since been implicated for contributing, in part to the westward expansion of WNV following migration routes (Reed et al. 2003). The documentation of sustained migratory activity by infectious birds further supports the importance of migratory patterns in the transmission cycle of WNV (Owen et al. 2006). WNV is now ubiquitous within the contiguous United States with reported human WNV disease cases varying on a yearly basis by geographic location. The prevalence of WNV infection in humans and mosquitoes has been found to be related to local meteorological, environmental and hydrologic variability (Miramontes et al. 2006, Shaman et al. 2010, Shaman et al. 2011, DeGroote and Sugumaran 2012).

WNV is transmitted by mosquitoes and can infect birds as well as humans, horses and other mammals (http://www.cdc.gov/ncidod/dvbid/westnile/qa/overview.html). Birds are the most important natural reservoir/amplification hosts (Fan et al. 2010). High viral titers can be detected in susceptible birds within 3-5 days after being bitten by an infected mosquito (Fan et al. 2010). Humans and horses do not develop sufficient viremia to infect feeding mosquitoes and therefore are considered to be dead end hosts for WNV (Barker et al. 2003, Fan et al. 2010).

Surveillance with established methods for mosquito data collection and WNV detection can be useful to forecast the risk for infection with mosquito-borne pathogens (Wegbreit and Reisen 2000, Diuk-Wasser et al. 2006) and provides the basis for comparisons of temporal trends in mosquito infection. Consistent data for mosquito abundance, obtained through a standardized trapping protocol, can be used to derive location specific and temporal baselines against which anomalies can be identified (Barker et al. 2010).

The study area that I focused on exists in the short grass prairie of the Great Plains in northeastern Colorado where the elevation gradient is below 1,600 m (Eisen et al. 2008). This region has historically presented the highest incidence of WNV neuroinvasive cases across Colorado, with the exception of 2004, since the first documentation of WNV in Colorado in 2002 (Barker et al. 2009a). The northern part of the Colorado Front Range has since come to be recognized as a high-risk area for WNV human infections. During the years of 2003-2011, the three-county Boulder-Larimer-Weld area alone reported 2,038 cases of WNV disease in humans out of a total 27,109 national reported cases during this period (http://diseasemaps.usgs.gov/wnv_historical.html). This three-county area thus accounted for 7.5% of the human cases reported in the U.S. from 2003-2011.

1.2 Application of Geographic Information Systems for Risk Prevention

Geographic Information System (GIS) and remote sensing (RS) based modeling has been widely used in identifying vector distribution and in the mapping of vector borne diseases (Hay et al. 1998, Tran et al. 2008, Winters et al. 2008b, Shaman et al. 2011). The ability to forecast both vector distribution and abundance are pivotal in reducing transmission risk from vector exposure. GIS data and RS retain the capacity to integrate ecological, entomological and virological factors for management and response (Beck at al. 1994, Dale et al. 1998). Remote sensing data can be used to identify larval mosquito habitats and thus provides the potential to predict the species occurrence of mosquitoes (Mushinzimana et al. 2006, Tran et al. 2008, Brown et al. 2008a). The practicality for the incorporation of remotely sensed environmental data into a GIS has greatly improved vector control operations and disease management response in terms of a better understanding for the spatial and temporal distribution patterns.

Culex tarsalis Coquillett is recognized as the primary species of concern in the transmission of WNV to humans in this study area (Bolling et al. 2007, Gujral et al. 2007). DeGroote and Sugumaran (2012) described the distribution of *Cx. tarsalis* across the Great Plains and this species positive association with irrigated areas as a contributing factor to WNV incidence for this region. Larvae of this species are known to prefer shallow aquatic habitats, with little pollution and moderate organic material (Du and Millar 1999). Additionally, from field observations, this species tends to prefer slightly alkaline environments with short emergent vegetation. *Cx. pipiens,* a second vector of WNV in the northern Colorado Front Range, has been found to favor dry summer conditions in Colorado (Shaman et al. 2010) and prefers polluted eutrophic water sources (Shaman et al. 2011).

Selection of an oviposition site by a female mosquito is likely dependent in part on the presence of microbes, algae and detritus, which provide nourishment to developing larvae in the water column and within the benthos (Chase and Knight 2003). Different types of vegetation have been found to emit a range of volatiles that may act to stimulate oviposition in certain mosquito species (Bruyne and Baker 2008). In work by Isoe and Millar (1995) bermuda grass (*Cynodon* spp.) infusions have been found to result in increased oviposition by *Cx. tarsalis*, while alfalfa (*Medicago sativa*) infusions elicited no change in oviposition behavior. In addition to the oviposition attractants mentioned above, optical density, water depth and permanency of the aquatic habitat can also drastically alter the dispersal by adult mosquitoes in oviposition site selection (Isoe and Millar 1995).

Identification of larval mosquito habitats using RS and ArcGIS, for example, can help classify oviposition sites based on the water source, the permanency and the presence of vegetation type. These tools provide the ability to identify suitable habitats for *Cx. tarsalis* oviposition based on the species preference for chemical and visual cues and can help target operational efforts to control larval mosquitoes.

Changes in human population and land use patterns over the past 20 years in the Great Plains have likely altered the dynamics of the epizootic transmission of mosquito-borne viruses (Barker et al. 2009a). Many of the studies which have documented the importance of spatial and temporal variables that modify mosquito life histories and WNV patterns have been performed at both the county and state level (Wegbreit and Reisen 2000, Miramontes et al. 2006, Trawinski and Mackay 2008, Winters et al. 2008b, Shaman et al. 2011, DeGroote and Sugumaran 2012). Larval habitat location, microclimate, and population density have been ascertained as spatial factors that affect risk of WNV exposure in humans (Hayes et al. 2005, Winters et al. 2008a).

Several studies have also forecasted human incidence and risk for WNV in Colorado through the use of remote sensing and GIS data (Bolling et al. 2007, Gujral et al. 2007, Winters et al. 2008a, Winters et al. 2008b, Barker et al. 2009b, Eisen et al. 2010). Modeling efforts for *Cx. tarsalis* have encompassed IKONOS satellite imagery (Maki 2005), remotely sensed data from the 2001 National Land Cover Dataset (Eisen et al. 2010) and Colorado GAP analysis data (Barker et al. 2009b). Studies on incidence of WNV disease using GIS based models for eastern and western Colorado revealed that human risk was highest along river basins associated with the Platte, Arkansas, and Colorado Rivers in the Colorado (Winters et al. 2008b). Many of the models and maps that have identified patterns of WNV risk for the northern Colorado Front Range have been based on coarse resolution temporal and spatial predictors or census tract data for reported human cases of WNV disease. There is limited information which incorporates the effect and proximity to larval mosquito habitats and land use patterns, over numerous study years for the three-county Boulder-Larimer-Weld area, to model areas of high risk for possible WNV amplification based on vector abundance at a municipal level.

1.3 Objectives and Research Intent

In the present work, I utilized raster based environmental covariates (independent or predictor variables) to elucidate the effects of environmental variables on mean monthly adult *Cx. tarsalis* abundance (dependent variable) in Fort Collins, Loveland and Johnstown, Colorado using GIS technology. Landscape-level models are useful in forecasting species distribution, richness or decline, in that this approach does not incorporate a specified scale but rather looks at both the biodiversity of the landscape and the contribution of the landscape to the species abundance (Aukema et al. 2006, Gottschalk et al. 2007, Otte et al. 2007). I anticipated that adult mosquito abundance is largely driven by a suite of discrete and continuous variables interacting together in space and time. I therefore used environmental GIS data to evaluate the predictive power of climate surfaces and landscape variables, at relevant spatial extents (buffers of 175 m, 250 m, 500 m and 1.0 km radii around mosquito trap locations), using a multi-model selection approach, to forecast *Cx. tarsalis* abundance at the municipal scale. I selected multiple buffer distances for variable analysis in an attempt to reduce biases that may result with extent, while still isolating the variables that improved the fit of monthly multiple regression models.

Included in this analysis was consideration for the effects of topographic and landscape heterogeneity. I hypothesized that landscape heterogeneity, proximity to and area of larval habitats and irrigated lands will have a significant effect on the population dynamics of adult *Cx. tarsalis* along the northern Colorado Front Range. Moreover, I anticipated that shallow temporary waters provide suitable oviposition sites and will result in elevated mosquito abundance around these waters and dispersal into adjacent vegetation.

The primary objectives of my study were to: 1) Develop models that quantify the effects of environmental variables on adult *Cx. tarsalis* mosquito abundance on a monthly basis, 2) Evaluate habitat classification for larval development sites from remotely sensed data against ground-truthed data for larval mosquito habitats obtained from Colorado Mosquito Control, Inc. (CMC), and 3) Detect foci for elevated risk of WNV amplification based on predicted vector abundance at a maximum extent of 1.0 km around trap locations.

The purpose of my study is to provide decision makers with additional empirical support, based on my statistical findings, to make sound operational choices regarding control efforts for the importance of public health based on landscape-level variables and monthly vector abundance. Identification of significant landscape parameters in this work will add to the resources used to monitor seasonal patterns of WNV risk along the northern Colorado Front Range.

2. LITERATURE REVIEW

2.1 Biology of *Culex tarsalis*

2.1.1 Adult Life History

An understanding for the species biology and interaction with the environmental factors which affect a vector species is imperative when trying to forecast temporal patterns in abundance. Much of the life history work published for *Cx. tarsalis* is based on studies from California (Nelson 1971, Reisen and Reeves 1990), for which the central Valley of California has similarities to the northern Colorado Front Range in terms of land use patterns and associated agricultural irrigation in an arid region. Snowmelt runoff, winter temperatures, photoperiod length, and local irrigation have been found to contribute to increases in adult *Cx. tarsalis* abundance (Nelson 1971, Reisen et al. 2010).

Reisen and Reeves (1990) reviewed the ability of *Culex* spp. females to enter diapause in response to shortening day length and cooler temperatures. *Culex tarsalis* has been documented to be active in the mild winters at the lower latitudes of southern California (Nelson 1971) while females overwinter in northern latitudes as inseminated, nulliparous, unfed females in a photoperiod induced and temperature maintained winter diapause (Reisen and Reeves 1990). Southern populations remain gonotrophically active throughout the winter with inactivity during cold periods (Reisen 1993). Mild winter temperatures in the Imperial Valley have been documented to result in weak expression and shortened duration of diapause (Nelson 1971). Warm winter temperatures have also been found to be associated with early gonotrophic activity and increased abundance of female *Culex* mosquitoes at lower latitudes of California (Reisen et al. 2010). The majority of overwintering females which survive mild winters do not acquire their first blood meal until the late winter or early spring (Nelson 1971).

More recent research conducted in Colorado found that *Cx. pipiens* (Bolling et al. 2007) emerged from storm basins and were collected in light traps on the Colorado Front Range in early March, after approximately 400 degree days using a 0^{o}C base. *Culex tarsalis* females have been collected as early as March at elevations below 1,600 m and in early May from elevations above 1,750 m in Colorado (Bolling et al. 2009). Bolling et al. (2009) found that *Cx. tarsalis* abundance in northeastern Colorado peaks in late summer and declines rapidly thereafter. *Culex tarsalis* abundance peaks were found to vary in Larimer County in 2006 and 2007 by habitat, with the initial peaks documented to occur in proximity to riparian areas, affected by receding water levels following snow melt runoff from higher elevations (Godsey et al. 2010).

Culex tarsalis temporal abundance in Larimer County has displayed a distinct bimodal pattern during epidemic seasons of WNV disease. In 2007, adult *Cx. tarsalis* abundance, measured by average mosquitoes per trap night, spiked in week 28 with a second peak in week 32 (CMC 2007). Godsey et al. (2010) recorded a spike in *Cx. tarsalis* mosquitoes at locations in both rural and urban Fort Collins on July 12 (week 29) and a second peak on August 8 (week 33) in rural areas during 2007. This bimodal pattern is consistent with the data collected near the Kern River in California during periods of riparian flooding associated with elevated snowpack at the Sierra Nevada mountains and late season agricultural irrigation (Reisen et al. 1992).

2.1.2 Temperature Effects on Larval Development and Habitat Preference

Culex tarsalis larval mosquito development begins during late spring and continues until early autumn throughout most of this species range, with several generations produced (Carpenter and LaCasse 1955). In the field setting in Larimer County, *Cx. tarsalis* abundance has been found to rapidly increase when mean air temperatures consistently exceeded 18.5^{o}C -19.5^{o}C (Bolling et al. 2009). Larval mosquito development ranges from seven days to less than 4 weeks and mortality is largely affected by water temperature (Hagstrum and Workman 1971, Eisenberg et al. 1995), micro floral bloom availability (Reisen 1993) and density dependence (Eisenberg et al. 1995). These findings support the importance of cooling degree days and the median temperatures during winter months to mediate early spring activity of *Cx. tarsalis*.

The rate at which larval *Cx. tarsalis* spends in each instar has been found to decrease with warmer temperatures, with a noticeable reduction in the duration of larval instars at stages I and III (Hagstrum and Workman 1971). Additionally, the feeding rate of larval *Cx. tarsalis* has been found to increase with cooler temperatures, with 52% more food consumed at 20^{o}C compared to 30^{o}C (Hagstrum and Workman

1971). Water temperature can have a profound effect on the larval development rate and subsequent vector abundance. Identification of larval mosquito habitats for larval mosquito control efforts should focus on the species of interest and target areas where waters offers a suitable depth and food resources, without causing larval mortality due to excessive temperatures as a result of solar radiation. Regression models for adult *Cx. tarsalis* in South Dakota identified the importance of temperature in the current week and 1 week prior to collections as being critical in driving *Cx. tarsalis* mosquito abundance (Chuang et al. 2011) likely because this range of temperatures in space and time were ideal for larval development.

Culex tarsalis is most abundant in western agro ecosystems and is known to preferentially oviposit in newly created surface pools and does not tolerate excessive pollution (Reisen 1993). Temporary pools are favored by many species of mosquitoes, including *Cx. tarsalis*, partly due to the lack of predators and high levels of heterotrophic bacteria (Mercer et al. 2005). The habitat types where larval *Cx. tarsalis* mosquitoes have been identified vary immensely from peridomestic sources to agricultural tail water (Reisen 1993). This species can be found in clear or foul water in irrigation systems, corrals and slaughter yards, or pools in stream beds (Carpenter and LaCasse 1955) to fresh and saline riparian wetlands (Reisen 1993). Identification of the areas with a high density of preferred larval mosquito habitats are ideal places to perform adult surveillance monitoring as the larval habitats will attract females to oviposit and can provide data for vector abundance.

2.1.3 Species Distribution, Host Seeking Behavior, and Oviposition Infochemicals

Culex tarsalis occurs from southern Canada to northern Mexico and from Baja California, Mexico to the southern Atlantic Coast (Reisen and Reeves 1990). Within Colorado, this species has been described from elevations of 1,200 m in the prairie plains landscape of the eastern Colorado to 1,450 m in low montane areas at the eastern edge of the Rocky Mountains (Barker et al. 2009a).

Hematophagous vectors are often forced to disperse from the habitats in which they emerge when a blood meal is not readily available. It is important to consider multiple variables when evaluating the dispersal patterns of adult female mosquitoes, including topography, relative humidity within surrounding harborage, proximity to oviposition sites, permanency of aquatic habitats and prevailing wind direction

(Lothrop and Reisen 2001, Godsey et al. 2010). *Culex tarsalis* seeks hosts at greater distances across the landscape when compared to other species. The vast majority of *Cx. tarsalis* have been recaptured from mark-release-recapture studies within 0.5 m to 1.0 km from the release point in Kern County (Reisen et al. 1992) and the Coachella Valley of California (Reisen and Lothrop 1995).

Work performed by Barker et al. (2009a) proposed that the Continental Divide serves as a barrier to dispersal of *Cx. tarsalis* and *Cx. pipiens* from the plains into the mountain plateau, which is likely an effect of unfavorable temperatures along the elevation gradient. Mosquito surveillance along the major water ways across the Great Plains has indicated that riparian habitats and associated land cover type serve as important dispersal corridors for *Cx. tarsalis* (Barker et al. 2009a), and can be used in evaluating the likelihood that mosquitoes may leave their emergence locations (Barker et al. 2009b) possibly in search of a blood meal or an oviposition site. This is a logical expectation considering the presence of ample foliage and moisture along these tree lined corridors.

Generalizing the flight range of *Cx. tarsalis* can prove to be both a challenging and daunting task as variations in habitat heterogeneity can affect distribution. *Culex tarsalis* is commonly found in landscapes dominated by grasslands, pasture and hay production when compared with urban environments and has been found to have a stronger spatial autocorrelation to these habitats when compared to other mosquito species (Chuang et al. 2011). Lothrop and Reisen (2001) found that *Cx. tarsalis* commonly harbor within ecotones with elevated vegetation in the Coachella Valley of Riverside County in California and that dispersal can be affected by landscape heterogeneity. Their study found that gravid females were often associated with dense *Typha* stands in proximity to larval habitats. The interaction between the physical and chemical cues that guide oviposition behaviors is a complex relationship and can be species dependent (Bentley and Day 1989). *Culex tarsalis* tend to remain in rural habitats when compared with dispersal rates into residential areas (Reisen et al. 1991). Distribution of *Cx. tarsalis* becomes reduced at locations associated with desert or grass, citrus, salt cedar or vineyard canopy (Lothrop et al. 2002), which suggests that infochemicals associated with these vegetation types or relative humidity within the associated vegetation may affect dispersal.

Efforts to monitor *Cx. tarsalis* dispersal in the Coachella Valley of California found reduced dispersal rates in winds exceeding 10 mph (Reisen et al. 2003). The semi-arid conditions of the northern Colorado Front Range often cause mosquitoes to move in search of suitable harborage as aquatic habitats dissipate during increased summer temperatures. High numbers of *Cx. tarsalis* have also been collected in surveillance traps that are hundreds of meters away from larval habitats, possibly located in less suitable habitats, which are considerably drier than emergence sites (Barker et al. 2009b). Abundance data collected from Bakersfield, California reveled that *Cx. tarsalis* dispersed from adjacent irrigated agricultural fields to riparian vegetation even when the river system was dry (Reisen et al. 1992).

2.1.4 West Nile virus Transmission

Temperature can have profound effects on larval and adult mosquito survival and population growth by affecting the larval development time, the length of the gonotrophic cycle, the daily survival rate and the biting frequency on susceptible hosts (Reisen et al. 2006, Reisen et al. 2010, Chuang et al. 2011). The effects of temperature on larval survivorship have shown that increased temperatures, to a critical threshold, can cause aquatic stages to develop more quickly (Hagstrum and Workman 1971). Warmer temperatures not only lead to a shorter gonotrophic cycle, but also a shorter extrinsic incubation period of WNV in *Culex* vectors (Reisen and Lothrop 1995, Reisen et al. 2006, Winters et al. 2008b). Laboratory studies have estimated the zero replication rate of WNV to be 14.3^{o}C (Reisen et al. 2006).

Changes in elevation have been widely documented to be correlated with changes in temperature and land cover (Barker et al. 2009a), which can drive vector abundance and associated transmission risk (Winters et al. 2008b). WNV activity and vector indices have been documented to decrease with elevations along the Front Range of Colorado (Winters et al. 2008b, Barker et al. 2009a).

Raddatz (1986) used hydrologic accounting of precipitation, evapotranspiration and runoff as estimates of wetness to forecast impending outbreaks for Western Equine Encephalitis virus (WEEV) transmitted by *Cx. tarsalis* in Manitoba, Canada. He found a three week lag time for meteorological variables as being the most significant for forecasting adult *Cx. tarsalis* counts. An assessment for the effects of hydrology on the enzootic transmission of WNV in Suffolk County, New York indicated that wetter winter conditions, warmer spring conditions and drier early summer land surface conditions all contributed to increased transmission within naïve *Culex* vectors (Shaman et al. 2011). Nielsen et al. (2008) identified the random spatial-temporal distribution of WNV in Davis, California which was affected by the heterogeneity of WNV vectors across their associated landscapes.

The aforementioned studies show that landscape-level heterogeneity and habitat preference of a vector species can serve as predictors of vector-borne disease risk. Without an understanding of the key factors that drive the mosquito biology and distribution across the landscape, little knowledge can be applied for the control of mosquito-borne diseases.

2.2 Use of Remote Sensing and GIS in Modeling Vector Abundance

The predictive power of regression models to forecast vector abundance is largely dependent on the species distribution, landscape heterogeneity and spatial and temporal patterns, as well as the scale at which models are being developed (Eisen and Eisen 2011). Spatial scale both in terms of extent and resolution can have significant implications on the ability to identify ecological patterns and understand the underlying processes that are driving those patterns (Scott et al. 2002). Species distribution models are a novel way to relate species abundance data to environmental characteristics within or across a landscape (Elith and Leathwick 2009). Additional challenges in predicting mosquito abundance lie in habitat-specific considerations of the mosquito larvae which include climatic factors, inter and intraspecific competition, density dependence and the effects of predation (Millar et al. 1994, Eisenberg et al. 1995, Van Dam and Walton 2008).

The ways that GIS applications and remote sensing have enabled significant improvements in the identification of larval mosquito habitats, vector, and disease distributions have been highlighted by Dale et al. (1998), Tran et al. (2008) and Eisen and Eisen (2011). Advancements in aerial satellite imagery and space borne sensors have produced relevant information which is capable of relating spatial variation in mosquito habitats with meteorological and vegetation variables (Hay et al. 1998).

Ruiz et al. (2010) provided a concise review for the conflicting outcomes of models measuring the effects of environmental factors on WNV patterns and infections in humans. Climatic, landscape and demographic variables that have repeatedly emerged in association with increased human WNV disease include distance to riparian corridors, vegetation measures, slope, elevation, human population numbers, housing and road density, urban land use, race, income, housing age and host community structure. Mosquito abundance models have highlighted the variability in meteorological patterns across the United States as one of the important factors driving vector abundance in the humid northeast (Degaetano 2005, Chuang et al. 2011). The arid conditions of the mid-west present a different pattern of meteorological events and land use patterns which can affect vector distribution and infection risk (Miramontes et al. 2006, Wimberly et al. 2008, Shaman et al. 2010).

Improved predictive power for vector abundance can be obtained by considering how landscape heterogeneity can provide suitable larval habitats and affect mosquito species distribution based on harborage differences and association with urban environments (Beck et al. 1994, Diuk-Wasser et al. 2006, Ruiz et al. 2010). Normalized Difference Vegetation Index (NDVI) and Drought Water Stress Index (DWSI) values extracted using a 50 m buffer around surveillance locations in Connecticut were found to be correlated with *Cx. salinarius* and *Aedes vexans* abundance (Brown et al. 2008a). *Culex tarsalis* were found to congregate at specific microhabitats, as created by vegetative patterns with preference for riparian ecotones in rural environments of the San Joaquin Valley of California (Reisen et al. 1992). Chuang et al. (2011) found *Cx. tarsalis* abundance to be positively correlated with hay in a landscape analysis using land cover data for South Dakota. *Culex tarsalis* abundance measured at a 50 m scale in Fort Collins, Colorado has been found to decrease with 2-3 land cover types versus that of a single vegetative class or multiple land cover vegetation classes (Barker et al. 2009b), thereby indicating a possible preference for vegetation types or pattern of dispersal. Predicative power for *Cx. tarsalis* near the Cache la Poudre River was the strongest when a 50 m buffer using 2001 National Land Cover Dataset was applied (Maki 2005). In an effort to model dispersal of *Cx. tarsalis* from larval habitats in northern Colorado, abundance was found to be higher at locations that were hundreds of meters away from larval habitats (Barker et al. 2009b). The vector species of interest and its associated behaviors and habitats are critical considerations when modeling abundance and species distribution (Ruiz et al. 2010).

The effects of water permanency can directly relate to predator presence and community ecology with an associated habitat (Chase and Knight 2003). Semi-permanent wetlands that experience seasonal drought-like conditions have been found to be more favorable for mosquito presence on an annual basis, due to reduced predation when compared to permanent wetlands where predator densities were higher (Chase and Knight 2003). Distances to major larval habitats derived from Colorado GAP analysis data were not correlated to *Cx. tarsalis* abundance within a 400 m range, while *Ae. vexans* abundance decreased significantly with increasing distance from larval habitats (Barker et al. 2009b). The findings of Barker et al. (2009b) provide support for the importance of dispersal by *Cx. tarsalis* to be driven by fine scale habitat heterogeneity.

Low correlation has been described between summer precipitation and *Cx. tarsalis* in Fort Collins, but inclusion of mean weekly temperature was found to improve abundance models (Brown et al. 2011). Wegbreit and Reisen (2000) found a strong relationship between *Cx. tarsalis* abundance and snow depth, snow water content, and river runoff, while presence was not correlated with rainfall in the San Joaquin Valley floor of California. Data from this eight year study by Wegbriet and Reisen (2000) for the effect of temporal trends and snow pack in the San Joaquin Valley floor of California showed that winter water content explained 70% of the variability in average *Cx. tarsalis* abundance. I selected multiple spatial and temporal predictors for this study based on the previous findings for significant environmental variables that contribute to *Cx. tarsalis* abundance in regions with similar topography as the spatial modeling area.

3. METHODS AND MATERIALS

3.1 Study Area

The spatial modeling area (Figure 3.1) included the cities of Fort Collins and Loveland in Larimer County, Colorado, and the town of Johnstown in the adjacent Weld County, located between $40^{o}36'$ and $40^{o}62'$N latitude and $-104^{o}93'$ and $-105^{o}05'$ W longitude. The elevation across these municipalities ranges between 1,448 m -1,562 m above sea level.

Variability in elevation over short distances in this region can have drastic effects on environmental variables including temperature, land cover, and precipitation (Barker et al. 2009a). The landscape is also heterogeneous across the study area with urban to suburban irrigated residential vegetation dominant in Fort Collins and irrigated agriculture comprising the lands east of the municipal boundaries of Fort Collins (Brown et al. 2011). The water surface area in Loveland is approximately 2.5 times that of neighboring Fort Collins (Gujral et al. 2007), as a result of an extensive reservoir storage system in the northeastern portion of the city and associated irrigated lands on the outer limits of the city. Irrigation water stored in the network of reservoirs is released according to surrounding municipal and agricultural needs.

The climate of the study area is characterized by cold winters and hot summers with low humidity (Winters et al. 2008a, Barker et al. 2009a). Conditions are semi-arid and precipitation is variable. The average annual rainfall in Fort Collins from 1971 to 2000 was 393 mm (Mountain States Weather Services, Fort Collins, Colorado). The confluence of the Poudre and Big Thompson Rivers, which emerge from the Rocky Mountains in western Larimer County, drain into the South Platte River in neighboring Weld County. The river corridors are lined with cottonwood (*Populus* spp.), willow (*Salix* spp.) (Brown et al. 2011) and often consist of oxbows that are filled with sediment and contain dense patches of cattails (*Typha* spp.).

The extent of the spatial modeling area was digitized in ArcGIS 9.3 using 2009 National Agriculture Imagery Program (NAIP) Ortho imagery for Larimer and Weld counties (http://datagateway.nrcs.usda.gov) in Universal Transverse Mercator (UTM) projection, Zone 13N and

Northern American 1983 datum (NAD 83). The polygon was extended 8.05 km beyond the larval control boundaries for associated municipalities, as was provided by the contractor for these communities, Colorado Mosquito Control, Inc. (CMC), Brighton, Colorado. This area encompasses 367,195 ha of land and water within Larimer and Weld counties.

This spatial modeling area, with an 8.05 km buffer from larval control activities, was chosen to reduce the effects mosquito dispersal into the landscape may have on the *Cx. tarsalis* abundance. I was attempting to detect variation in abundance, based on fine scale land use patterns and vegetation types within a 1.0 km extent of mosquito trap locations. It should be noted that landscape variables beyond control limits also have an impact in driving migratory mosquitoes into city limits, especially along the river corridors and ecotones. I therefore used a large buffer when processing the topographic variables to account for the unknowns in dispersal by female *Cx. tarsalis* from outside areas. I used the topography of the foothills west of the cities of Fort Collins and Loveland as a natural barrier for the western-most boundary in this modeling project.

3.2 Mosquito Surveillance Locations and Field Data

Mosquito surveillance data were collected weekly during Julian weeks 23-35 for the years 2007-2010, encompassing approximately the first week of June through the first week of September for each year. I divided the data into two subsets for processing 1) Fort Collins and 2) Loveland and Johnstown. I created this assignment based on the integrated mosquito management program approaches for the municipalities. Each of these communities performs larval mosquito control within city limits to reduce larval mosquito populations. The municipalities of Loveland and Johnstown perform mosquito adulticiding around surveillance trap locations when more than 50 adult *Culex* spp. mosquitoes are collected in one night. This spray threshold, termed a disease threshold, encompasses mosquito species compositions totaling 50 or more mosquitoes for *Cx. tarsalis*, *Cx. salinarius* and *Cx. pipiens* or combined species totals in a single trap. The City of Fort Collins does not perform mosquito adulticiding unless elevated levels of West Nile virus activity in mosquitoes, humans or birds warrant public health response. I attempted to reduce the effect of mosquito spraying across the landscape by grouping data with similar approaches to account for the effect of mosquito adulticiding on monthly abundance. Additionally, I grouped Loveland and Johnstown adult mosquito abundance data together as these communities exist in proximity to the river drainage of the Big Thompson. There were 41 mosquito trap locations from which abundance data were collected for Fort Collins and 44 locations included in Loveland and Johnstown.

Adult mosquitoes were collected using Centers for Disease Control (CDC) miniature light traps (John W. Hock Company, Gainesville, Florida) that were suspended 1.5 – 2.0 m above the ground and operated from afternoon (1600-1800 hours) until morning (0700-0900) hours. The CDC trap (Figure 3.2) uses a motor driven rotary fan to draw mosquitoes attracted to the light source and CO_2 from dry ice stored in a container above the trap down a plastic cylinder into a collection net attached beneath the trap (Anderson et al. 2004). Each trap was baited with 1.8 kg of dry ice and was operated with a 6 volt battery, and 2,180 RPM motor fan. Traps were set the same day of each week, unless impeded by weather, in which case the trap was set on the following night if conditions permitted. Traps were not set or data were not recorded when winds exceeded 15 mph for extended periods of time in a given trap night or consistent rainfall occurred during prime host seeking times. Mosquitoes were recovered from the traps each morning and immobilized with dry ice and transported to the lab for identification. Specimens were identified to the species level using the key of Darsie and Ward (2005). Total species counts were recorded into Colorado Mosquito Control's Comprehensive Mosquito Management System (CMMS) database and monthly abundance data were exported by Excel spreadsheets for averaging.

3.3 Topographic and Environmental Parameter Selection and Processing

3.3.1 Landfire Land Cover Classification Data

Landfire uses land cover classifications defined by NatureServes's ecological systems classifications (http://www.natureserve.org/explorer/classeco.htm#vegetationClass) which are ecological units at mid-scale resolution. Landfire land cover data for 2006 from the United States Forest Service was obtained from the LANDFIRE website (http://www.landfire.gov/products_national.php) in the native projection of Albers Conical Equal Area, datum NAD 1983 (Table 3.1). I re-projected the 30 m GRID to Universal Transverse Mercator (UTM) projection, Zone 13N and NAD 83 within ArcGIS 10.

The original landfire values were reclassified from 205 attribute classes to Open Water (11), Developed Open Space (21), Non Suitable Habitat (22), Barren Land (31), Pasture and Hay (81), Cultivated Crops (82), Woody Wetland (90), and Herbaceous / Introduced Wetland (95) following the categorical classification methods described by Eisen et al. (2010) (Figure 3.3). Majority vegetative class was extracted from a 250 m and 500 m buffer around trap locations using Zonal Statistics in ArcGIS 10 (Table 3.2). I chose these buffer distances based on previous findings by Barker et al. (2009b).

3.3.2 Topographic Exposure

A 10 m resolution Digital Elevation Model (DEM) in Universal Transverse Mercator (UTM) projection, Zone 13N and NAD 83 was downloaded from the National Elevation Dataset, United States Geological Survey (USGS) seamless server website (http://nationalmap.gov/viewer.html) (Table 3.1). Topographic exposure was calculated as the difference between 10 m DEM elevations from those of a 500 m surface GRID. This GRID was generated using Focal Statistics in ArcGIS 10, with a mean map unit of 500 m. The Focal Statistic procedure calculates a statistic from a raster layer over a specified buffered area (Diuk-Wasser et al. 2006). I used raster calculator to create the topographic exposure GRID from which I extracted the mean value for trap locations (Table 3.2).

3.3.3 Impervious Surface

The 2006 National Land Cover Dataset (NLCD) Percent Developed Impervious Surface was downloaded from the USGS seamless server. The 30 m TIFF was converted to a 30 m GRID and re-projected from Albers Conical Equal Area to Universal Transverse Mercator (UTM) projection, Zone 13N and NAD 83. I used the Statistics tool in ArcGIS 10 to calculate a 500 m circular map unit mean using the 2006 NLCD GRID and extracted the mean value for trap locations (Table 3.2).

3.3.4 MODIS Normalized Difference Vegetation Index (NDVI)

Calculated range in Normalized Difference Vegetation Index (NDVI) was obtained at 250 m spatial resolution from the National Aeronautics and Space Administration's (NASA) moderate resolution imaging spectroradiometer (MODIS) instrument data (https://wist.echo.nasa.gov/wist-bin/api/ims.cgi) (Table 3.1). MODIS imagery is useful for deriving Land-Use Land-Cover (LULC) information with low spatial but high temporal resolution (Li and Fox 2012). The range in NDVI contains information on vegetation greenness as a measure of photosynthetic activity and vegetative productivity (Kumar et al. 2009) and can serve as a proxy for soil moisture (Shaman et al. 2002). I anticipated that higher values of NDVI would exist along riparian corridors and near lakes and ponds. I also included an assessment of standard deviation in NDVI values to evaluate the heterogeneity in the landscape, with higher values of standard deviation in NDVI reflecting more diverse landscapes. The higher values of mean and standard deviation of NDVI values may provide some insight as to more suitable harborage areas for *Cx. tarsalis*.

The study area was covered by two MODIS tiles in 16 day composite images for 2009 and 2010. NDVI HDF layers were processed using the mosaic tool in ArcGIS 10 to create new GRIDs for each 16 day period. I then clipped the GRIDS to the spatial modeling extent and re-projected each GRID to UTM projection, Zone 13N and NAD 83. The mean and standard deviation pixel values from the 16 day composite images for NDVI were extracted from 250 m and 500 m radii buffers of trap locations using Zonal Statistics (Table 3.2).

For the correlation assessment of NDVI with mosquito abundance, I used the mean and standard deviation of NDVI values for the period in which mosquito abundance data were collected, termed the current week, by matching the abundance data to the 16 day composite image in which that week's data were collected. To also capture the effect of NDVI on subsequent mosquito abundance data I used a 32 day and 16 day lag of mean and standard deviation in NDVI values.

3.3.5 Elevation, Slope, and Aspect

The 10 m DEM grid was used to extract topographic predictors including mean elevation, majority aspect class and mean slope (in degrees) within a 500 m buffer of trap locations (Table 3.2). I sought to explore if there was an effect of snow melt runoff along the northern Front Range across the Poudre and Big Thompson corridors or if the municipalities differed in aspect or degree slope at the landscape level. It was considered that elevation may serve as an adequate proxy for mosquito abundance on a local scale given the habitat preference for *Cx. tarsalis* to select temporary pools for oviposition. My choice to include the Digital Elevation Model was based on the past success to generate hydrology models for mosquitoes associated with flood and swamp waters (Shaman et al. 2002) and the occurrence for West Nile Virus risk to decrease with increasing mean elevation in the northern Great Plains (Chuang et al. 2012). Prior work has also shown that elevation often affects mosquito survivorship, as a direct effect of variation in temperature associated with elevation (Mushinzimana et al. 2006).

I used the Surface Tool in ArcGIS 10 to generate GRIDs for slope and aspect (in degrees). The Focal Statistics tool was used to derive a 500 m circular map unit mean of elevation and slope using the 10 m DEM. For statistical analysis of aspect I reclassified the circular map unit mean values to eight categorical classes based on degrees. The classes were divided by natural breaks into -1 to 45, 45 to 90, 90 to 135, 135-180, 180-225, 225-270, 275-315 and 315-360.

3.3.6 Digitized Layers

Surveillance Point Locations

Surveillance mosquito trap locations were digitized using 2009 NAIP Orthoimagery and personal knowledge of site locations. All point locations were assigned a unique ID for which discrete and continuous values for environmental variables could be extracted (Table 3.1). There were 41 locations surveyed for Fort Collins, 40 locations in Loveland and 4 locations in Johnstown. The surveillance monitoring networks for the cities of Fort Collins and Loveland utilize a gridded format to measure mosquito abundance. Each of the programs maintains a surveillance monitoring network that consists of traps set approximately 1.3 km apart across city limits (Brown et al. 2011).

Perimeter and Distance to Larval Habitats

To assess the effect of perimeter of larval mosquito habitat on adult mosquito abundance, I converted the polygon shape file of larval mosquito habitats to a line file using the Features tool in ArcGIS 10. I used the polyline to raster conversion tool to generate a GRID and set the cell size to 1. I utilized buffer distances of 175 m, 250 m, 500 m and 1.0 km from trap locations to evaluate the significance total perimeter of larval mosquito sites within buffered extents. Pixel counts were summed for total perimeter included within the buffer distances around the trap locations and the values were extracted from the GRID for all four buffer distances for every trap using Zonal Statistics (Table 3.2). I selected total perimeter as the variable for which to measure predictive power as I was concerned that area may be less accurate and introduce bias for this landscape parameter. The rationale behind perimeter was that open surface water such as large reservoirs with little vegetation contribute rather little to larval mosquito abundance versus a line of vegetation, such as cattails, along a ditch that may impeded flow and serve as a viable habitat for larval *Cx. tarsalis* mosquitoes.

The mean distance to larval habitats at buffers of 175 m, 250 m, 500 m and 1.0 km from trap locations was obtained by converting the polygon shape file for larval mosquito habitats from Colorado Mosquito Control, Inc. (CMC) to a GRID with a cell size of 1.0 m (Table 3.2). I then reclassified the count field to 1. I used the Euclidian Distance tool in ArcGIS 10 to calculate the mean distance to larval habitats from each trap location.

Habitat and Water Source for Larval Mosquito Habitats

I performed a join with the habitat type and water source info using the larval mosquito habitat polygon shape file obtained from CMC (Table 3.1). CMC uses the following categorical assignment to designate the type of larval habitats to which I assigned these numerical values for extraction of majority type, Temporary standing water (1), Irrigation (2), Lake (3), Marsh (4), Swamp (5), Riparian (6), Ditches (7), Depressions (8), and Retention ponds (11). I omitted all ornamental ponds and artificial containers from CMC's GIS data layers before geoprocessing, as these were not suitable habitats for *Cx. tarsalis* larvae to occur. Majority water source categories as described by CMC were designated as follows, Flooding (1), Groundwater seepage (2), Irrigation (3), Manually controlled waters (4), Other types (5), Rain (6) Seepage (7), Watering (8). I converted the shape files for water source and habitat types to a 1.0 m GRID and extracted the majority habitat and water source from the respective GRIDs within 175 m, 250 m, 500 m and 1.0 km buffered distances for each trap location (Table 3.2). The corresponding area of land included in each buffer was 9.6 ha (175 m), 19.6 ha (250 m), 78.5 ha (500 m), and 314.2 ha (1.0 km) (Figure 3.4)

3.3.7 Irrigated Lands

Irrigated lands data were obtained for Division 1 from the Northern Colorado Water Conservancy District (NCWCD), Berthoud, Colorado for 2007 (Table 3.1). The polygon shape file was the most current data available at the time of this study and it should be noted that this layer does not consider new development in the following years nor any detailed information about water use. The absence of water data use on a monthly or annual basis makes it difficult to make temporal comparisons with water use and *Cx. tarsalis* abundance, but provides a spatial component for the area of and proximity to irrigated lands.

The polyline file of irrigated lands was converted to a 1.0 m raster projected in Universal Transverse Mercator (UTM) projection, Zone 13N and NAD 83. I utilized two buffers, 500 m and 1.0 km to evaluate the significance for proximity to irrigated lands (Table 3.2). Distance to irrigated lands was obtained by calculating the Euclidean distance from each surveillance trap site to the nearest irrigated lands in ArcGIS 10. I also created a 10 m surface for which the area of irrigated lands was calculated for each trap location within 500 m and 1.0 km radii buffers (Figure 3.5).

3.3.8 Interpolation of Climate Layers from PRISM, CoAgMet and NCWCD

Given the fine scale of the modeling area at the municipal level, I faced numerous challenges in accessing gridded data which would reflect the anomalies in climatic variables. In an attempt to capture the relationship that topographic variation may have on mosquito abundance on a monthly basis, I generated surfaces using multiple linear regression in R (R Development Core Team, 2010). I used data for elevation, slope, aspect, monthly solar radiation, and mean monthly temperature from PRISM and mean monthly temperature data from nine local weather stations to model climate surfaces in the spatial modeling area. All new surfaces were generated for the months April-August of 2009 and 2010. Where needed variables were transformed $\log_{10}$(N+1) to provide data that were close to normal.

My initial intent was to model climate on a weekly basis, but I selected a monthly basis to remain consistent with PRISM and solar radiation calendars. I did not include an assessment of precipitation in my models for April-August based on low correlations reported from previous modeling efforts by Brown et al. (2011) in Fort Collins. Local weather data was obtained from the Northern Colorado Water

Conservancy District (NCWCD) website (http://www.northernwater.org) in Berthoud, Colorado, and from CoAgMet (http://climate.colostate.edu/~coagmet/). I calculated the mean monthly temperature from hourly observations and converted these values to degree Celsius so that comparison could be made with PRISM data. I used data for the raw months (ex. June 1-30) given that PRISM data are not based on an epidemiological or Julian week.

Maximum and minimum temperature GRIDS were obtained from the PRISM Climate Group (http://www.prism.oregonstate.edu/) and mean values were calculated. The PRISM datasets are gridded weather datasets which are generated via interpolation of point measurements for temperature and precipitation from weather stations. The GRIDS obtained from PRISM climate group provide monthly temperature (^{o}C) at a 4.0 km spatial resolution. The units are “mm x 100” for precipitation and “degree C x 100” for max and minimum temperature. There is a scaling factor of 100 which is used to make the production of GRIDS easier. PRISM notes that to convert the data to real values, users should divide the integer grid cell values by 100.

PRISM layers were clipped to the spatial modeling area extent in geographic coordinate system (GCS) projection, NAD 1983 datum. I then projected the minimum and maximum temperature GRIDs to Universal Transverse Mercator (UTM) projection, Zone 13N and NAD 83. I resampled the GRIDs to 90 m using ArcGIS 10 and clipped the GRIDs to the spatial modeling area in Universal Transverse Mercator (UTM) projection, Zone 13N and NAD 83. I then used raster calculator to derive the final mean temperature GRIDs for each month. The new mean temperature surfaces were generated using “mtemp” = (maxtempyear + mintempyear)/200. I then snapped the new mean temperature grid to the same extent as that of elevation, slope and aspect GRIDs so that the cell sizes matched. Solar radiation was obtained from the 10 m DEM using the Spatial Analyst tool in ArcGIS 10 and was resampled to 90 m to match the resolution of other climatic layers. I created monthly solar radiation grids using the point solar radiation tool with default settings in ArcGIS 10. The point value for mean temperature was obtained from the new climate surfaces at each trap location (Figure 3.6).

Table 3.1 Description of GIS data layers used in model predictions. Final projection of GIS data was North America Datum (NAD) 1983 projection UTM 13N.

Layer	Type	Format	Accessed from	Original Projection	Processed to
Normalized Difference Vegetation Index (NDVI)	Raster	GeoTiff	http://globalmontoring.sdstate.edu/projects/weld	Albers Conical Equal Area	NAD 1983 UTM 13N
LANDFIRE Vegetation	Raster	GRID	www.landfire.gov	NAD 1983 Albers	NAD 1983 UTM 13N
Irrigated Lands	Vector	Polygon Shapefile	Northern Colorado Water Conservancy District	North America 1983 UTM 13N	NAD 1983 UTM 13N
Digital Elevation Model (DEM)	Raster	GRID	USGS Seamless Server (retired July 2012)	North America 1983 UTM 13N	NAD 1983 UTM 13N
Larval Mosquito Habitats	Vector	Polygon Shapefile	Colorado Mosquito Control, Inc.	Colorado North State Plane	NAD 1983 UTM 13N
Surveillance Trap Locations	Vector	Point Shapefile	Colorado Mosquito Control, Inc.	Colorado North State Plane	NAD 1983 UTM 13N
Weather Station Locations	Vector	Point Shapefile	Digitized using Orthophoto	Colorado North State Plane	NAD 1983 UTM 13N

Table 3.2 Definition of parameters with buffer distances from trap locations included in the landscape-level analysis. Mean, majority and standard deviation for buffer distances was obtained from the final GRID for each parameter, with original resolution listed in parenthesis.

Continuous Parameters	**Buffer distance within trap location**
Slope in degrees (10 m)	Mean 500 m
Aspect in degrees (10 m)	Majority 500 m
Elevation (10 m)	Mean 500 m and 250 m
Topographic Exposure (10 m)	Mean 500 m
Impervious Surface (30 m)	Mean 500 m and 250 m
Solar Radiation (90 m)	Point value at trap
Distance to Larval Sites (1 m)	Mean at 1 km, 500 m, 250 m, 175 m
Perimeter of Larval Sites (1 m)	Sum at 1 km, 500 m, 250 m, 175 m
Distance to Irrigated Lands (10 m)	Mean at 1 km and 500 m
Area of Irrigated Lands (1 m)	Sum within 1 km and 500 m
Normalized Difference Vegetation Index (250m)	Mean and Standard Deviation at 500 m and 250 m
Categorical Parameters	**Buffer distance within trap location**
LANDFIRE Vegetation Class (30 m)	Majority 500 m and 250 m
Water Source of Larval Sites (1 m)	Majority at 1 km, 500 m, 250 m, 175 m
Land Use Heterogeneity at Larval Sites (1 m)	Majority at 1 km, 500 m, 250 m, 175 m
Weather Variables	
PRISM Mean Monthly Temperature (4 km)	Point value at trap
NCWCD/CoAgMet Mean Monthly Temperature (10 m)	Point value at trap

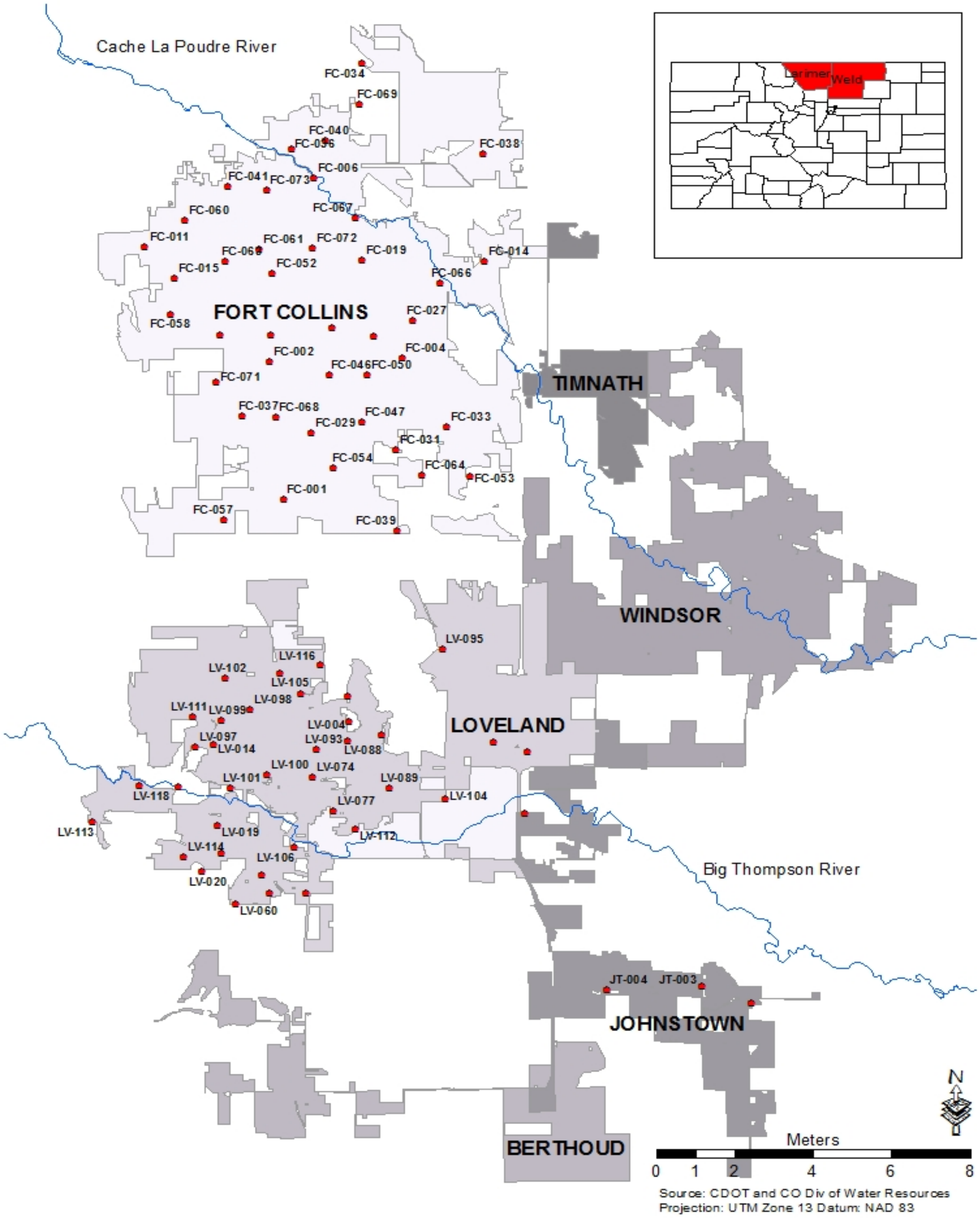

Figure 3.1 Distribution of mosquito traps within the spatial modeling area along the Northern Colorado Front Range. The municipalities of Fort Collins and Loveland are located in eastern Larimer County and Johnstown in western Weld County, as highlighted on the inset map. Municipal boundaries are indicated in shades of grey.

Figure 3.2 CDC CO_2 baited light traps used in the collection of adult *Cx. tarsalis* mosquitoes. Photo obtained from Colorado Mosquito Control, Inc.

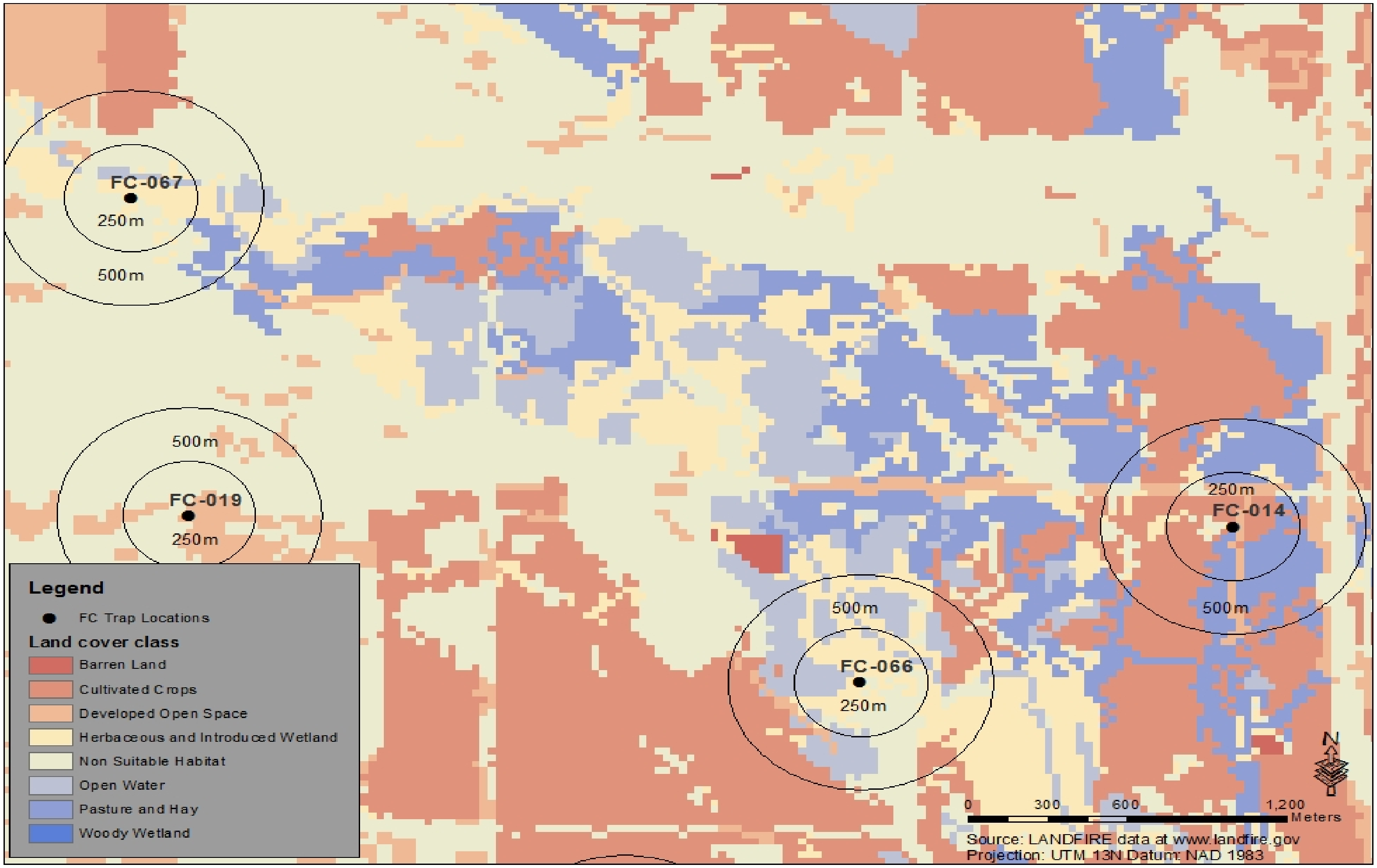

Figure 3.3 Reclassification of land cover types from the LANDFIRE vegetation data layer performed for Fort Collins, Loveland and Johnstown. This figure represents the land cover types within buffer distances around mosquito trap locations in Fort Collins. Majority of land cover types were extracted from the buffered area around trap locations. Comparison of the majority of land cover types indicates habitat suitability for adult mosquitoes around trap locations within the study area.

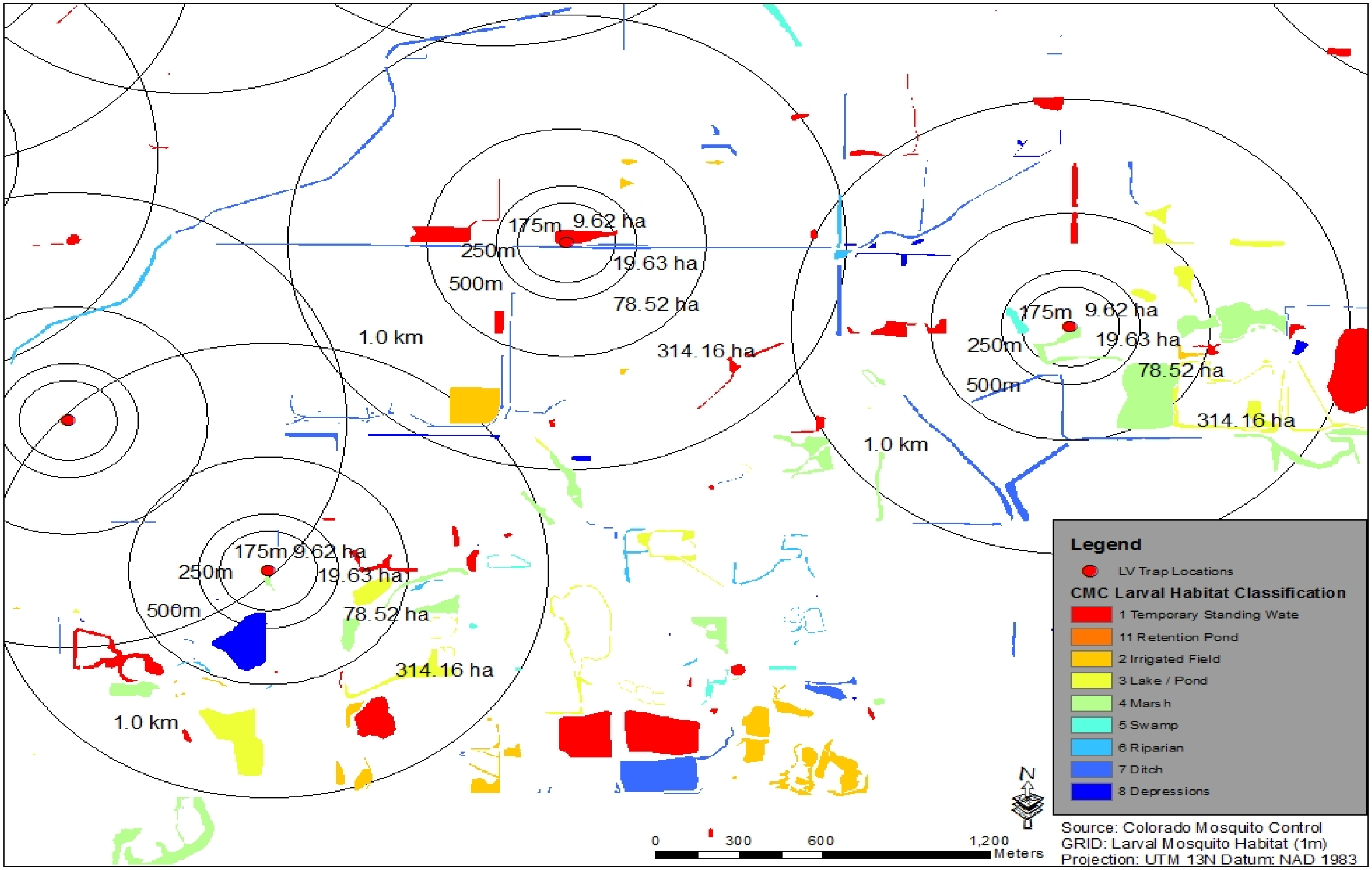

Figure 3.4 Majority of larval mosquito habitat types, by categorical classification obtained from CMC, within buffers of trap locations in Fort Collins, Loveland and Johnstown. Categorical classification, by CMC, for larval mosquito habitats are detailed in the legend. Majority of larval mosquito habitats were extracted from the buffered area around trap locations, providing a comparison for the dominant type of larval mosquito habitats. Hectares (ha) of lands included within buffer radii of trap locations is listed right of the trap location.

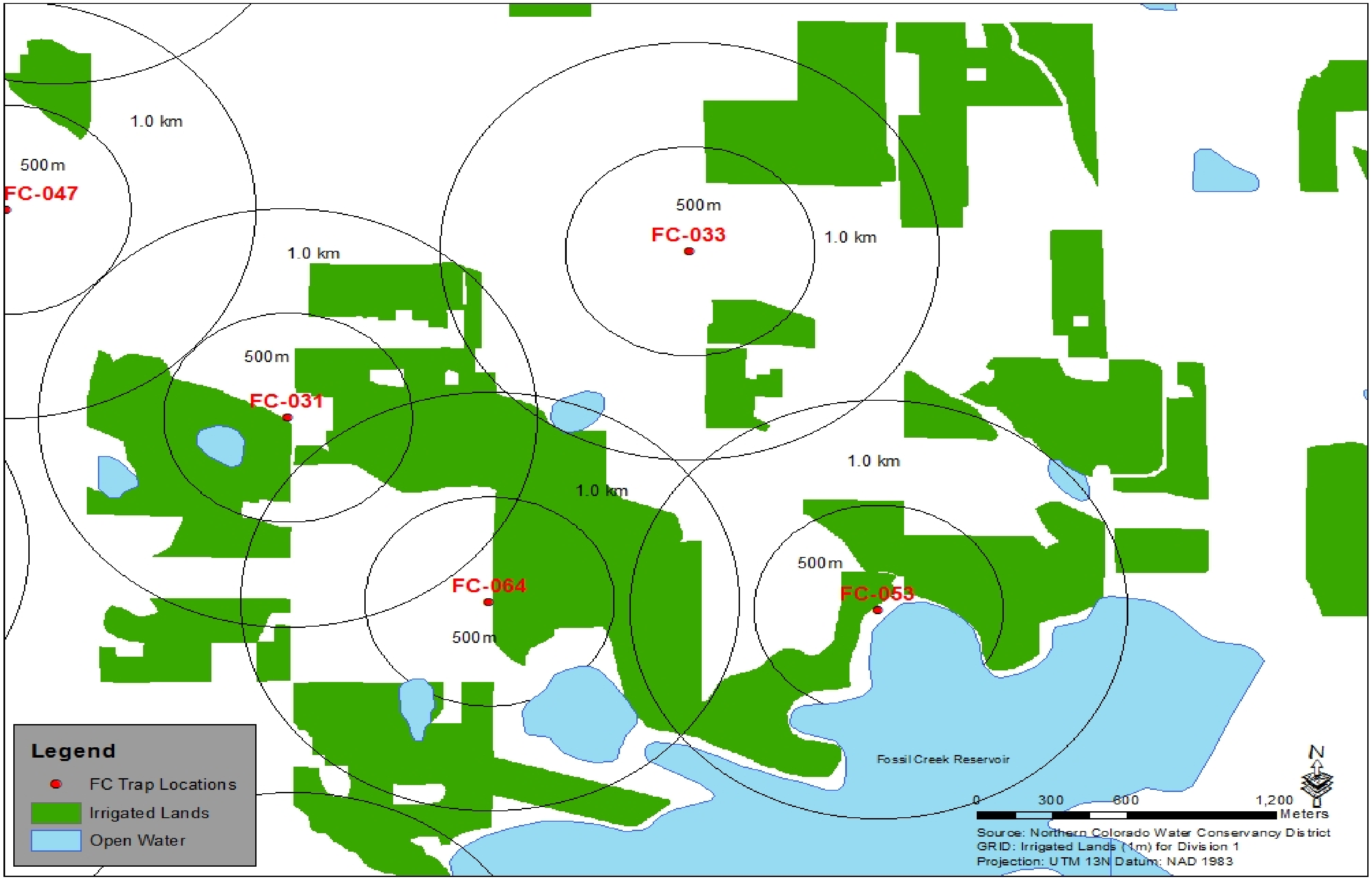

Figure 3.5 Density of irrigated lands from the 2007 Region 1 irrigated lands layer from the Northern Colorado Water Conservancy District. The irrigated lands layer was used to generate a mean distance to and total area of irrigated lands within a 500 m and 1.0 km buffer of mosquito trap locations with the spatial modeling area.

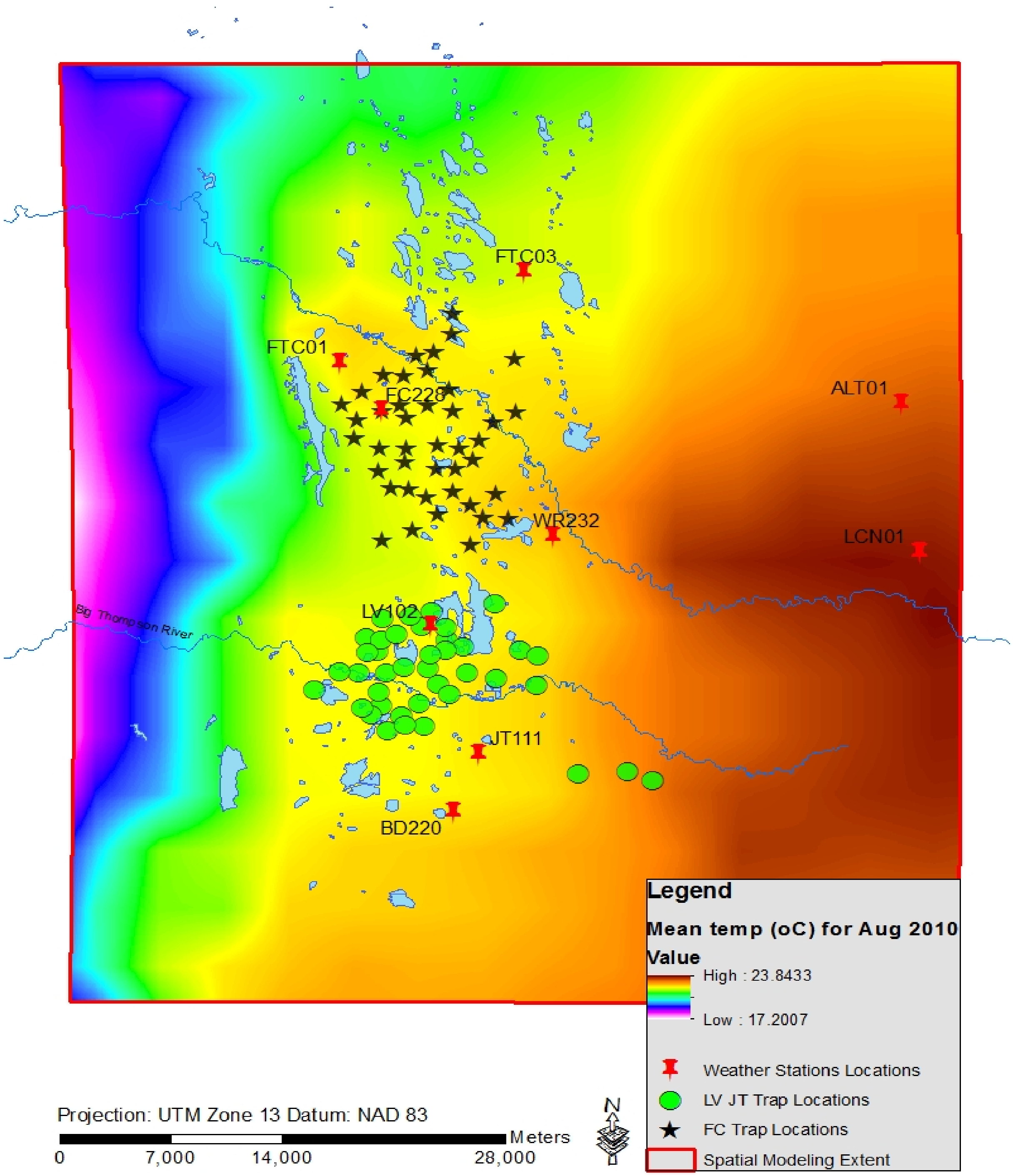

Figure 3.6 Climate surface model for August 2010 generated from PRISM mean temperature data, mean temperature from nine weather locations maintained by CoAgMet and NCWCD, solar radiation, slope and aspect resampled to 90 m GRIDS.

3.4 Statistical Analysis

3.4.1 Mosquito Abundance Data

Dependent variables were organized by week and assigned to the months June, July or August for the years 2007, 2008, 2009 and 2010. For 2007 and 2008 mean monthly abundance were calculated for June (weeks 23-26), July (weeks 27-31), and Aug (weeks 32-35). For 2009 mean monthly abundance were calculated for June (weeks 22-25), July (weeks 26-30), and Aug (weeks 31-34). For 2010 mean monthly abundance were calculated for June (weeks 23-27), July (weeks 28-31), and Aug (weeks 32-36). This created a mean monthly abundance value for each of the trap site within the spatial modeling area for which univariate analysis could be performed to identify directionality for relationships between topographic variables with monthly mosquito averages. I opted to use monthly averages by trap location instead of weekly abundance at each location based on the improved sample size that resulted with monthly averaging. I was concerned that the variability in individual CDC CO_2 baited traps combined with weekly variation in weather data would result in biases and would be too inconsistent for comparison of environmental parameters. Mean monthly abundance data were used in multiple regression models to identify significant ($P<0.05$) static and dynamic dependent variables.

In the case where no data were collected for the four or five week period that comprised monthly means, the trap location was omitted from the monthly analysis of abundance. Weeks that were missing abundance data, because the trap was not operational or not set that week, were not included in the formula to calculate mean monthly abundance. Trap locations were omitted in the development of abundance foci maps in the case where a trap location did not produce predicted abundance data from multiple regression modeling. Mosquito abundance data were log transformed using Log_{10} (monthly average from total trap nights +1) to account for zero values in the instance where mosquito traps collected no mosquitoes in a month and to reduce the variance in mosquitoes collected.

3.4.2 Static and Dynamic Predictors

Static and dynamic variables were log transformed after geoprocessing at buffer radii in ArcGIS, using $\log_{10}$ (N) or $\log_{10}$ (N+1) where no data values existed. Close to normal distribution was achieved for mean monthly adult mosquito abundance data, climate and landscape predictors. Pearson's correlation coefficients were used to evaluate the relationships between landscape-level predictors and mean monthly mosquito abundance with uncorrected p values in Systat (Version 12, SYSTAT Software Inc.) for all spatial extents. Spearman rank correlation was used to identify the strength of correlations between categorical landscape predictors and mean monthly mosquito abundance. Multicollinearity was checked using Systat and only one variable from a set of highly correlated variables ($r = 0.75$) was used in the multiple regression models.

3.5 Model Development

Multiple regression modeling using stepAIC was chosen for this analysis in part as a result of the number of sampling locations and the ability of multiple regression models to handle numerous predictors. Akaike's Information Criterion (AIC) is a useful tool in the identification of spatial scale (Diuk-Wasser et al. 2006) because this modeling approach tests model fit while weighing the number of variables included (Akaike 1974). The decision to use stepAIC was based on the objective of identifying a spatial extent within the landscape heterogeneity that is important to the overall contribution to adult *Cx. tarsalis* mosquito abundance. Previous work by Reisen et al. (1991) described the typical flight range of *Cx. tarsalis* to average between 0.5 m – 1.0 km in a night, so I therefore set a maximum buffer distance of 1.0 km with the objective of detecting the importance of landscape variables within the standard flight range of *Cx. tarsalis*. I opted to use the extents of 175 m, 250 m, 500 m, and 1.0 km radii buffers to evaluate the importance of landscape variables on mosquito abundance.

The MASS library package for stepAIC in R was used to identify landscape variables that contributed the most predictive power to monthly mosquito abundance. I selected quantative and categorical landscape variables that had the most predictive power based on stepAIC and multiple R^2 to build multiple regression models with scale appropriate spatial heterogeneity considerations. In cases where the significance ($P<0.05$) of a specific subcategory of categorical variables provided predictive power from stepAIC, this variable was included in multiple regression modeling. Examples of this include the larval mosquito habitat attribute of a marsh for the majority of larval mosquito habitats or majority land cover type of grass/ hay pasture from LANDFIRE.

All dependent variables were back transformed in R to provide monthly comparisons of training data or the original abundance data, to test data, referred to as predicted abundance hereafter. The objective of this modeling approach was to evaluate model fit on a monthly basis to detect environmental variables that may affect abundance data through the use of observed abundance data. The fit of the regression models for predicted abundance was evaluated using the adjusted R^2 values and plots of predicted versus observed abundance data. Significance ($P<0.05$) of environmental variables that improved the predictive power was assessed in the final models.

4. RESULTS

4.1 Relationship of Significant Quantative Static and Dynamic Predictors

In the analysis for significant static and dynamic predictors, mean monthly adult *Cx. tarsalis* abundance was negatively correlated (P<0.05) with mean elevation within 250 m and 500 m buffers across Fort Collins in all months (Table 4.1). Similarly mean elevation was negatively correlated with mean monthly adult *Cx. tarsalis* abundance in all months except June 2009 in Loveland and Johnstown (Table 4.2). A stronger correlation was observed at buffer distances of 500 m versus 250 m using stepAIC, indicating that elevation is more variable across the landscape of the spatial modeling area at coarser extents than at finer spatial extents of 250 m. Mean monthly adult mosquito abundance was negatively correlated with elevation within a 500 m buffer in Fort Collins during all months (P<0.01) (Figure 4.1). Elevation contributed to the predictive power of abundance models in Fort Collins during the months July 2007 (P<0.05), June 2008 (P<0.0001), July 2009 (P<0.05), June 2010 (P<0.05), and July 2010 (P<0.05) (Table 4.4).

The correlation with elevation within a 500 m buffer and mean monthly adult *Cx tasalis* abundance was also significant (Table 4.2) and negatively correlated (P<0.05) in Loveland and Johnstown during all months except June of 2009. In Loveland and Johnstown mean elevation within a 500 m buffer contributed to the predictive power of abundance models during all months (June, July and August) in 2007 (P<0.01), June (P<0.05) and August 2008 (P<0.0001), July and August 2009 (P<0.01) and July and August 2010 (P<0.0001) (Table 4.5). It is important to note that elevation within a 500 m buffer in Loveland and Johnstown contributed to abundance models in August for all years.

A positive relationship between topographic exposure within a 500 m buffer and mean monthly adult mosquito abundance was found in Fort Collins, but the significance varied by month (Figure 4.2). The positive correlation between mean topographic exposure and mean monthly mosquito abundance in Fort Collins was the strongest during the month of August 2009 (P<0.01) (Figure 4.2). Topographic exposure was significant in August 2008 (r=0.312, P<0.05), July 2009 (r=0.365, P<0.05), August 2009 (r=0.465, P<0.01), June 2010 (r=0.309, P<0.05), July 2010 (r=0.374, P<0.05) and August 2010 (r=0.316, P<0.05) (Table 4.1). Topographic exposure contributed significantly (P<0.05) to the predictive power of abundance models in August 2008, July 2009, August 2009, June 2010, July 2010 and August 2010 in Fort Collins (Table 4.4). Topographic exposure was found to be positively correlated with mean monthly mosquito abundance in June 2009 (r=0.433, P<0.01), June 2010 (r=0.390, P<0.01) and August of 2010 (r=0.322, P<0.05) (Table 4.2) in Loveland and Johnstown, but was not a significant predictor in abundance models using stepAIC (Table 4.5).

The relationship between slope (in degrees) and mean monthly *Cx. tarsalis* abundance was not significant in Fort Collins, except in the month of July 2010 (r= -0.319, P<0.05). Mean monthly adult mosquito abundance was negatively correlated with slope within a 500 m buffer in Loveland and Johnstown during June 2007 (P<0.05), July and August 2008 (P<0.05), July and August of 2009 (P<0.01), and all months of 2010 (P<0.05) (Figure 4.3). Mean slope within a 500 m buffer increased the predictive power of mosquito abundance models in Loveland and Johnstown during July 2008 (P<0.05), July 2009 (P<0.05), July 2010 (P<0.05), August 2008 (P<0.01), August 2009 (P<0.01) and August 2010 (P<0.01) (Table 4.5). Slope was not significant in any month of June in abundance models for the years 2007-2010.

I observed variation in the directionality and significance of relationships between the perimeter of larval mosquito habitats with mean monthly adult mosquito abundance (Figure 4.4). The positive relationship between the perimeter of larval mosquito habitats in Fort Collins in the month of June (2007-2010) and mean monthly mosquito abundance indicated the importance for fine scale spatial extent at 1.0 km, in modeling adult *Cx. tarsalis* abundance. A positive relationship between mean monthly adult *Cx. tarsalis* abundance and the perimeter of larval habitats was present in June 2007 (r=0.321, P<0.05), June 2008 (r=0.429, P< 0.01), June 2009 (r=0.346, P<0.05) and June 2010 (r=0.332, P<0.05) (Table 4.1). This landscape variable contributed to mosquito abundance models in June 2007 (P<0.01) and June 2008 (P<0.01) in Fort Collins (Table 4.4).

Distance to irrigated lands within a 500 m buffer in Fort Collins and mean monthly adult *Cx. tarsalis* abundance showed no direct relationship and correlation coefficients were not significant from univariate analysis with Systat. Distance to irrigated lands within a 1.0 km buffer in Fort Collins and mean monthly adult *Cx. tarsalis* abundance showed a positive relationship, although this relationship was only significant in June 2007 (r=0.315, P<0.05). The area of irrigated lands within a 500 m buffer was positively correlated with mean monthly adult mosquito abundance in June 2007 (r=0.434, P<0.01), August 2007 (r=0.316, P<0.05), June 2008 (r=0.311, P<0.05), July 2008 (r=0.414, P<0.01), August 2008 (r=0.363, P<0.05) and June of 2009 (r=0.398, P<0.01) (Table 4.1). The area of irrigated lands within a 1.0 km buffer was positively correlated with mean monthly adult mosquito abundance during all months (June, July and August) in 2007 and 2008 (P<0.05), June 2009 (r=0.488, P<0.01), August 2009 (r=0.328, P<0.05), and June 2010 (r=0.400, P<0.01) (Table 4.1). Analysis of irrigated lands using stepAIC in R presented significant relationships (p<0.05) for the distance to irrigated lands within a 500 m buffer and the area $\log_{10}$ (N+1) of irrigated lands within a 1.0 km buffer in Fort Collins. Distance to irrigated lands within a 500 m buffer contributed to mosquito abundance models in July 2007 (P<0.05), August 2007 (P<0.0001), July 2008 (P<0.05), August 2008 (P<0.05) and June 2009 (P<0.05) in Fort Collins (Table 4.4).

A positive relationship existed between both the distance to irrigated lands within 1.0 km and mean monthly adult *Cx. tarsalis* abundance and the area of irrigated lands within a 500 m buffer (Figure 4.5) and mean monthly adult *Cx. tarsalis* abundance existed in Loveland and Johnstown. Distance to irrigated lands within a 500 m buffer in Loveland and Johnstown and mean monthly adult *Cx. tarsalis* abundance showed no direct relationship and correlation coefficients were not significant from univariate analysis. Distance to irrigated lands within a 1.0 km buffer in Loveland and Johnstown and mean monthly adult *Cx. tarsalis* abundance showed a positive relationship and was significant during all months (June, July and August) in 2007 (P<0.05), June 2008 (r=0.340, P<0.05), during all months (June, July and August) in 2009 (P<0.05), and during all months (June, July and August) in 2010 (P<0.05) (Table 4.2). The area of irrigated lands within a 500 m buffer was positively correlated with mean monthly adult mosquito abundance in all months in all years 2007-2010 (P<0.05) (Table 4.2). The area of irrigated lands within a 1.0 km buffer was positively correlated with mean monthly adult mosquito abundance during all months

(June, July and August) in 2007, 2009 and 2010 ($P<0.05$). Multiple regression modeling using stepAIC in R presented consistent significant relationships ($P<0.05$) for distance to irrigated lands within a 1.0 km buffer and for area $\log_{10}(N+1)$ of irrigated lands within a 500m buffer. Distance to and the area of irrigated lands did not significantly contribute to abundance models for any month in any year in Loveland and Johnstown (Table 4.5). The lack of expression in these land-use patterns may be a result of the inclusion of irrigated lands in the larval habitat layer obtained from CMC, Inc.

Distance to larval habitats at the spatial extents of 1.0 km, 500 m, 250 m and 175 m in Fort Collins and mean monthly mosquito abundance was significant only in June 2008 ($r=-0.382$, $P=0.05$) at the extent of 500 m. There was a negative relationship between the distance to larval sites within a 500 m buffer and mean monthly adult *Cx. tarsalis* abundance in Loveland and Johnstown (Figure 4.6). The relationship between distance to larval habitats and mean monthly mosquito abundance was significant in Loveland and Johnstown in June 2007 ($r=-0.558$, $P<0.0001$), July 2007 ($r=-0.600$, $P<0.0001$), August 2007 ($r=-0.459$, $P<0.01$), June 2008 ($r=-0.548$, $P<0.0001$), July 2008 ($r=-0.419$, $P<0.05$), June 2009 ($r=-0.307$, $P<0.05$), June 2010 ($r=-0.424$, $P<0.01$), and August 2010 ($r=-0.337$, $P<0.05$) (Table 4.2). The predictive power of distance to larval habitats within a 500 m buffer was expressed in multiple abundance models for Loveland and Johnstown, possibly as a result of the density of larval habitats compared to irrigated lands information. The inclusion and effect of this landscape variable contributed to predicted abundance models in June, July, and August of 2007 ($P<0.0001$), June ($P<0.0001$) and July 2008 ($P<0.05$), June ($P<0.01$) and August 2010 ($P<0.01$) for Loveland and Johnstown (Table 4.5). No relationship was detected between majority aspect and mean monthly *Cx. tarsalis* abundance in Fort Collins, Loveland, or Johnstown.

Mean NDVI presented weak correlations and p values were not significant for buffers within 500 m and 250 m of trap locations. Standard deviation in NDVI within a 500 m buffer was significant in multiple weeks of 2009 and 2010 and significance varied with lags in the standard deviation of NDVI values (Table 4.3). Standard deviation for NDVI at a 32 day lag within a 500 m buffer and mean *Cx. tarsalis* abundance for a two week period was statistically significant across all weeks ($P<0.05$) in both

2009 and 2010 (Table 4.3). Analysis of NDVI presented a positive relationship between standard deviation in NDVI within a 500 m buffer and adult mosquito abundance for a two week average in 2009 (Figure 4.7) and 2010 (Figure 4.8). Standard deviation in NDVI values at a 500 m spatial extent for the current month and the month prior was dropped from all abundance models when I used stepAIC to model mosquito abundance. Standard deviation for the study month (e.g. July) and the month prior (e.g. June) did not contribute to the predictive power for monthly abundance models in the study month (e.g. July).

4.2 Seasonal Comparison of Categorical Predictors in the Spatial Modeling Area

Adult mosquito abundance data obtained from CMC for 2007-2010 indicates that July contributes the largest proportion of mosquitoes on average over a season within the spatial modeling area. Of the total 15,607 *Cx. tarsalis* mosquitoes collected in Fort Collins during 2007-2010, 64.3% were collected during the month of July. This pattern was also seen in Loveland and Johnstown with 58.1% of the total 16,312 *Cx. tarsalis* mosquitoes collected in June, July and August from 2007-2010 resulting in the month of July. Bolling et al. (2009) similarly found that *Cx. tarsalis* peaks in early July along the plains of northeastern Colorado.

The predictive power of the twenty four models developed varied by month across the seasons 2007-2010 for Fort Collins, Loveland and Johnstown. Additionally, expression of predictors was variable between the two study areas within the spatial modeling area, likely a result of multiple environmental and biological interactions specific to adult *Cx. tarsalis*. In Fort Collins the best model for a single month explained 72.5% of the variation in *Cx. tarsalis* abundance (Table 4.4). The best predictors for that particular month included the perimeter of larval mosquito habitats obtained from CMC within a 1.0 km buffer of trap locations, the majority water source within a 1.0 km buffer and the majority land cover type from LANDFIRE within a 250 m buffer of mosquito trap locations. The typical explanatory power for models in Fort Collins ranged from 68.7% in June 2009 to 42.7% in August 2008 (Figure 4.9).

In Loveland, the best model for a single month explained 67.9% of the variation in mosquito abundance (Table 4.5). The best predictors in this abundance model included mean elevation, slope and the distance to larval habitats at a spatial extent of 500 m. The typical explanatory power for models in Loveland ranged from 63.8% in July 2007 to 36.2% in June 2009 (Figure 4.10).

Of the nine categorical variables used to classify larval mosquito habitats by CMC ditches in June 2010 ($P<0.05$), depressions in July 2010 ($P<0.05$) and swamps in August 2010 ($P<0.05$) contributed to the overall model fit with the respective months in Fort Collins (Table 4.4). In June 2007 the majority of water source, classified by CMC, Inc. groundwater seepage ($P<0.05$) and manual control of water in July 2008 ($P<0.01$) and August 2007 ($P<0.01$) contributed to the predictive models for Fort Collins in these months (Table 4.4).

The majority of land cover type from landfire vegetation class for introduced wetlands ($P<0.05$) in June 2007 and open space ($P<0.05$), pasture and hay ($P<0.05$), and wetlands ($P<0.05$) at a spatial extent of 500 m contributed to the predictive model for Fort Collins in July 2009 (Table 4.4). The expression of these vegetative classes reflects the importance of pasture/ and grass hay and wetlands to contribute to *Cx. tarsalis* mosquito abundance. The variability in the significance and expression of these categorical variables highlights the effects of landscape heterogeneity at varying spatial extents.

4.3 Model Evaluation and Predictive Abundance Maps

The predictive power of monthly models for *Cx. tarsalis* abundance varied by month and year (Figure 4.14 and 4.15) likely as a result of variable expression. Observed abundance was plotted on the y-axis and predictive abundance on the x-axis based on the findings of Piñeiro et al. (2008). Over predictions in the models can be seen in the spread along the y axis while under predictions are detectable along the x axis (Figure 4.9 and 4.10).

To compare the predictive power of models for mean monthly abundance I also plotted the actual versus predicted mean monthly mosquito abundance for which less variability in monthly abundance averages were detected from error bars (Figure 4.11 and 4.12).

Foci maps of predicted mean monthly abundance by trap location were generated to describe *Cx. tarsalis* distribution across the study area based on a minimal to elevated abundance index (Figure 4.13 and 4.14). I chose the levels for the mosquito abundance index based on the disease threshold for Loveland and Johnstown that would trigger spraying for adult mosquitoes. The maps provide an overview for the areas of elevated mean monthly mosquito abundance and highlight the density of vector populations on the periphery of the northern and eastern boundaries of Fort Collins and in association with the extensive reservoir system on the northeastern portion of Loveland.

Table 4.1 Pearson correlation coefficients for static predictors from univariate analysis in Systat for Fort Collins, Colorado. Coefficients were obtained for the relationship between landscape variable and $\log_{10}$ (N+1) mean monthly adult abundance for *Cx. tarsalis*. Spearman correlation coefficients are noted by **. Correlation coefficients which were statistically significant (P<0.05) are highlighted in bold.

Month	June-07	July-07	August-07	June-08	July-08	August-08	June-09	July-09	August-09	June-10	July-10	August-10
elev500	**-0.625**	**-0.637**	**-0.474**	**-0.596**	**-0.600**	**-0.536**	**-0.627**	**-0.475**	**-0.400**	**-0.599**	**-0.545**	**-0.417**
elev250	**-0.618**	**-0.629**	**-0.462**	**-0.590**	**-0.588**	**-0.523**	**-0.612**	**-0.457**	**-0.381**	**-0.583**	**-0.528**	**-0.400**
topoexp500	0.106	0.191	0.248	0.191	0.219	**0.312**	0.284	**0.365**	**0.465**	**0.309**	**0.374**	**0.316**
imper500	**-0.416**	-0.199	**-0.361**	-0.252	-0.281	-0.181	-0.276	-0.134	-0.132	-0.217	-0.123	-0.071
imper250	**-0.513**	-0.223	**-0.334**	**-0.357**	**-0.315**	-0.141	**-0.307**	-0.176	-0.164	-0.194	-0.130	-0.069
log slope	0.109	-0.193	-0.044	-0.141	0.007	-0.170	0.002	-0.115	-0.177	-0.095	**-0.319**	-0.280
distL1km	-0.296	-0.038	-0.062	**-0.316**	-0.119	-0.012	-0.245	0.200	**0.361**	-0.256	0.051	0.170
log distL500	-0.180	-0.138	-0.006	**-0.382**	-0.078	-0.011	-0.204	0.227	0.275	-0.245	0.085	0.162
log distL250	-0.075	-0.093	-0.077	-0.263	-0.030	0.003	-0.087	0.248	0.240	-0.144	0.185	0.227
log distL175	-0.078	-0.117	0.057	-0.225	-0.054	-0.022	-0.061	0.224	0.219	-0.152	0.178	0.235
log perimlar1km	**0.321**	0.110	0.002	**0.429**	0.195	0.123	**0.346**	-0.110	-0.168	**0.332**	0.033	-0.071
log perimlar500	**0.351**	0.065	0.074	**0.404**	0.168	0.037	**0.313**	-0.204	-0.283	0.300	-0.096	-0.190
log perimlar250	-0.068	-0.015	-0.146	0.189	-0.077	-0.107	-0.040	-0.301	**-0.305**	0.187	-0.117	-0.181
log perimlar175	-0.078	0.007	-0.084	0.141	-0.060	-0.102	-0.100	-0.281	-0.302	0.058	-0.182	-0.207
distirr500	-0.012	0.088	-0.089	0.083	0.003	-0.030	-0.074	-0.200	-0.191	0.043	-0.188	-0.235
log areairr500	**0.434**	0.243	**0.316**	**0.311**	**0.414**	**0.363**	**0.398**	0.203	0.277	0.287	0.126	0.151
distirr1km	**0.315**	0.249	0.299	0.248	0.296	0.280	0.256	0.090	0.153	0.158	0.078	0.231
log areairr1km	**0.485**	**0.364**	**0.466**	**0.370**	**0.459**	**0.402**	**0.488**	0.224	**0.328**	**0.400**	0.182	0.233
**MajW1km	-0.068	0.040	0.079	-0.231	-0.035	0.014	-0.166	-0.072	0.034	-0.013	-0.080	-0.015
**MajW500	-0.068	0.040	0.079	-0.231	-0.035	0.014	-0.166	-0.072	0.034	-0.013	-0.080	-0.015
**MajW250	-0.058	0.157	0.135	-0.168	0.069	0.121	-0.066	0.027	0.121	0.018	0.004	0.092
**MajW175	-0.100	0.110	0.101	-0.210	0.024	0.079	-0.100	-0.013	0.081	-0.024	-0.037	0.055
**MajH1km	-0.433	-0.391	-0.375	-0.210	-0.417	-0.451	-0.564	-0.287	-0.295	-0.411	-0.195	-0.205
**MajH500	-0.220	-0.056	-0.134	0.161	-0.149	-0.033	0.011	0.130	0.183	-0.226	0.026	0.126
**MajH250	-0.165	0.005	-0.072	-0.061	-0.043	-0.055	-0.142	0.038	0.128	-0.033	0.158	0.263
**MajH175	-0.063	0.052	-0.090	0.014	0.051	0.025	0.024	0.171	0.253	0.005	0.263	0.244
**MajLCT500	0.508	0.499	0.481	0.293	0.591	0.436	0.295	0.221	0.220	0.521	0.392	0.495
**MajLCT250	0.382	0.362	0.165	0.389	0.370	0.359	0.558	0.232	0.318	0.373	0.259	0.279
**Majaspt	0.192	0.152	0.198	0.153	0.114	0.043	-0.085	-0.023	-0.017	0.190	0.039	0.102

[1]

[1] Elev= mean elevation 500 m and 250 m, topoexp= mean topographic exposure 500 m, imper= mean impervious surface 500 m, mean slope 500 m, distL= mean distance to larval habitats 1.0 km, 500 m, 250 m, and 175 m, perimlar= sum of perimeter of larval mosquito habitats 1.0 km, 500 m, 250 m, and 175 m, distirri= mean distance to irrigated lands 1.0 km and 500 m, areairri= area of irrigated lands 1.0 km and 500 m, **MajW= majority of water source 1.0 km, 500 m, 250m, and 175 m, **MajH= majority habitat type 1.0 km, 500 m, 250m, and 175 m, **MajLCT=majority of land cover type 500 m and 250 m, **MajAspt=Majority Aspect 500 m.

Table 4.2 Pearson correlation coefficients for static predictors from univariate analysis in Systat for Loveland and Johnstown, Colorado. Coefficients were obtained for the relationship between landscape variable and $\log_{10}$(N+1) mean monthly adult abundance for *Cx. tarsalis*. Spearman correlation coefficients are noted by **. Correlation coefficients which were statistically significant (P<0.05) are highlighted in bold.

Month	June-07	July-07	August-07	June-08	July-08	August-08	June-09	July-09	August-09	June-10	July-10	August-10
elev500	**-0.463**	**-0.544**	**-0.647**	**-0.326**	**-0.586**	**-0.669**	-0.224	**-0.504**	**-0.647**	**-0.423**	**-0.618**	**-0.582**
elev250	**-0.453**	**-0.533**	**-0.636**	-0.312	**-0.579**	**-0.656**	-0.195	**-0.493**	**-0.636**	**-0.401**	**-0.607**	**-0.569**
topoexp500	0.158	0.148	0.205	0.180	0.102	0.150	**0.433**	0.157	0.186	**0.390**	0.208	**0.322**
imper500	-0.254	-0.287	-0.172	**-0.421**	-0.079	-0.085	**-0.470**	-0.149	-0.171	**-0.390**	-0.184	-0.196
imper250	-0.304	**-0.279**	-0.264	**-0.382**	-0.163	-0.105	-0.274	-0.079	-0.132	-0.265	-0.090	-0.125
log slope	**-0.340**	-0.279	-0.264	-0.200	**-0.391**	**-0.415**	-0.209	**-0.448**	**-0.524**	**-0.311**	**-0.443**	**-0.433**
distL1km	**-0.350**	**-0.407**	-0.236	**-0.350**	-0.146	-0.067	-0.289	-0.007	0.104	**-0.324**	-0.027	-0.187
log distL500	**-0.558**	**-0.600**	**-0.459**	**-0.548**	**-0.419**	-0.279	**-0.307**	-0.200	-0.131	**-0.424**	-0.233	**-0.337**
log distL250	**-0.462**	**-0.509**	**-0.373**	**-0.447**	**-0.354**	-0.209	-0.084	-0.129	-0.088	-0.255	-0.160	-0.207
log distL175	**-0.414**	**-0.462**	**-0.340**	**-0.376**	**-0.319**	-0.183	-0.026	-0.115	-0.088	.-167	-0.150	-0.175
log perimlar1km	0.127	0.057	-0.054	**0.632**	**0.485**	0.254	0.131	-0.103	-0.169	0.179	-0.101	0.017
log perimlar500	**0.568**	**0.406**	**0.370**	**0.339**	0.122	-0.100	0.183	0.129	0.106	0.306	0.232	0.253
log perimlar250	**0.417**	0.249	0.261	**0.340**	**0.399**	0.220	0.058	0.072	0.028	0.138	0.133	0.141
log perimlar175	0.382	0.198	0.255	0.250	**0.324**	0.164	0.091	0.168	0.092	0.148	0.172	0.181
distirr500	0.305	0.311	0.228	0.293	0.181	0.094	-0.026	0.054	0.073	0.096	0.149	0.137
log areairr500	**0.550**	**0.502**	**0.446**	**0.338**	**0.342**	**0.358**	**0.562**	**0.481**	**0.508**	**0.603**	**0.410**	**0.474**
distirr1km	**0.415**	**0.484**	**0.456**	**0.340**	0.316	0.264	**0.443**	**0.338**	**0.439**	**0.508**	**0.343**	**0.491**
log areairr1km	**0.481**	**0.596**	**0.553**	0.264	**0.417**	**0.492**	**0.332**	**0.494**	**0.528**	**0.501**	**0.466**	**0.478**
**MajW1km	-0.187	-0.219	-0.173	-0.278	-0.203	-0.169	-0.438	-0.331	-0.315	-0.382	-0.265	-0.382
**MajW500	-0.268	-0.131	-0.127	-0.219	-0.116	-0.060	-0.295	-0.369	-0.256	-0.307	-0.035	-0.185
**MajW250	-0.211	-0.167	-0.065	-0.176	-0.065	-0.018	-0.205	-0.278	-0.208	-0.282	0.145	-0.043
**MajW175	-0.404	-0.389	-0.226	-0.318	-0.276	-0.162	-0.251	-0.195	-0.104	-0.306	0.055	-0.234
**MajH1km	-0.243	-0.146	-0.162	-0.197	-0.153	-0.047	-0.206	-0.032	-0.087	-0.130	-0.078	-0.161
**MajH500	-0.400	-0.239	-0.230	-0.180	-0.297	-0.069	-0.319	-0.073	0.037	-0.296	-0.227	-0.062
**MajH250	-0.313	-0.132	-0.202	-0.246	-0.190	-0.082	-0.290	-0.164	-0.084	-0.318	-0.196	-0.059
**MajH175	-0.326	-0.139	-0.175	-0.105	-0.140	-0.005	-0.434	-0.105	0.077	-0.318	-0.247	-0.051
**MajLCT500	0.396	0.580	0.492	0.463	0.337	0.470	0.264	0.291	0.340	0.552	0.361	0.498
**MajLCT250	0.423	0.561	0.505	0.490	0.304	0.372	0.437	0.310	0.301	0.414	0.223	0.179
**Majaspt	-0.036	-0.049	-0.056	0.037	-0.102	-0.026	0.009	0.018	0.100	-0.060	-0.139	-0.257

[2]

[2] Elev= mean elevation 500 m and 250 m, topoexp= mean topographic exposure 500 m, imper= mean impervious surface 500 m, mean slope 500 m, distL= mean distance to larval habitats 1.0 km, 500 m, 250 m, and 175 m, perimlar= sum of perimeter of larval mosquito habitats 1.0 km, 500 m, 250 m, and 175 m, distirri= mean distance to irrigated lands 1.0 km and 500 m, areairri= area of irrigated lands 1.0 km and 500 m, **MajW= majority of water source 1.0 km, 500 m, 250m, and 175 m, **MajH= majority habitat type 1.0 km, 500 m, 250m, and 175 m, **MajLCT=majority of land cover type 500 m and 250 m, **MajAspt=Majority Aspect 500 m.

Table 4.3 Pearson correlation coefficients from univariate analysis in Sysstat for dynamic predictors of NDVI for Fort Collins, Colorado. Coefficients were obtained for the relationships between standard deviation (Std) in NDVI (90 m) at a 32 day lag, a 16 day lag and the current week of the composite image during which *Cx. tarsalis* mosquitoes were collected. Correlation coefficients which were statistically significant ($P<0.05$) are highlighted in bold.

2009	32dlag Std NDVI	16dlag Std NDVI	Current week Std NDVI
Week 23-24	**0.486**	**0.339**	**0.444**
Week 25-26	**0.481**	**0.530**	**0.511**
Week 27-28	**0.332**	**0.316**	0.316
Week 29-30	**0.313**	**0.336**	0.254
Week 31-32	**0.325**	0.253	**0.417**
Week 33-34	**0.328**	**0.327**	**0.334**
2010	32dlag Std NDVI	16dlag Std NDVI	Current week Std NDVI
Week 23-24	**0.525**	**0.486**	**0.525**
Week 25-26	**0.409**	**0.499**	**0.474**
Week 27-28	**0.497**	**0.518**	**0.458**
Week 29-30	**0.396**	**0.468**	**0.386**
Week 31-32	**0.359**	**0.309**	0.293
Week 33-34	**0.320**	0.270	**0.309**

Table 4.4 Multiple regression model results for landscape-level predictors at significant spatial extents in Fort Collins, Colorado. Significant variables are highlighted in bold (P<0.05). The adj. R^2, F statistic and p value for each model is listed in grey.

June 2007	p	June 2008	p	June 2009	p	June 2010	p
R^2=0.725		**R^2=0.430**		**R2=0.689**		**R^2=0.570**	
Elev500m	0.208	Elevation 500m	< **0.0001**	Elev500m	0.078	Elev500m	**0.016**
MajW1km.f2 (groundwater seepage)	**0.034**	Perimeter Larval 1km	**0.010**	imper_250m	**0.034**	topoexp_10m	**0.046**
MajW1km.f3	0.156			MajW1km.f2	0.800	MajLCT500.f21	0.095
MajW1km.f4	0.579			MajW1km.f3	0.198	MajLCT500.f22	0.259
MajW1km.f6	0.283			MajW1km.f4	0.059	MajLCT500.f81	0.097
MajW1km.f7	0.982			MajW1km.f6	0.053	MajLCT500.f82	0.574
MajH1km.f2	0.650			MajW1km.f7	0.216	MajLCT500.f95	0.234
MajH1km.f3	0.086			log.PerimLar1km	0.135	MajH500.f2	0.242
MajH1km.f4	0.208			DistIrr500m	**0.031**	MajH500.f3	0.623
MajH1km.f6	0.061			log.AreaIrr1km	**0.006**	MajH500.f4	0.835
MajH1km.f7 (ditches)	**0.005**			MajLCT500.f21	0.729	MajH500.f5	0.492
MajH1km.f8	0.809			MajLCT500.f22	0.960	MajH500.f7 (ditches)	**0.014**
MajH1km.f11	0.590			MajLCT500.f81	0.313	MajH500.f8	0.939
DistIrr500m	0.124			MajLCT500.f82	0.076	MajH500.f11	0.454
log.PerimLar1km	**0.003**			MajLCT500.f95	0.166	log.PerimLar1km	0.118
log.AreaIrr1km	0.067						
MajLCT250.f21	0.201						
MajLCT250.f22	0.459						
MajLCT250.f81	0.894						
MajLCT250.f82	0.960						
MajLCT500.f95 (introduced wetland)	**0.029**						
F-statistic: 6.026 on 21 and 19 DF	**< 0.0001**	**F-statistic: 16.45 on 2 and 39 DF**	**< 0.0001**	**F-statistic: 6.898 on 15 and 25 DF**	**< 0.0001**	**F-statistic: 4.533 on 15 and 25 DF**	**< 0.0001**
July 2007	**p**	**July 2008**	**p**	**July 2009**	**p**	**July 2010**	**p**
R^2=0.438		**R^2=0.572**		**R^2=0.464**		**R^2=0.554**	
Elevation 500m	**0.012**	Elev500m	0.099	Elev500m	**0.036**	lag32dNDVI_Std500m	0.206
DistIrr500m	**0.046**	imper_250m	0.177	topoexp_10m	**0.021**	Elev500m	**0.014**
		MajW1km.f2	0.074	DistIrr500m	0.081	topoexp_10m	**0.008**
		MajW1km.f3	0.582	MajLCT500.f21 (developed open space)	**0.045**	MajH500.f2	0.932
		MajW1km.f4 (manually controlled)	**0.001**	MajLCT500.f22	0.100	MajH500.f3	0.123
		MajW1km.f6	0.411	MajLCT500.f81 (pasture and hay)	**0.013**	MajH500.f4	0.637
		MajW1km.f7	0.164	MajLCT500.f82	0.186	MajH500.f5	0.227
		DistIrr500m	**0.017**	MajLCT500.f95 (introduced wetland)	**0.024**	MajH500.f7	0.378
						MajH500.f8 (depressions)	**0.019**
						MajH500.f11	0.501
F-statistic: 16.56 on 2 and 38 DF	**< 0.0001**	**F-statistic: 7.676 on 8 and 32 DF**	**< 0.0001**	**F-statistic: 5.432 on 8 and 33 DF**	**< 0.0001**	**F-statistic: 5.959 on 10 and 30 DF**	**< 0.0001**
August 2007	**p**	**August 2008**	**p**	**August 2009**	**p**	**August 2010**	**p**
R^2=0.466		**R^2=0.427**		**R^2=0.558**		**R^2=0.439**	
MajW1km.f2	0.182	Elev500m	0.128	CurrentNDVI_Std500m	0.087	Elev500m	0.173
MajW1km.f3	0.372	topoexp_10m	**0.014**	Elev500m	0.172	log.slope	0.067
MajW1km.f4 (manually controlled)	**0.006**	DistIrr500m	**0.013**	topoexp_10m	**<0.0001**	topoexp_10m	**0.036**
MajW1km.f6	0.911			Dist Larval1km	**<0.0002**	MajH500.f2	0.183
MajW1km.f7	0.076			DistIrr500m	0.135	MajH500.f3	0.190
DistIrr500m	**<0.0001**					MajH500.f4	0.249
						MajH500.f5 (swamp)	**0.017**
						MajH500.f7	0.156
						MajH500.f8	0.213
						MajH500.f11	0.766
						DistIrr500m	0.083
						log.AreaIrr1km	0.246
F-statistic: 6.821 on 6 and 34 DF	**< 0.0001**	**F-statistic: 11.19 on 3 and 38 DF**	**< 0.0001**	**F-statistic: 11.33 on 5 and 36 DF**	**< 0.0001**	**F-statistic: 3.613 on 12 and 28 DF**	**0.002**

Table 4.5 Multiple regression model results for landscape-level predictors at significant spatial extents in Loveland and Johnstown, Colorado. Significant variables are highlighted in bold (P<0.05). The adj. R^2, F statistic and p value for each model is listed in grey.

June 2007	p	June 2008	p	June 2009	p	June 2010	p
R^2=0.531		**R^2=0.384**		**R2=0.362**		**R^2=0.466**	
Elevation 500m	**0.001**	Elevation 500m	**0.013**	topoexp_10m	0.104	Dist Larval Habitats 500m	**0.001**
Dist Larval Habitats 500m	**<0.0001**	Dist Larval Habitats 500m	**< 0.0001**	imper_500m	**0.015**	topoexp_10m	0.067
Slope	0.080			MajW1km.f2	0.500	DistIrr1km	0.131
				MajW1km.f3	0.629		
				MajW1km.f4	0.870		
				MajW1km.f6	0.260		
				MajW1km.f7	0.302		
				MajW1km.f8	0.732		
F-statistic: 14.61 on 3 and 33 DF	**<0.0001**	**F-statistic: 12.24 on 2 and 34 DF**	**< 0.0001**	**F-statistic: 3.76 on 8 and 31 DF**	**0.004**	**F-statistic: 11.46 on 3 and 33 DF**	**< 0.0001**
July 2007	**p**	**July 2008**	**p**	**July 2009**	**p**	**July 2010**	**p**
R^2=0.638		**R^2=0.679**		**R^2=0.527**		**R^2=0.443**	
Elevation 500m	**<0.0001**	Elev500m	**<0.0001**	Elevation 500m	**0.010**	Elevation 500m	**< 0.0001**
Dist Larval Habitats 500m	**<0.0001**	log.slope	**0.014**	log.slope	**0.022**	Slope 500m	**0.017**
		Log.Dist500m	**0.014**	MajW1km.f2	0.556		
		MajLCT250.f21	0.322	MajW1km.f3	0.271		
		MajLCT250.f22	0.911	MajW1km.f4	0.843		
		MajLCT250.f81	0.421	MajW1km.f6	0.153		
		MajLCT250.f82	0.160	MajW1km.f7	0.389		
		MajLCT250.f95	0.484	MajW1km.f8	0.889		
F-statistic: 32.73 on 2 and 34 DF	**< 0.0001**	**F-statistic: 10.76 on 8 and 29 DF**	**< 0.0001**	**F-statistic: 6.427 on 8 and 31 DF**	**< 0.0001**	**F-statistic: 16.5 on 2 and 37 DF**	**< 0.0001**
August 2007	**p**	**August 2008**	**p**	**August 2009**	**p**	**August 2010**	**p**
R^2=0.626		**R^2=0.557**		**R^2=0.565**		**R^2=0.607**	
Elev500m	**<0.0001**	Elevation 500m	**< 0.0001**	Elevation 500m	**<0.0001**	Elevation 500m	**< 0.0001**
DistIrr1km	0.124	Slope 500m	**0.009**	Slope 500m	**0.002**	Slope 500m	**0.010**
Log.Dist500m	**<0.0001**			Log.AreaIrr500m	0.065	Dist Larval Habitats 500m	**0.001**
Log.AreaIrr500m	0.076					Log.AreaIrr500m	0.077
F-statistic: 16.06 on 4 and 32 DF	**< 0.0001**	**F-statistic: 24.28 on 2 and 35 DF**	**< 0.0001**	**F-statistic: 17.85 on 3 and 36 DF**	**< 0.0001**	**F-statistic: 16.03 on 4 and 35 DF**	**< 0.0001**

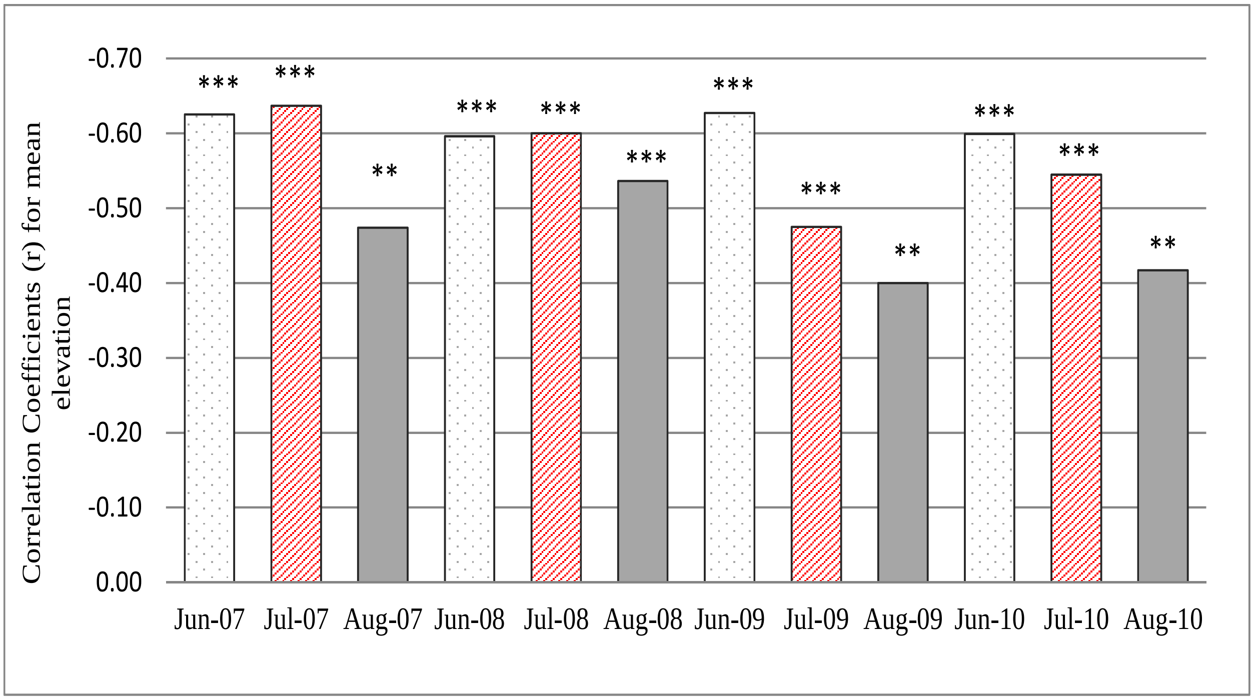

Figure 4.1 Relationships between elevation within a 500 m buffer and mean monthly *Cx. tarsalis* abundance in Fort Collins, Colorado for 2007-2010. P values indicted as *P<0.05, **P<0.01, ***P<0.0001; ns represents non-significance.

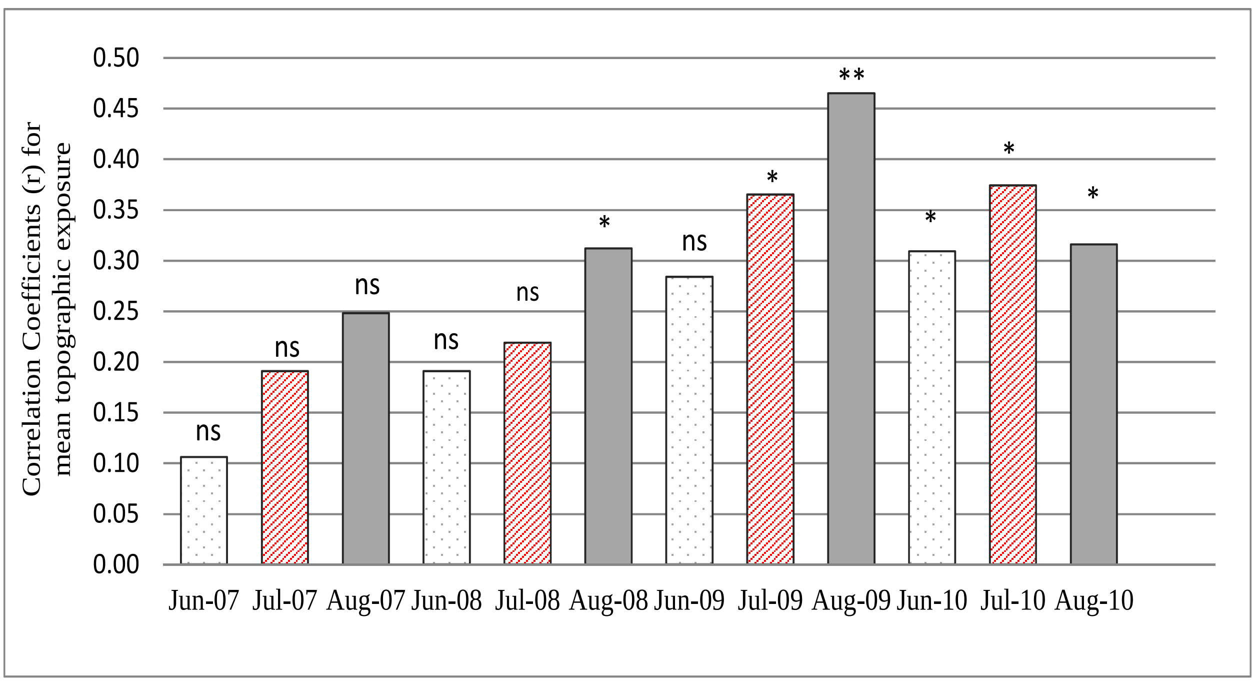

Figure 4.2 Relationships between topographic exposure within a 500 m buffer and mean monthly *Cx. tarsalis* abundance Fort Collins, Colorado for 2007-2010. P values indicted as *P<0.05, **P<0.01, ***P<0.0001; ns represents non-significance.

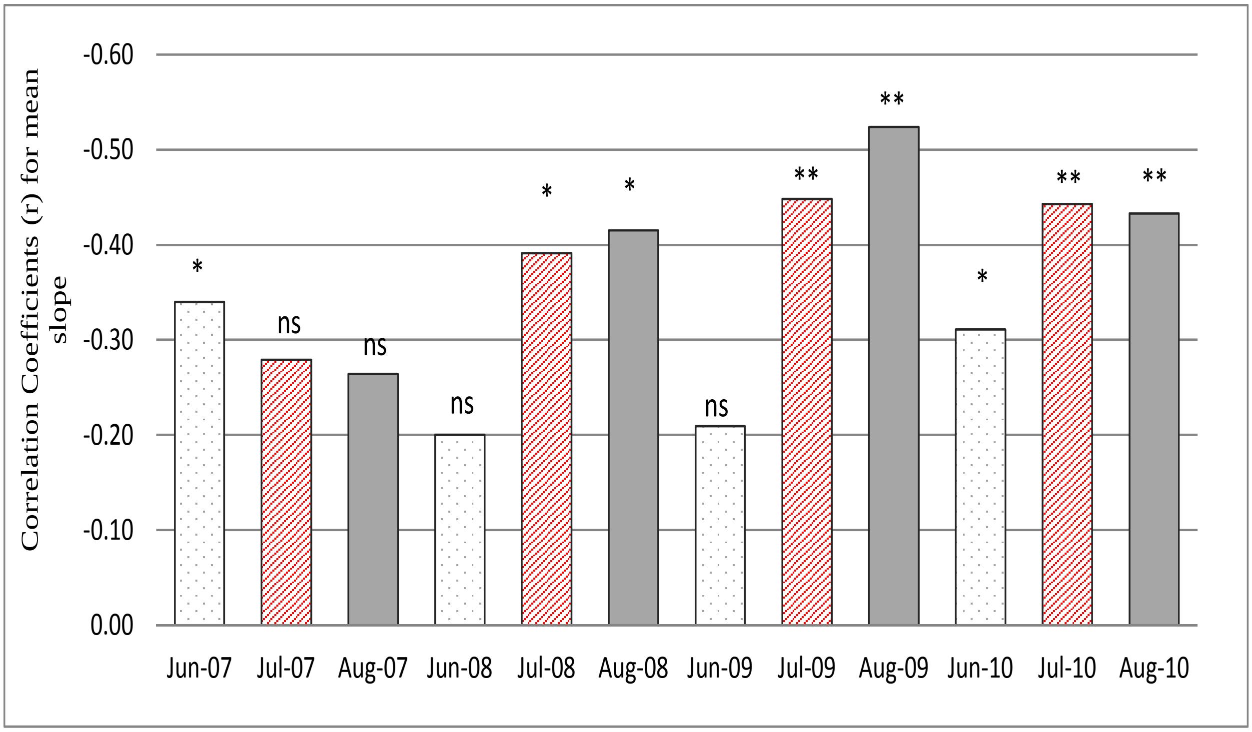

Figure 4.3 Relationships between slope within a 500 m buffer and mean monthly *Cx. tarsalis* abundance in Loveland and Johnstown, Colorado for 2007-2010. P values indicted as *P<0.05, **P<0.01, ***P<0.0001, ns represents non-significance.

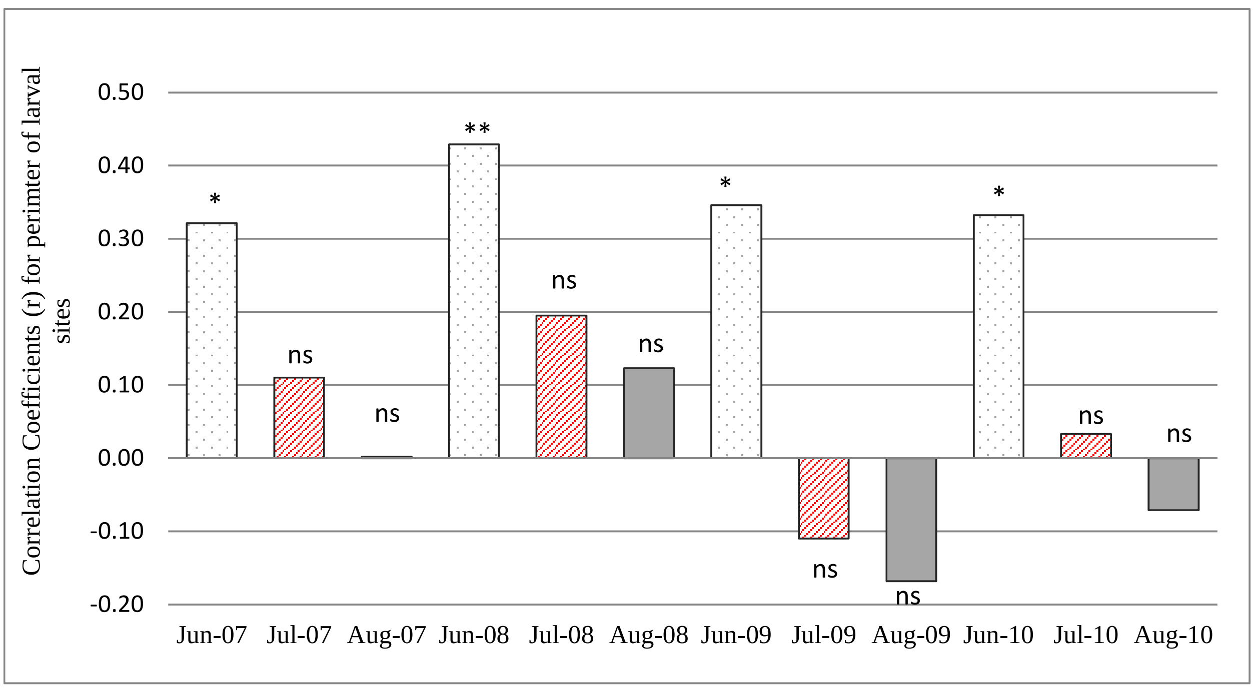

Figure 4.4 Relationships between perimeter of larval mosquito habitats within a 1.0 km buffer and mean monthly *Cx. tarsalis* abundance in Fort Collins, Colorado for 2007-2010. P values indicted as *P<0.05, **P<0.01, ***P<0.0001, ns represents non-significance.

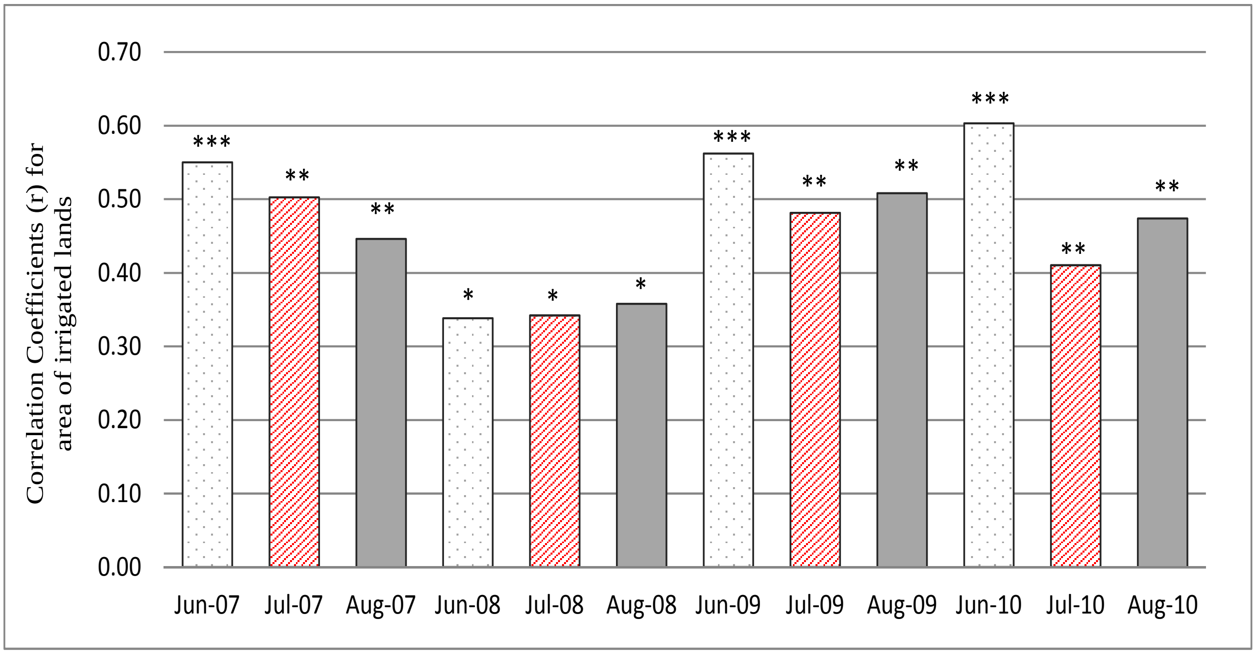

Figure 4.5 Relationships between area of irrigated lands (Log_{10}) to larval sites within a 500 m buffer and mean monthly *Cx. tarsalis* abundance in Loveland and Johnstown, Colorado for 2007-2010. P values indicted as *P<0.05, **P<0.01, ***P<0.0001, ns represents non-significance.

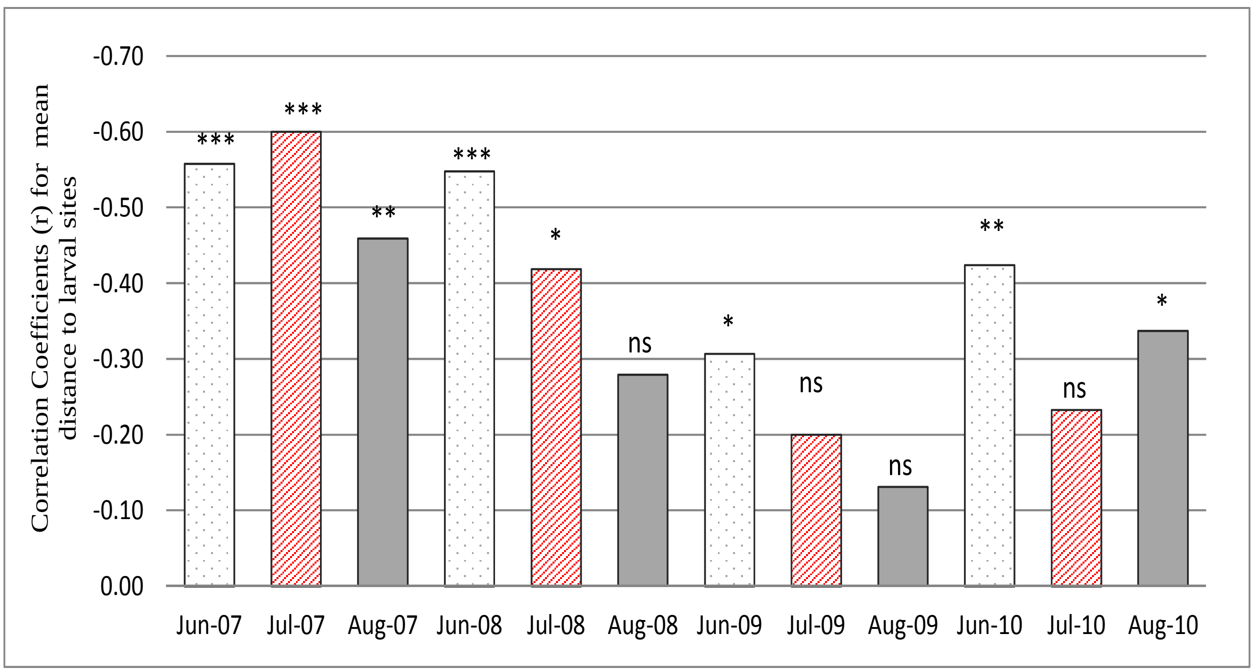

Figure 4.6 Relationships between mean distance (Log_{10}) to larval sites within a 500 m buffer and mean monthly *Cx. tarsalis* abundance in Loveland and Johnstown, Colorado for 2007-2010. P values indicted as *P<0.05, **P<0.01, ***P<0.0001, ns represents non-significance.

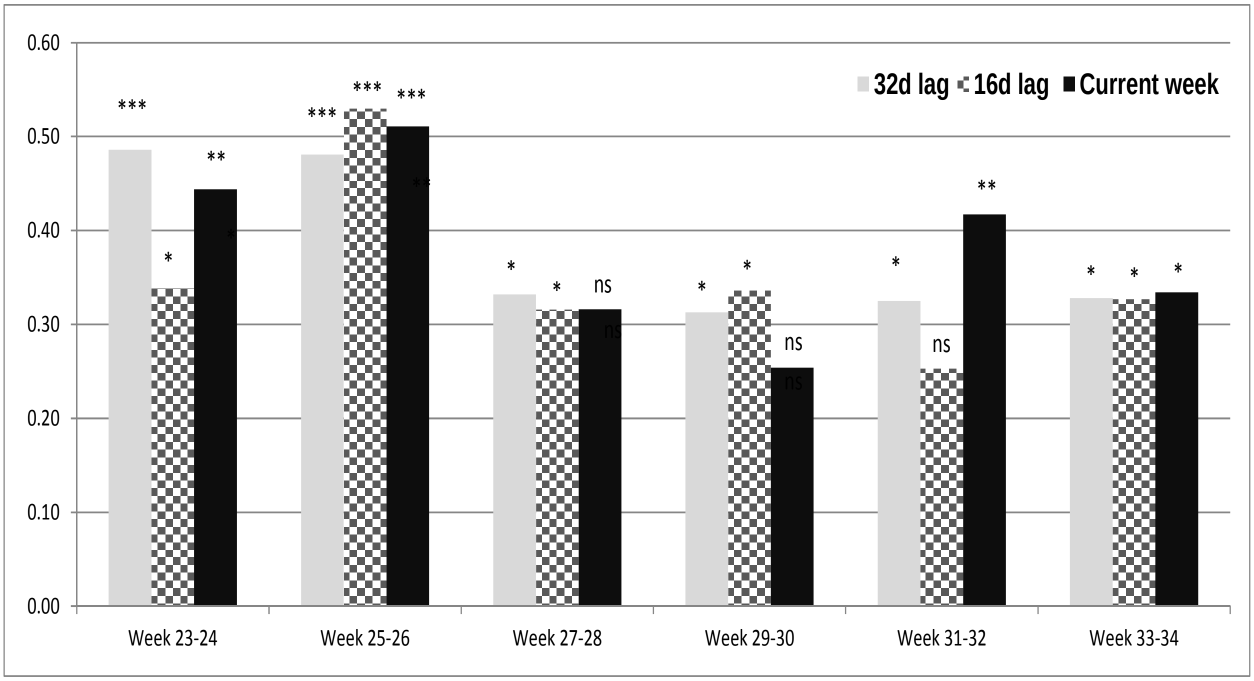

Figure 4.7 Relationships between standard deviation in NDVI and mean *Cx. tarsalis* abundance in Fort Collins, Colorado for 2009 within a 500 m buffer of trap locations. Mean abundance was obtained as an average of two weeks, weeks represented on the x axis. Correlation coefficients are represented on the y axis. P values indicted as *P<0.05, **P<0.01, ***P<0.0001, ns represents non-significance.

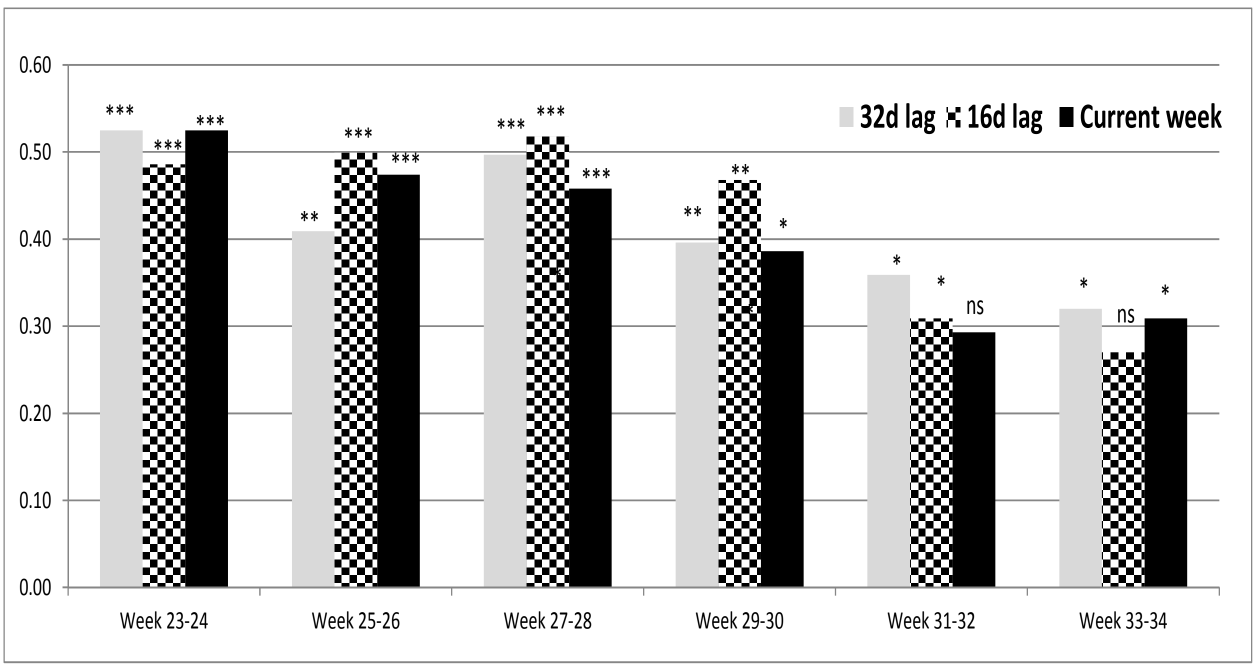

Figure 4.8 Relationships between standard deviation in NDVI and mean *Cx. tarsalis* abundance in Fort Collins, Colorado for 2010 within a 500 m buffer of trap locations. Mean abundance was obtained as an average of two weeks, weeks represented on the x axis. Correlation coefficients are represented on the y axis. P values indicted as *P<0.05, **P<0.01, ***P<0.0001, ns represents non-significance.

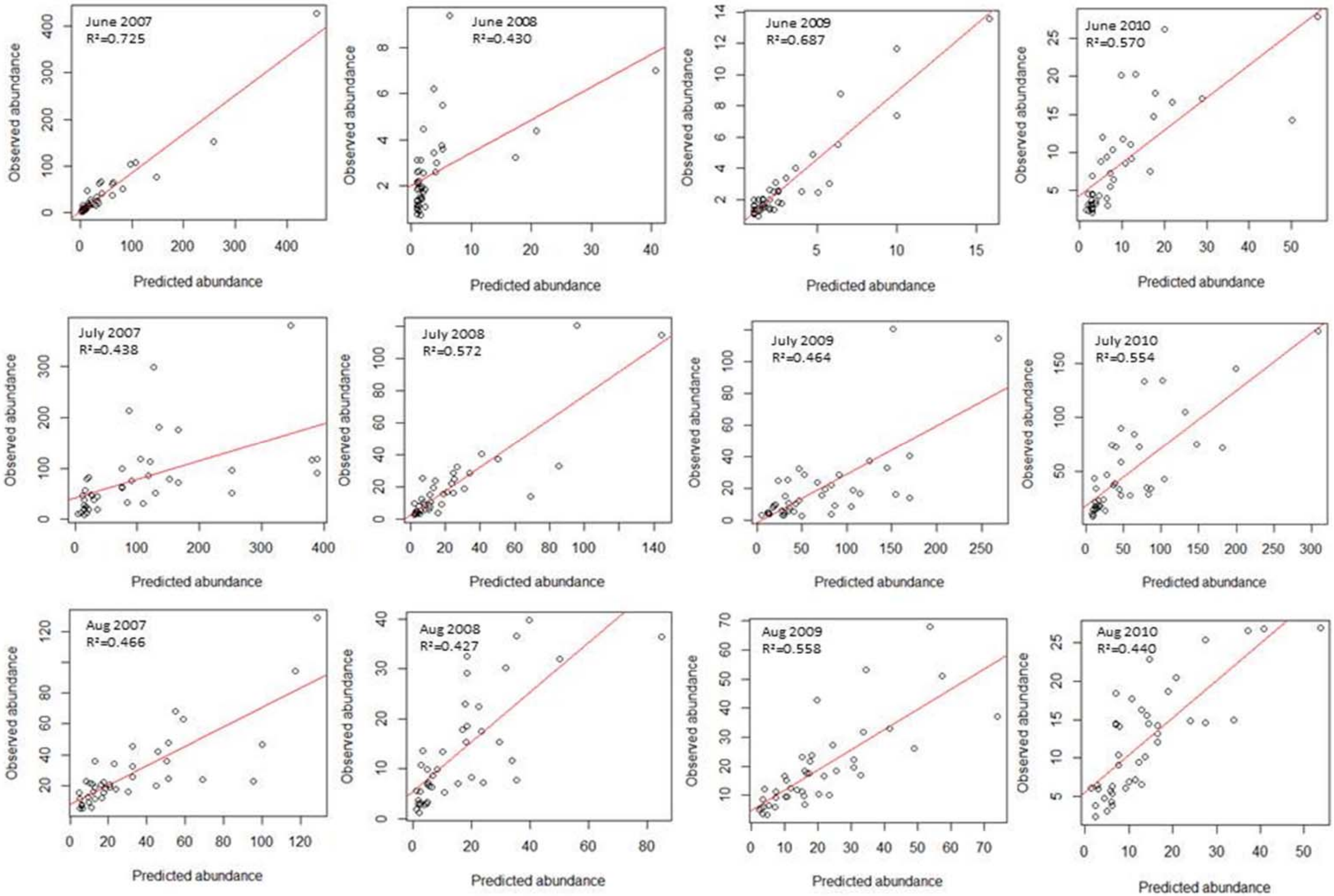

Figure 4.9 Relationships between predicted mean monthly *Cx. tarsalis* abundance and observed abundance by month of year in Fort Collins, Colorado.

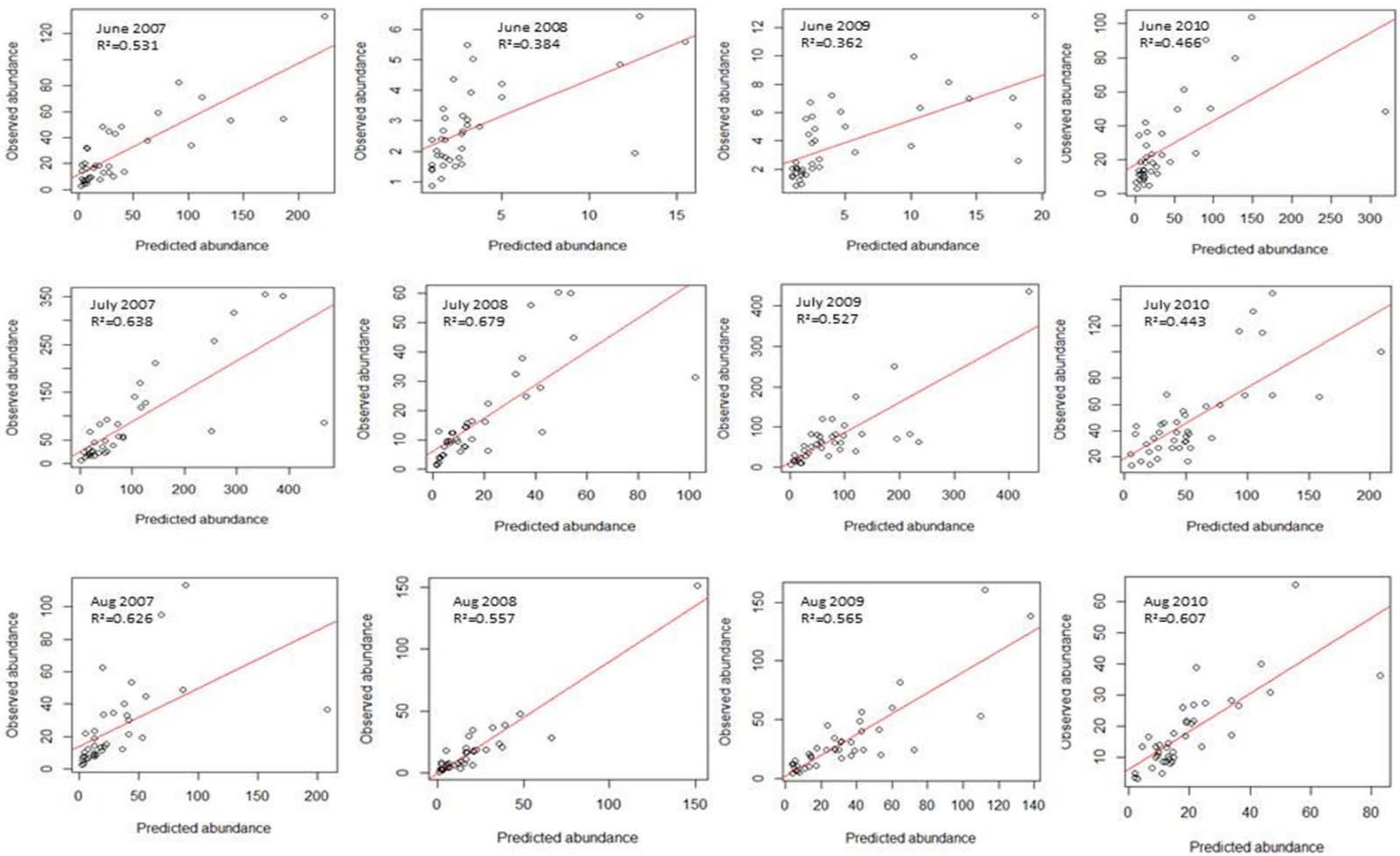

Figure 4.10 Relationships between predicted mean monthly *Cx. tarsalis* abundance and observed abundance by month of year in Loveland and Johnstown, Colorado.

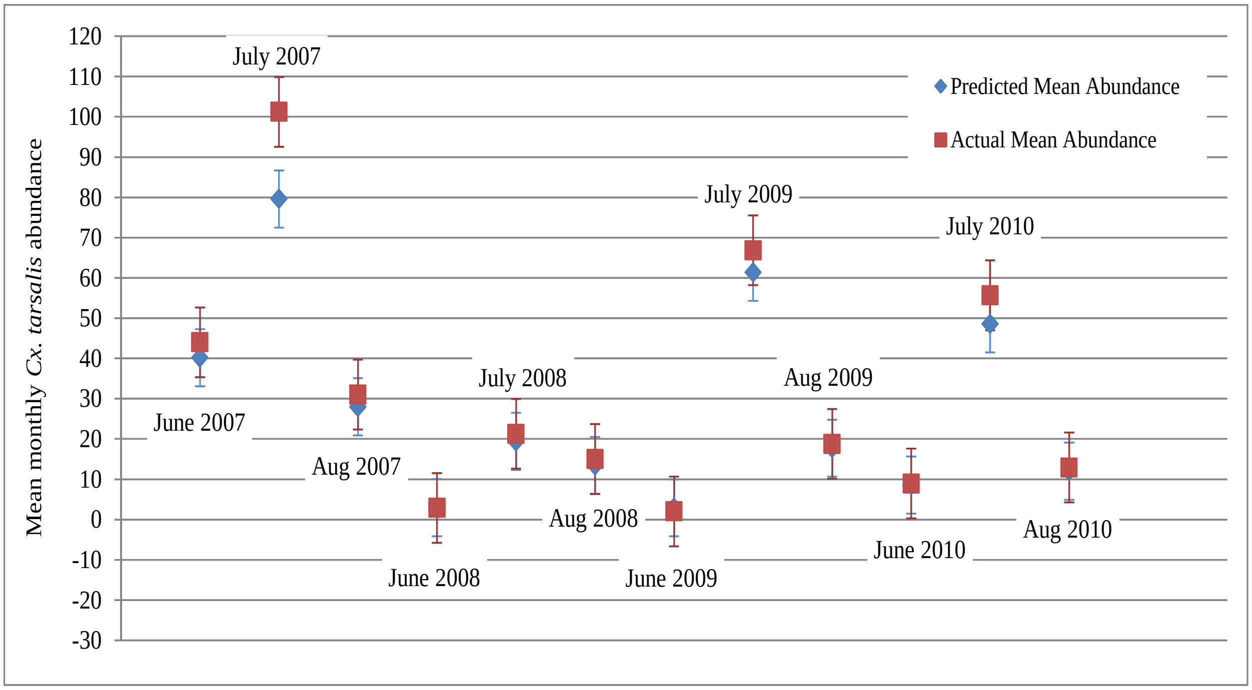

Figure 4.11 Predicted versus actual mean monthly adult *Cx. tarsalis* abundance (on y axis) with standard error in Fort Collins, Colorado. Mean actual and predicted abundance data for *Cx. tarsalis* was back transformed from $\log_{10}$ (N+1).

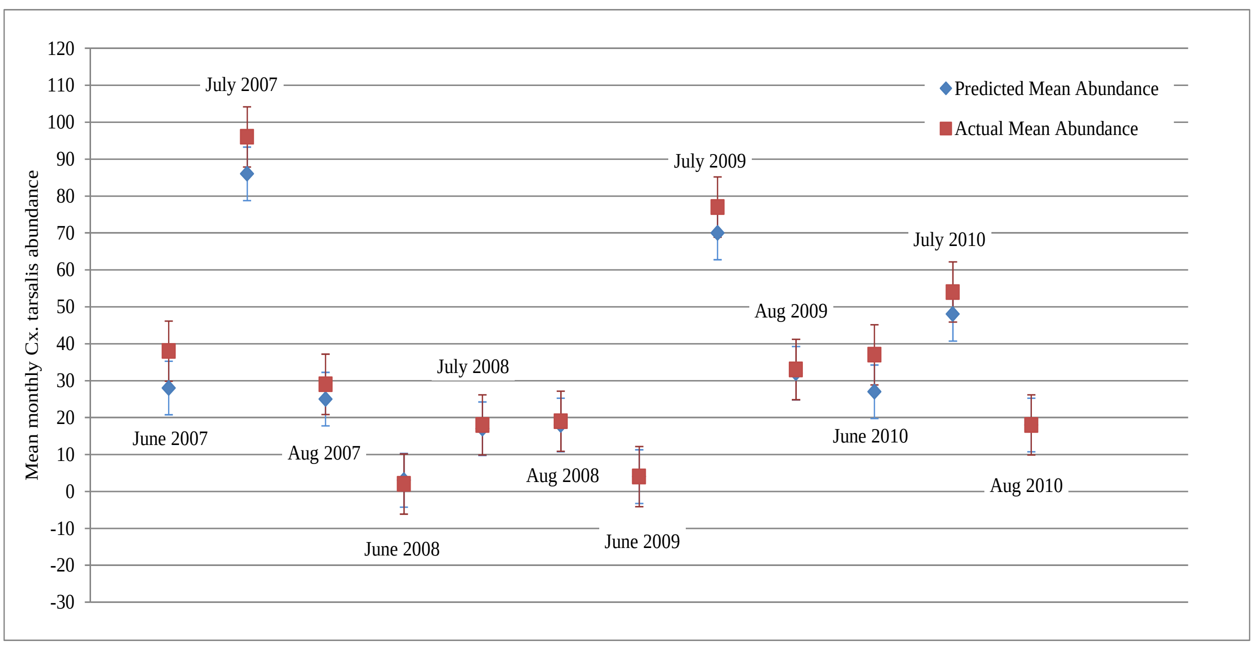

Figure 4.12 Predicted versus actual mean monthly adult *Cx. tarsalis* abundance (on y axis) with standard error in Loveland and Johnstown, Colorado. Mean actual and predicted abundance data for *Cx. tarsalis* was back transformed from $\log_{10}$ (N+1).

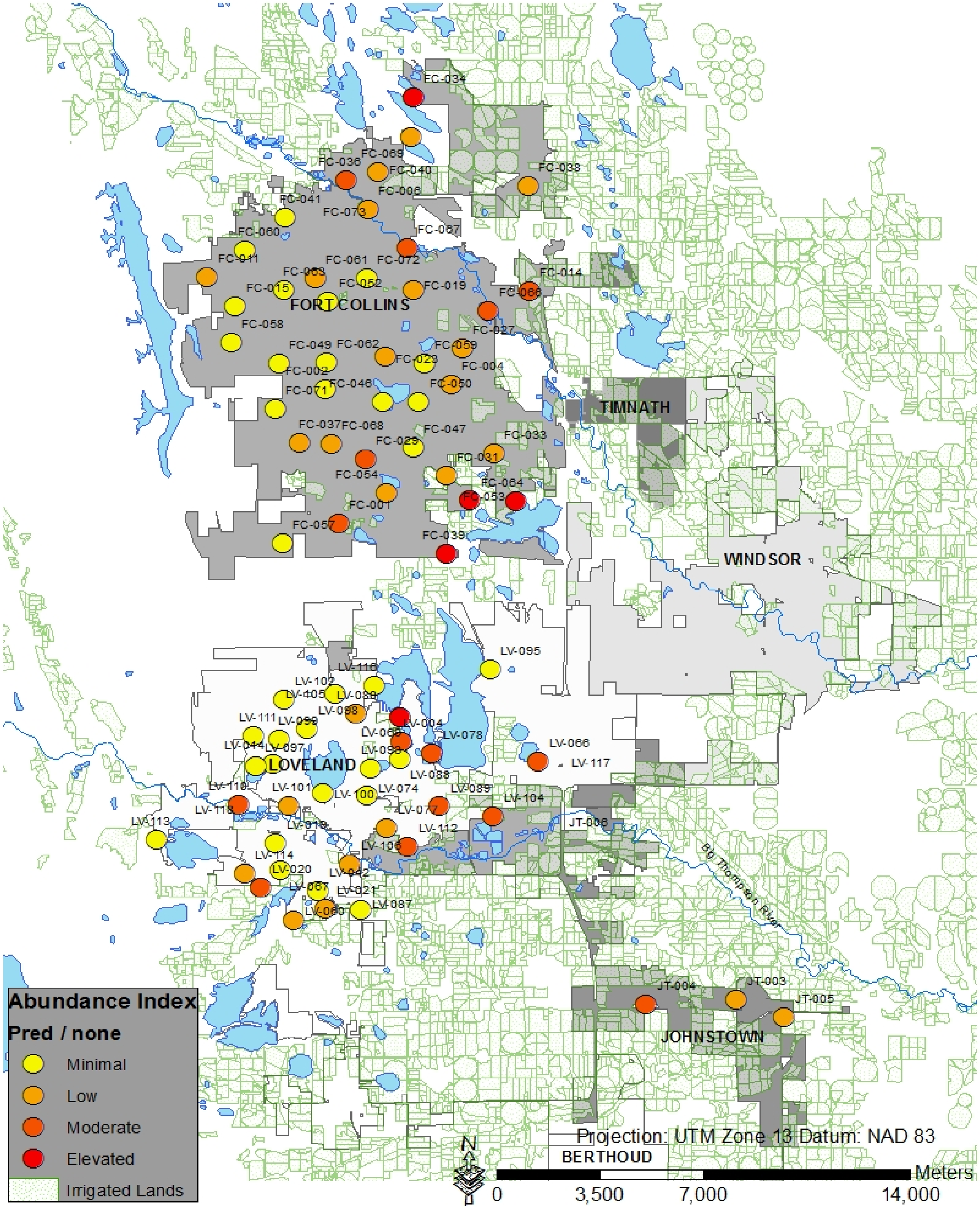

Figure 4.13 *Culex tarsalis* abundance model for June 2007 reflecting predicted mean monthly totals by trap location in the spatial modeling area. Abundance index is based on the mean monthly abundance of *Cx. tarsalis*. Minimal=0-10, Low=11-50, Moderate=51-100, Elevated=<101 mean mosquitoes predicted on a monthly basis. Irrigated lands are detailed in green and municipal boundaries are outlined in shades of white, grey and black.

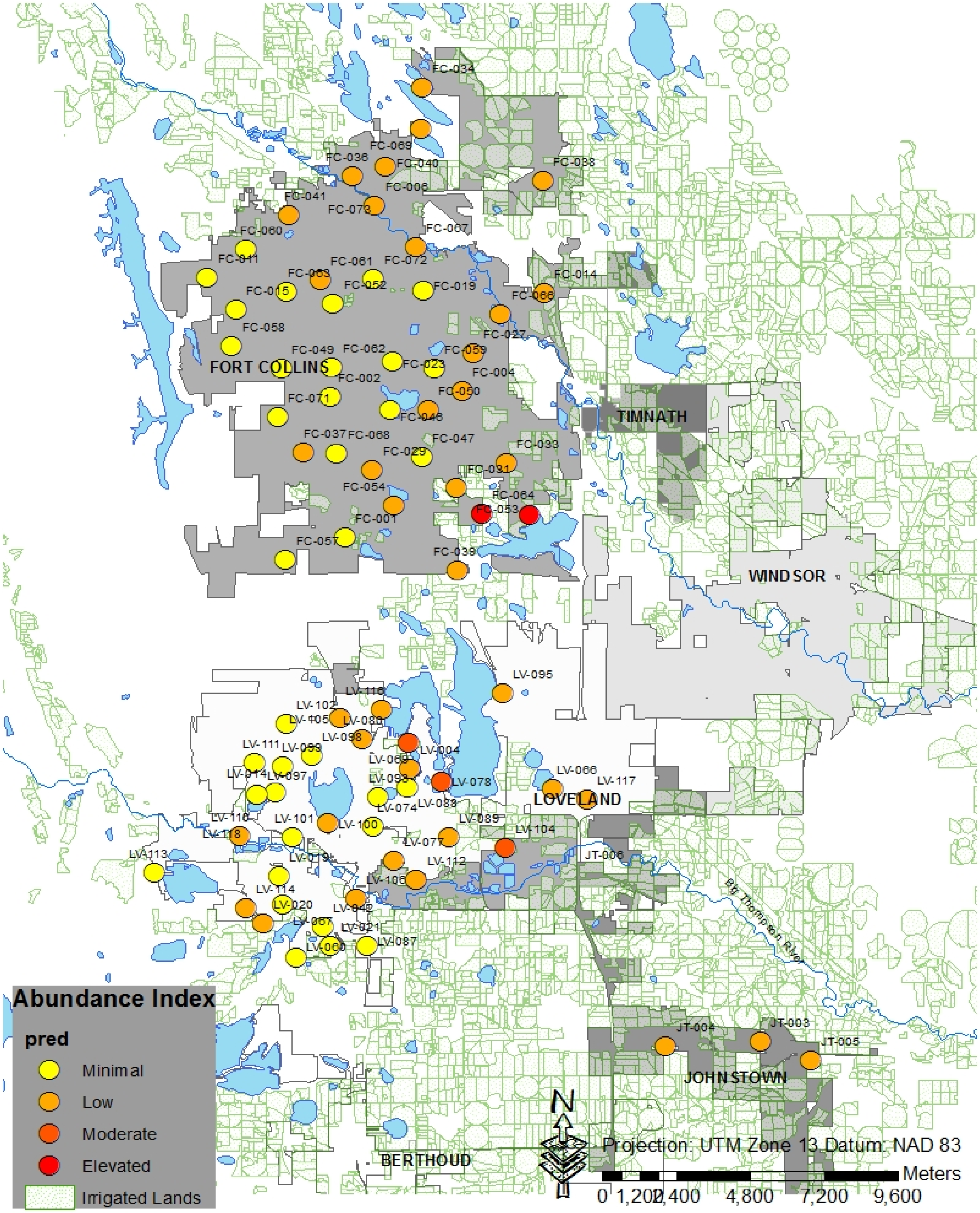

Figure 4.14 *Culex tarsalis* abundance model for July 2008 reflecting predicted mean monthly totals by trap location in the spatial modeling area. Abundance index is based on the mean monthly abundance of *Cx. tarsalis*. Minimal=0-10, Low=11-50, Moderate=51-100, Elevated=<101 mean mosquitoes predicted on a monthly basis. Irrigated lands are detailed in green and municipal boundaries are outlined in shades of white, grey and black.

5. DISCUSSION

5.1 Biological Importance of Landscape-Level Variables

Significance of landscape-level variables was identified based on vector abundance training data and the use of multiple regression models to detect areas of higher monthly *Cx. tarsalis* mosquito abundance. Identification of these variables can assist in understanding the seasonality of mosquito abundance based on the landscape dynamics and biological relevance to target control efforts.

Mean elevation within a 500 m buffer significantly contributed to the predictive power of models for Fort Collins during the following months: July 2007, June 2008, July 2009, June 2010, and July 2010. Mean elevation within a 500 m buffer contributed to predictive models in all months across all years except June 2009 and June 2010 in Loveland and Johnstown. This suggests, and is not a novel idea, that *Cx. tarsalis* mosquito abundance increases with decreasing elevations within the study area, which is consistent with spatial patterns for increasing WNV disease incidence with decreasing elevation (Winters et al. 2008b). This relationship may work in combination with slope of the local landscape to foster an ideal environment for larval *Cx. tarsalis* mosquito development because of poor drainage at some locations within this spatial modeling area and beyond. This postulation is based on the work by Barker et al. (2009a) where higher presence of *Cx. tarsalis* abundance was found between elevations of 1,200 m – 1,450 m with decreasing abundance at elevations above 1,450 m. Increasing elevations offer increased slope along the foothills and canyons that lead to the Continental Divide. Mosquito species richness in northern Colorado has also been found to be higher in elevations below 1,600 m (Eisen et al. 2008), which is likely in part a result of drainage from mountain elevations along the riparian corridor and preference for habitat suitability at lower elevations because of warmer temperatures. The mean elevation within 500 m buffers in Loveland and Johnstown varied from 1,456 m – 1,561 m. In Fort Collins the mean elevation within 500 m buffers at trap locations ranged from 1,487m -1,563 m.

The importance of elevation in regression models, which serves as a proxy for temperature and solar radiation, can cause dramatic shifts in *Cx. tarsalis* abundance on a weekly and monthly basis. Additionally inclusion of slope in multiple regression models for Loveland and Johnstown highlights another difference in the topography of the municipalities included in this study. Slope was a significant predictor for Loveland and Johnstown in July 2008 ($P<0.01$), August 2008 ($P<0.01$), July 2009 ($P<0.05$), August 2009 ($P<0.01$), July 2010 ($P<0.05$) and August 2010 ($P<0.01$), but was not included in any of the abundance models for Fort Collins, further suggesting a probable difference in the landscape in Loveland and Johnstown versus that of Fort Collins. The negative correlation between mosquito abundance and slope suggests that mosquito abundance not only increases with decreased slope, but that these results are specific to the area of Loveland and Johnstown. It seems plausible that the degree of slope within the landscape may affect the permeation of water into the soil or runoff after rainfall, thereby causing larval mosquito habitats to persist longer in Loveland and Johnstown compared to Fort Collins. The importance of slope in the abundance models may have also been attributed to the amount of rainfall in the previous month or current month combined with slope of the landscape. The cumulative monthly rainfall in the months of June 2009 in central Fort Collins was 122.55 mm in June 2009, 79.76 mm in July 2009 and 5.08 mm in August 2009, versus 49.91 mm in June 2009, 52.71 mm in July 2009 and 24.13 mm in August 2009 in central Loveland, as obtained from the NCWCD (http://www.northernwater.org). The differences in cumulative monthly rainfall totals also highlight climate variability between the two municipalities. These rainfall total differences may also affect the tendency for water to be flushed across the landscape gradient. To the best of my knowledge this is the first analysis completed in the northern Front Range of Colorado that has considered the contribution of mean slope and elevation with 500 m buffered distances across the local landscape into modeling vector abundance for adult *Cx. tarsalis.*

Likewise the effect of snowpack and the manual control of water along the Cache La Poudre River may affect current and subsequent weekly mosquito abundance data. Spikes in mosquito abundance are probable following peak runoff or diversion of water for irrigation use. Larval habitats recede along the floodplain of the river or pools form along the ditches used to carry water and offer suitable sites for oviposition by *Cx. tarsalis* as these areas stagnate. A positive relationship between the mean monthly *Cx. tarsalis* abundance and perimeter of larval habitat was consistent in June 2007 ($r= 0.321$, $P<0.05$), 2008 ($r=0.429$, $P< 0.01$), 2009 ($r=0.346$, $P<0.05$) and 2010 ($r=0.332$, $P<0.05$) for Fort Collins. These findings are further supported by the identification for the importance of majority water source, groundwater seepage during the month of June 2007. This suggests that in times of significant snow melt runoff and high snow water content, that adult mosquito abundance in the weeks to follow may be positively impacted by the rise in the groundwater table. It is probable that the perimeter of larval habitats along the northern Colorado Front Range are more important in the early season abundance of *Cx. tarsalis* as larval habitats are positively affected by groundwater seepage along the river corridor with spring snowmelt runoff. Similar results for the correlation between surface wetness and *Cx. pipiens* abundance was detected in work by Shaman et al. (2002) where the authors highlight that mosquito abundance is a function of mosquito biology and variability in surface wetness. Operations managers for larval mosquito control programs could respond to the local importance of increased size of larval mosquito habitats, because of snow pack, by selecting residual larval control products after the water levels recede.

The habitat classes which generated predictions in June 2010 and July 2010 in Fort Collins highlight another interesting interaction of landscape variables and mean monthly adult mosquito abundance. In June 2010, ditches within 500 m improved the predictive power ($P<0.05$) in this monthly model, while in the following month the majority habitat of depressions within a 500 m buffer provided predictive power ($P<0.05$). This suggests that the proximity of ditches to trap locations and possible relative humidity within the vegetation along the ditches provides suitable harborage for *Cx. tarsalis*. Locally, depressions are often left behind when ditch water is no longer being used for residential and agricultural irrigation, and this could have in turn contributed to the habitat suitability for adult *Cx. tarsalis* to remain in proximity to the ditches and not disperse from associated vegetation. Additionally, the large systems of ditches on the northern portion of Fort Collins may serve as a dispersal corridor from associated irrigated lands into the more urban areas of north Fort Collins. This postulation would need to be validated with mark-release-recapture studies to provide empirical data for the importance of ditches on local vector dispersal.

Topographic exposure can identify areas of exposure or protection, often times from wind, across the landscape structure (Mikita and Klimanek 2010). The positive relationship between topographic exposure and mosquito abundance identified from Fort Collins suggests that topographic exposure across a landscape may aid in the identification of areas where more adult mosquito harborage is likely available. More importantly, the variability in statistical importance of topographic exposure across months is likely working in combination with local weather patterns.

The positive association between irrigated lands and vector mosquito abundance or human WNV infection is consistent with previous findings (Miramontes et al. 2006, Eisen et al. 2010, DeGroote and Sugumaran 2012). This study showed that proximity to irrigated agriculture contributes to increased vector abundance. The relationship between the areas of irrigated lands with mosquito abundance was positive in Fort Collins, Loveland and Johnstown, indicating that the area of irrigated lands contributes significantly to mean monthly mosquito abundance. The habitat preference for shallow waters by *Cx. tarsalis* provides biological relevance for these results. In this work the findings for significant spatial extent of irrigated lands varied across the study area, which may be a result in the difference in density or clustering of irrigated lands, as well as potential issues with the data layer and reporting of irrigated lands.

Significant differences were detected for the spatial extent of distance to and area of irrigated lands within each of the two study areas. The distance to irrigated lands was statistically significant ($p<0.05$) within a 500 m buffer in Fort Collins and a 1.0 km buffer in Loveland and Johnstown. In Fort Collins the area of irrigated lands contributed more predictive power ($p<0.05$) for a 1.0 km buffer versus a 500 m buffer in Loveland and Johnstown. These results suggest that a higher abundance of *Cx. tarsalis* mosquitoes are associated with area of irrigated lands at coarser spatial extents in Fort Collins, while the area of irrigated lands in Loveland and Johnstown are more densely clustered. It is possible that these differences are also affected by the tendencies for *Cx. tarsalis* to disperse into municipalities surrounded by irrigated lands if less suitable harborage surrounds those irrigated lands. Although distance to irrigated lands within a 1.0 km buffer was included in the multiple regression models for Loveland and Johnstown, the significance of this variable was removed during stepAIC. The landscape variable that carried higher predictive power was the distance to larval habitats within a 500 m buffer. These results are indicative of the characteristics of these communities which include residential development around irrigated lands and wetlands in Loveland and Johnstown, which all contribute to the density of adult *Cx. tarsalis* mosquitoes within these municipalities. These findings provide a strong basis for the importance of adequate larval control buffers, beyond 500 m of city limits to enable effective reduction of *Cx. tarsalis* mosquitoes.

Confounders for the importance of irrigated lands may exist in the digitizing of these lands according to the parcel layer and the perspective of the person who mapped the polygons used for the creation of this layer. Water use and coverage is variable across a season and may be underreported so the polygons used to build the irrigation layers have inherent errors associated with them, which may alter the true relevance of this variable. It is important to note that the layer used in the calculation of distance to and area of irrigated lands was obtained from the most recent data available at the time, which encompassed lands up to 2007. There has since been significant development on the eastern and southeastern portions of Fort Collins which may have produced different conditions for comparison across years and led to variable direction for correlation. Improved analysis for the effect of reduced irrigated lands since 2007 in modifying mosquito abundance since residential development should include more current data for this effect to truly be understood. I believe that although the findings suggest the importance of distance to irrigated lands in predicting mosquito abundance in Fort Collins, additional comparisons across years should be studied.

5.2 Trap Biases and Effects of Weather

The effects of trap type (Anderson et al. 2004, Brown et al. 2008b, Lothrop and Reisen 2001) and placement along ecotones have been documented. Both the species of interest and host congregation should be considered when selecting an applicable trap and trapping locations (Thiemann et al. 2011). Comparisons of mosquito traps have shown that biases are intrinsic and trap type can alter the diversity and abundance estimates of the mosquito species collected (Brown et al. 2008b). Bolling et al. (2009) found variation among trap locations in seasonal patterns for WNV infection rates, suggesting the effect for density of harborage and how proximity to harborage may attribute to higher risk areas for WNV.

Godsey et al. (2010) reported that differences in relative and seasonal abundance may also be affected by weather and water usage patterns. In this study, rainfall events in the month of August 2007, compared to 2006 resulted in a spike in *Aedes* and followed by a spike in *Culex* associated with natural, rural and sub-rural areas (Godsey et al. 2010). This variability in weather patterns even at a fine scale makes comparisons across seasons difficult without inclusion of weather patterns.

Previous work by Maki (2005) found that average temperature from trap locations near the Cache La Poudre River did not differ significantly between herbaceous, residential, water filled and agricultural habitat types, but did vary across sampling repetitions, which seems logical given the scale at which temperature data were collected. It is also worth noting that mosquito catch was inversely related to relative humidity and relative humidity was higher in water filled areas, as well as herbaceous and residential areas (Maki 2005). These findings support trap placement in proximity to larval habitats and adequate harborage, as these factors can aid in obtaining a better representation of actual abundance as opposed to selecting a trap location in a hospitable environment.

5.3 Limitations of Project

5.3.1 Limitations of Climate Modeling

Unforeseen problems arose with modeling climate at the landscape level of the entire spatial modeling extent. Daymet and WorldClim data did not cover the time period for which I had collected adult mosquito abundance data. I selected PRISM data despite the 4 km coarse resolution because of its wide application in modeling efforts and monthly accessibility for mean temperature for the study period. When I compared mean monthly data from weather locations in northern Colorado, other simulation models at finer scales reflected variability from station observations ranging from 1-3^{o}C.

The inherent problem with using a coarser resolution data such as the 4 km resolution for PRISM in modeling temperature along the northern Colorado Front Range was the likely inclusion of temperature or pixel values associated with the foothills. This probably decreased the average temperature across Fort Collins and Loveland and under-predicted mosquito abundance. The sampling scheme of weather station locations in the study area may have also created the possibility that multiple surveillance locations fell within 1 cell for PRISM data, at the resolution of 4 km. I included data from nine weather stations maintained by CoAgMet and the NCWCD but opted to not include privately operated weather stations, which left large gaps in the ability to model climate surfaces across the spatial modeling area. My reason for this approach was to reduce the variability that could come from independent weather stations associated with issues of maintenance and calibration of weather monitoring instruments. Utilization of GIS data from CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/ or current PRISM data at an 800 m resolution may prove to be useful in refining the effects of temporal patterns on *Cx. tarsalis* abundance.

5.3.2 Limitations in NDVI Analysis

My initial intent was to utilize 30 m resolution Landsat satellite derived NDVI data layers to model its impact on mosquito abundance for all years of this study. During data download I encountered problems with the NDVI layers. Large bands of missing data were present in the GRIDS which resulted in negative values present across multiple months that I planned to model. Because of these reasons I had to drop the idea of using 30-m Landsat NDVI data layers and instead used MODIS NDVI data layers at 250 m resolution. I believe that although the initial 250 m GRIDs for NDVI were resampled to 90 m to achieve a more local extent, that the scale was still too large for accurate consideration for the effect of NDVI in the modeling area. NDVI has been an important predictor in previous studies (Diuk-Wasser et al. 2006), but I believe the effect of NDVI was lost in the extent in which I tried to apply it to. Although the Pearson's correlation coefficients were significant at a 500 m extent for standard deviation in NDVI, this dynamic predictor did not hold up against other predictors during stepAIC, which may have produced different results at a finer scale.

5.4 Conclusions

Efforts to model the abundance of adult *Cx. tarsalis* on a monthly basis using landscape-level predictors in Larimer County indicated that topography (elevation and slope) is negatively correlated with adult *Cx. tarsalis* abundance. The variability in the expression of elevation, topographic exposure, and slope in abundance models is likely dependent on climate variables, including temperature, wind speed and precipitation, which act to modify the dynamics of larval and adult *Cx. tarsalis* abundance. The contribution of irrigated lands and wetlands within a 500 m buffer to improve model fit highlight the importance of these habitats to be significant larval *Cx. tarsalis* habitats in Larimer County. These findings are consistent with habitats associated with elevated WNV incidence in humans (Eisen et al. 2010, DeGroote and Sugumaran 2012). The proximity of area of irrigated lands is positively correlated with mosquito abundance while the distance to larval habitats is negatively correlated with adult mosquito abundance on a monthly basis. Abundance maps which used model predictions to reflect areas where the distribution of mosquito abundance is likely to be elevated revealed that abundance is higher at the periphery of the eastern edges for the municipal boundaries of Fort Collins and Loveland. These results stress the importance for adequate boundaries for larval control which include habitats that are suitable larval *Cx. tarsalis* sites to improve the efficacy of mosquito management efforts and reduce adult mosquito abundance.

5.5 Future Directions

The findings for the differences in landscape heterogeneity obtained from this study show the effect of fine scale variation at the landscape level on *Cx. tarsalis* abundance. Additionally, the variability in the predictors in abundance models is likely being driven by temporal components. It is possible that weekly climate patterns contribute to the monthly and seasonal differences in the vector biology, which in turn can alter the ability to model vector abundance on a temporal scale. The effects of local climate across the landscape, including solar radiation, relative humidity, cooling degree days, and maximum and minimum temperatures should be included in future studies to enhance the understanding for the temporal patterns of both larval and adult *Cx. tarsalis* mosquitoes.

A long term study including more detailed weather patterns and identification of anomalies in mean temperature, relative humidity, and degree days at permanent trap locations across a fine scale landscape may aid in building a conceptual model that incorporates the effect of weather patterns into seasonal mosquito abundance trends. A comprehensive example of this is the conceptual model developed by Barker et al. (2003) for the California State Mosquito-Borne Virus Surveillance and Response Plan. This plan uses numerous surveillance indicators to classify and forecast seasonal levels of risk for Western Equine Encephalitis (WEE) and St. Louis Encephalitis (SLE) and could likely aid in improving the forecasts for WNV risk and incidence.

The effects of relative humidity based on residential watering, vegetation type and density of larval habitats to create more favorable habitats for mosquitoes to harbor may help to understand the site specific variation in distribution and areas of higher abundance for *Cx. tarsalis*. Inclusion of water use associated with agricultural irrigation and proportion of land use patterns or vegetation density could also provide an additional understanding for dispersal of *Cx. tarsalis* from irrigated lands into residential areas. In effect, if irrigated fields are not drying out as quickly because of continued water use and offer suitable harborage and oviposition sites, then female mosquitoes are less likely to disperse at greater distances.

Also worth considering in future studies would be the host aggregation and roost distribution of birds within residential areas and wetlands across the spatial modeling area. The preference for *Cx. tarsalis* to blood feed on doves, sparrows and the American robin (Kent et al. 2009) stresses the importance for understanding the distribution of these birds within the community. Models that could forecast host aggregation throughout the year and *Cx. tarsalis* abundance in peak months for WNV risk may provide improved analysis for possible clusters of increased WNV risk. These considerations for future studies provide an overview for the possible variability in adult mosquito trapping data on a spatial and temporal basis.

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