DROUGHT AND FOREST DISTURBANCE IMPACTS ON HYDROLOGY
UNDER CHANGING CLIMATE CONDITIONS

by
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ABSTRACT

Freshwater is one of the world’s most important natural resources. It is essential to human health, ecosystem function, and livelihoods, but is a finite resource and needs to be appropriately managed. As global demand grows, there is increasing competition for resources between the water, agriculture, energy, livestock, fisheries, forestry, mining, transport, and other sectors. Conceptual frameworks for water policy such as integrated water resources management and the water-energy-food nexus have emerged to balance these competing interests. However, the policy challenges to meeting societal demands for water while maintaining ecosystem function are exasperated by the modification of water availability due to changing land use and climate conditions. Reliable methods to monitor and predict water availability are essential for understanding the vulnerability of water resources to future changes in land use, climate, and policy. The overarching objective of this dissertation is to better understand how changing patterns of land use and climate conditions impact the distribution and availability of freshwater resources.

This dissertation first examines the impact of the current mountain pine beetle (MPB, Dendroctonus ponderosae) outbreak in the western United States (US) on surface water resources. In the Western US, the current MPB epidemic has affected more than five million hectares since its start in 1996, including headwater catchments that supply water to much of the Western US. There is widespread concern that the hydrologic consequences of the extensive pine tree die-off will impact water supply across the Western US. While forest disturbance studies have shown that streamflow increases in response to tree harvest, the actual effect of bark beetle infestations on water supply remains widely debated among MPB researchers. This study evaluates watershed-level response following bark beetle outbreak for 33 watersheds in seven western states. Streamflow records were investigated to assess whether the timing and amount of stream discharge during bark beetle outbreak and early recovery periods were significantly different to pre-outbreak conditions. Results show no significant modification in peak flows or average daily streamflow following bark beetle infestation and that climate variability may be a stronger driver of streamflow patterns and snowmelt timing than chronic forest disturbance.

The second part of this dissertation examines how surface water resources in the Awash River Basin, in Ethiopia, were impacted by the 2015 regional drought and their subsequent
recovery. This study presents a new method to develop accurate, high-resolution maps of waterbodies. Cloud-based computing resources and machine learning techniques are used to merge Sentinel 1 synthetic aperture radar (SAR) and Landsat observations to generate monthly waterbody maps at a 10-meter resolution. The accuracy of this method is shown to be comparable to waterbody map products generated by high performance computing resources. The technique is demonstrated by mapping surface water change over the Awash River basin in Ethiopia during the 2015 regional drought. Results indicate that the downstream sub-catchments were most strongly impacted by drought and that surface water in all catchments recovered to pre-drought surface water area after the 2016 summer rains. The mapping illustrates the acute impact the drought had on surface water area, but this study could not determine surface water volume because measurements of the change in water body depth are not available. The upcoming Surface Water and Ocean Topography (SWOT) mission will provide global satellite altimetry measurements of water levels. The APWC technique combined with SWOT measurements of water elevation will be a powerful tool for monitoring changes in surface water volume in data-sparse regions. To our knowledge, this study is the first to merge passive and active sensors to generate waterbody maps and the first to create waterbody maps at a 10-meter resolution. This technique will help earth scientists better monitor and understand the impact of environmental changes on global freshwater ecosystems.

The final part of this dissertation examines how small, seasonal deformations induced by the West African Monsoon maybe used to better understand the distribution of water resources and geology of the Ara Watershed, a small catchment located in the Sudanian ecoregion of northern Benin, in West Africa. West Africa is undergoing unprecedented growth and development. Its population has been increasing by 2.75% each year and is expected to double in 25 years. This growth is intensifying pressure on regional and local water resources while changes in climate and land use are modifying the regional hydrology. The consequential changes to water availability are not fully understood, due in part to the scarcity of in-situ data across the region. This study uses interferometry of synthetic aperture radar (InSAR) techniques to map the dynamics of seasonal deformation across the Watershed. Seasonal deformation was found to be closely linked to monsoon precipitation. Riparian areas and the seasonally water-logged areas in the headwaters of small streams called bas-fonds in French-speaking West Africa may experience larger and more rapid deformations than adjacent upland areas, regions of
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CHAPTER 1
INTRODUCTION

Freshwater is one of the world’s most important natural resources. It is essential to human health, ecosystem function, and livelihoods, but is a finite resource and needs to be appropriately managed. As global demand grows, there is increasing competition for resources between the water, agriculture, energy, livestock, fisheries, forestry, mining, transport, and other sectors (Vörösmarty et al 2010, World Water Assessment Programme 2015). Conceptual frameworks for water policy such as integrated water resources management (UN-Water Decade Programme on Advocacy and Communication 2010) and the water-energy-food nexus (Bazilian et al 2011) have emerged to balance these competing interests. However, the policy challenges in meeting societal demands for water while maintaining ecosystem function are exasperated by the modification of water availability due to changing land use and climate conditions. Reliable methods to monitor and predict water availability are essential for understanding the vulnerability of water resources to future changes in land use, climate, and policy. The overarching objective of this dissertation is to better understand how changing patterns of land use and climate conditions impact the distribution and availability of freshwater resources.

Watersheds in the Western United States (US) are undergoing unprecedented levels of tree die-off due to wildfire, drought, and insect outbreaks (Williams et al 2010, Anderegg et al 2012, Adams et al 2012). The region has experienced warming temperatures since the 1900s (Kunkel et al 2013a, 2013b). The higher temperatures and low annual precipitation during the mid-1990’s have been linked to the ongoing mountain pine beetle (MPB, Dendroctonus ponderosae) outbreak in the western United States, which started in 1996 (Chapman et al 2012, Meddens et al 2012). Many species of bark beetle introduce blue-stain fungi into the tree xylem, which inhibits water flow (Paine et al 1997). The interruption of transpiration in MPB-attacked pine trees occurs in weeks to months (Hubbard et al 2013) ultimately leading to tree mortality (Edburg et al 2012).

Bark beetle outbreaks are typically endemic, causing minimal impact to catchment areas. However, the ongoing MPB epidemic has affected conifer forests at historic levels (Raffa et al 2008). Over 6 million forested hectares in the US and British Columbia have been impacted by bark beetles, with more than 5 million hectares affected by the MPB outbreak alone (Meddens et
This includes headwater catchments to the Colorado, Arkansas, Rio Grande, and Missouri Rivers, leading to concern that hydrologic consequences of the extensive pine tree die-off will impact water supply across the Western US. While forest disturbance studies have shown that streamflow increases in response to tree harvest, the actual effect of bark beetle infestations on water supply remains widely debated. The second chapter of this dissertation evaluates the streamflow and baseflow response of 33 watersheds in seven western states using several hydrologic metrics, including timing and amount of peak flows and daily streamflow statistics. Watershed statistics after bark beetle outbreak were compared to pre-infestation conditions to answer the question: To what degree is the timing and amount of watershed discharge across the Western US modified by bark beetle infestation? Results can be utilized by water supply managers and policy makers to better anticipate changes to water supply resulting from the MPB outbreak in the western US. The results of this study were published in Slinski et al. (2016).

Inland surface water is critical for human health and livelihoods (Costanza et al. 1997, Finlayson et al. 2005) as well as high-level biodiversity (Gardner et al. 2015). Surface water is also important to climate regulation via the land-atmosphere interactions in the water, energy, and carbon cycles (Raymond et al. 2013, Tranvik et al. 2009). Small waterbodies, in particular, provide critical ecological habitat and are important to buffer climate variability; they provide habitat for highly specialized plant and animal communities (Zedler 2003, Leibowitz 2003), as well as nesting for migratory waterbirds (Dodman and Diagana 2006). Carbon dioxide and methane emissions from small lakes and ponds also play a disproportionately important role in the global carbon cycle (Holgerson and Raymond 2016, Downing 2010). Climate change, land-use change, and other environmental changes affect the extent of inland water bodies. High resolution monitoring of surface water occurrence and persistence is critical to understanding the impact of environmental changes on freshwater ecosystems and modeling future change. However, only a very small proportion of global lakes and ponds are systematically monitored (Palmer et al. 2015), especially in data-sparse regions like East Africa. New methods using satellite remote sensing data are necessary to generate accurate, high resolution maps of inland surface water to understand drought impacts on surface water in these areas.

Satellite remote sensing techniques using passive and active sensors have long been recognized as a viable approach to monitoring surface water dynamics, particularly in data-
sparse regions (Palmer et al 2015, Bukata 2013). However, sensor and methodological limitations as well as data storage and processing capacity hinder the automated generation of high resolution single sensor waterbody maps. Work in this chapter introduces a new method that fuses optical and synthetic aperture radar (SAR) satellite data to generate high resolution maps of inland surface water over the Awash River Basin in Ethiopia. This study assesses the accuracy of the new active-passive water classification (APWC) method and answers the research questions: 1) Which areas of the Awash Basin were most heavily affected by the drought? and 2) Have surface water resources in the basin returned to pre-drought conditions. Accurate mapping surface water resources during drought and drought-recovery enable water resource managers and policy makers to better mitigate the impact of water shortages across the drought-prone areas such as the Awash River Basin. Surface water mapping generated by the APWC technique is one way to provide these critical data.

Changing land use and climate conditions are modifying the distribution of surface and underground water storage in West Africa (Descroix et al 2009, Mahé et al 2013). The region experienced a severe drought from 1970 to 1990 (Mahé et al 2001, Nicholson 1980, Hunt 2000). The hydrological response to the drought varied by ecoregion. Despite experiencing a 30% precipitation deficit during the drought, streamflow increased in West African Sahelian rivers (Leblanc et al 2008, Mahé and Paturel 2009, Mahé et al 2013, Gardelle et al 2009). Sahelian streamflow is driven by overland flow (Séguis et al 2004, Casenave and Valentin 1992). Land clearance from agricultural development has caused soil crusting, resulting in less pervious surfaces and increased runoff in the Sahelian region, and explaining the paradox of increased streamflow during a period of drought (Leblanc et al 2008, Mahé and Paturel 2009, Mahé et al 2013, Gardelle et al 2009). Conversely, runoff in the West African Sudanian region substantially decreased during the drought (Mahé et al 2013). For example, the upper Ouémé catchment in Benin experienced a 40% deficit in streamflow under 15-20% rainfall deficits (Lebel and Ali 2009). Other areas experienced up to 60% streamflow deficits (Mahé and Olivry 1999). Infiltration-driven subsurface flow is important to streamflow in Sudanian rivers (Séguis et al 2011b, Hector et al 2015). Reduced baseflow due to the lower groundwater table under drought conditions partially explains the reduction in streamflow (Mahé 2009). Seasonal perched groundwater has also shown to be an important contribution to streamflow in Sudanian
rivers (Séguis et al 2011b, Hector et al 2015). However, the hydrology of Sudanian ecoregion is not yet fully understood (Descroix et al 2009).

Modification of surface, vadose, and aquifer water content causes displacements at the ground surface via changes to fluid pressure, moisture content, and vertical loading. Interferometry of synthetic aperture radar (InSAR) using satellite data is increasingly being used to measure surface deformation because of its precision, spatial coverage, and cost efficiency (Castellazzi et al 2016a). InSAR methods have been used to detect millimeter to centimeter precision changes in elevation between SAR acquisitions (Galloway and Hoffmann 2007). The overarching goal of this study is to better understand hydrologic processes in the Ara Watershed under changing climate and land use conditions. The study area has been studied by the African Monsoon Multidisciplinary Analysis - Coupling the Tropical Atmosphere and the Hydrological Cycle (AMMA-CATCH) observatory (AMMA-CATCH 1990) since 2002. However, only small portions have been extensively instrumented. InSAR methods were developed to map the dynamics of seasonal deformation across the watershed. The deformation anomaly dataset was analyzed in the context of the in-situ data collected by the AMMA-CATCH observatory and previous work at the study area (e.g., (Séguis et al 2011b, Descloitres et al 2011, Hector et al 2015, Vouillamoz et al 2015) to answer the research questions: 1) What are the physical processes driving the spatial and temporal trends in surface deformation? and 2) How does the new data augment the existing site data to refine the current understanding of site geology and hydrology?
CHAPTER 2
RECENT BARK BEETLE OUTBREAKS HAVE LITTLE IMPACT ON STREAMFLOW IN THE WESTERN UNITED STATES

Modified from a manuscript published in Environmental Research Letters¹

Kimberly Slinski²,³, Terri Hogue², Aaron Porter⁴, and John McCray²

Abstract

In the Western United States (US), the current mountain pine beetle (MPB; Dendroctonus ponderosae) epidemic has affected more than five million hectares since its start in 1996, including headwater catchments that supply water to much of the Western US. There is widespread concern that the hydrologic consequences of the extensive pine tree die-off will impact water supply across the Western US. While forest disturbance studies have shown that streamflow increases in response to tree harvest, the actual effect of bark beetle infestations on water supply remains widely debated. The current study evaluates watershed-level response following bark beetle outbreak for 33 watersheds in seven western states. Streamflow records were investigated to assess whether the timing and amount of stream discharge during bark beetle outbreak and early recovery periods were significantly different to pre-outbreak conditions. Results show no significant modification in peak flows or average daily streamflow following bark beetle infestation, and that climate variability may be a stronger driver of streamflow patterns and snowmelt timing than chronic forest disturbance.

2.1 Introduction

Watersheds in the Western United States (US) are undergoing unprecedented levels of tree die-off due to wildfire, drought, and insect outbreaks (Williams et al 2010, Anderegg et al 2012, Adams et al 2012). Bark beetle outbreaks are typically endemic, causing minimal impact to catchment areas. However, the ongoing mountain pine beetle (MPB; Dendroctonus ponderosae,) epidemic has affected conifer forests at historic levels (Raffa et al 2008). Over 6

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million forested hectares in the US and British Columbia have been impacted by bark beetles, with more than 5 million hectares affected by the MPB outbreak alone (Meddens et al 2012). This includes headwater catchments to the Colorado, Arkansas, Rio Grande, and Missouri Rivers. Many species of bark beetle introduce blue-stain fungi into the tree xylem, which inhibits water flow (Paine et al 1997). The interruption of transpiration in MPB-attacked pine trees occurs in weeks to months (Hubbard et al 2013) ultimately leading to tree mortality (Edburg et al 2012). This is termed the “green phase” of the attack. Frank et al (2014) hypothesize that mortality takes longer in spruce forests because, unlike pine trees, spruce trees can survive without tightly coupling stomatal conductance to plant hydraulics. The needles on the MPB-attacked tree change from green to red during the year following the attack (termed the “red phase”), eventually falling off within three to four years following attack and the tree appears gray (Edburg et al 2012, Wulder et al 2006).

Alterations to watershed vegetation can have a profound impact on the forest hydrology (Brown et al 2005, Adams et al 2012). An extensive body of literature exists on the hydrological consequences of tree harvest and has been used to predict the impact of bark beetle outbreaks on water resources (Edburg et al 2012, Adams et al 2012). Review of paired watershed studies by Brown et al (2005) and Stednick (1996) concludes that deforestation leads to an initial increase in streamflow due to reduced interception and transpiration and increased baseflow, with a more intense impact observed in wetter regions. The water yield increase is reduced as regrowth occurs and the streamflow eventually returns to pre-harvest conditions (Brown et al 2005, Adams et al 2012). Canopy reduction decreases intercepted snow while also increasing through-canopy solar radiation, leading to higher snow accumulation in tree harvest areas and earlier, faster snowmelt (Jost et al 2007, Varhola et al 2010). However, the progressive reduction in forest canopy due to bark beetle outbreaks is different from forest harvest disturbance in that it occurs gradually and does not cause the complete removal of understory vegetation and canopy or directly impact non-host trees, muting the disturbance signal and making it challenging to predict the impact of widespread bark beetle infestation on watershed hydrology (Adams et al 2012, Mikkelson et al 2013).

The literature supporting hydrologic change resulting from bark beetle outbreak is limited and conflicting. While early watershed studies by Potts (1984) and Bethlahmy (1974) report increased streamflow, more recent paired watershed studies found highly variable streamflow...
modification (Stednick and Jenson 2007, Somor 2010) or no impact to streamflow (Biederman et al 2015) following bark beetle outbreak. Increased baseflow was reported by Bearup et al (2014) and remote sensing based studies report reduced MODIS-based evapotranspiration following bark beetle attack (Bright et al 2013, Maness et al 2013, Vanderhoof and Williams 2015). In contrast, several recent studies using eddy-covariance methods found that increased evapotranspiration by understory, secondary structure, and surviving canopy vegetation and the soil offset reductions due to tree mortality (Biederman et al 2014b, Brown et al 2014, Reed et al 2014).

The results of snowpack studies are also inconsistent. While several stand-level studies report increased snow water equivalent in the snowpack under gray phase forests (Boon 2007, 2012, Pugh and Small 2012, 2013), Boon (2012) found this effect was diminished during high snow years due to the ability of large snowfall to exceed the interception capacity of the canopy. Pugh and Small (2012) found earlier spring snowmelt in red and gray phase forests in Colorado. Biederman et al (2014a) found that increased snowpack sublimation compensated for decreased canopy sublimation, resulting in no net change to snow water equivalent in gray phase forests. Recent literature suggests that the hydrologic response to bark beetle infestation is complex and dependent not only on tree mortality, but on ecosystem response to tree die-off, physical characteristics of the watershed, and regional climate.

The limited number and scale (stand or hillslope) of recent studies make it difficult to predict streamflow response to beetle infestation at larger, watershed scales, where water resource managers are tasked with critical decision-making. In addition, there is a paucity of literature that considers the hydrologic response of more than a few watersheds. The current study evaluates the streamflow and baseflow response of 33 watersheds in seven western states using a several hydrologic metrics, including timing and amount of peak flows and daily streamflow statistics. Watershed statistics after bark beetle outbreak were compared to pre-infestation conditions to answer the question: to what degree is the timing and amount of watershed discharge across the Western US modified by bark beetle infestation?
2.2 Data Collection and Methods

2.2.1 Study Area Description

Spatial data identifying areas of bark beetle infestation in the contiguous Western US from 1997-2014 were obtained from the United States Forest Service Insect and Disease Detection Survey database (USDA Forest Service, Forest Health Protection and its partners 2015). The spatial data is based on aerial detection surveys (ADSs) conducted by the USDA. Accuracy assessments of ADSs data collected in USDA Forest Service Rocky Mountain Region compared to ground reference points show >70% accuracy at a 500-m scale, indicating that ADS data are appropriate for assessing forest disturbance at coarse scales (Johnson and Ross 2008). The tree mortality data contained in the ADS database were not used in this study because they

Figure 2.1 Locations of the 33 catchment areas included in this study are shown in red. Areas of MPB and/or spruce beetle infestation identified by the 1997-2014 ADSs are indicated by gray shading.
have been shown to be inaccurate (Meddens et al. 2012). Tree mortality estimates may be obtained using high resolution satellite imagery [e.g., as shown by Meddens et al. (2012)]; however, it was not feasible to obtain these data products over all 33 watersheds included in this study. The ADS data were intersected with watershed boundaries from the GAGES II: Geospatial Attributes of Gages for Evaluating Streamflow dataset (GAGES II; Falcone 2011, Falcone et al. 2010) to derive a time series of annual percent watershed area impacted by the MPB and spruce beetle (Dendroctonus rufipennis) for the catchment area of each GAGES II reference gage. The GAGES II reference gages are U.S. Geological Survey (USGS) stream gages considered to have minimal regulation in their contribution catchments.

Watersheds were included in this study if 15% or more of their area was impacted by MPB and/or spruce beetle during at least one year between 1997 and 2014. This resulted in 33 watersheds (shown on figure 2.1) for the analyses. The cumulative area impacted since 1997 ranged from 21% to 90% of the total watershed area, with five watersheds having greater than 75% area impacted, 13 watersheds having between 50% and 75% area impacted, and 15 watersheds having between 21% and 50% area impacted. Dominant forest types in the bark beetle-impacted area, identified by the National Atlas of the United States (2002), are: lodgepole pine (Pinus contorta; 14 watersheds), ponderosa pine (Pinus ponderosa; eight watersheds), fir-spruce (mixed species; ten watersheds), and Douglas fir (Pseudotsuga menziesii; one watershed). Catchment size ranged from 15.5 to 3,355 square kilometers. The portion of precipitation falling as snow ranged from 20.5% to 72.3% (Falcone 2011).

2.2.2 Identification of Infection Periods and other Impacts to the Study Area

The ADS-derived time series of bark beetle impact were used to delineate three infestation periods for each watershed: (i) a pre-infestation phase representing the period prior to the bark beetle outbreak in the watershed; (ii) a mixed/red phase representing the period of most intense bark beetle infestation; and (iii) an early gray phase representing the early recovery period after the bark beetle outbreak. The mixed/red phase period was defined as the period inclusive of the first and last year where the ADSs indicate that MPB and/or spruce beetle impacted 15% or more of the watershed area. This is considered a mixed outbreak phase because the watershed includes trees in the green, red, and gray phases during this period. Because the ADSs data identify ongoing bark beetle infestation by the red foliage signature, the
green phase is missed by the surveys and the gray phase is not recorded (Ciesla 2000). The early gray phase period was inferred from the ADS data as the five years immediately after the last year of the mixed/red phase period. The year immediately prior to the first year of the mixed/red phase period was considered to be the first year of the bark beetle attack (green phase) and was not included in the pre-outbreak period. Outbreak periods with gaps in the mixed/red phase period where the bark beetle-impacted area dropped below 15% were considered separate outbreaks if they included two or more consecutive years. This study did not include data collected during the second outbreak.

This study considers the watershed impact of the MPB and spruce beetle outbreaks together because these infestations tend to occur concurrently within western watersheds, though sometimes at a lagged timescale, based on our analysis of the ADSs data. The ADSs database indicates that some watersheds were impacted by other bark beetles (primarily the Douglas fir beetle \textit{[Dendroctonus pseudotsugae]}, western balsam beetle \textit{[Dryocoetes confuses]}, and fir engraver beetle \textit{[Scolytus ventralis]} during the red/mixed phase period, but not at levels above 10% areal impact prior to the outbreak phases or during the early grey phase periods. The maximum area burned in any watershed is less than 7% of the total watershed area.

2.2.3 Streamflow Data

Time series of mean daily discharge and peak instantaneous flow data for the USGS gages corresponding to the 33 study area catchments were obtained from the USGS (USGS 2015) for water years (WYs) 1970-2014 (the water year begins on October 1). The streamflow dataset includes a complete hydrologic record for seven or more water years prior to the green phase period of each study area watershed, as well as a complete hydrologic record for the red/mixed phase periods. Streamflow data is available for the complete early gray phase period for 20 of the 33 study area watersheds. A shorter period of record is available for the early gray phase of the 13 remaining watersheds due to late onset of the outbreak or the presence of a second outbreak.

2.2.4 Climate Data

Temperature and precipitation data for the contiguous Western US for WYs 1970-2014 were obtained from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) database at a spatial resolution of approximately 4-km (Daly \textit{et al} 2008, PRISM Climate Group,
Oregon State University 2015). Time series of mean monthly temperature and total monthly precipitation depth for each watershed were derived from the gridded data.

2.2.5 Streamflow and Climate Statistics

Statistics describing streamflow distribution, magnitude, high flows, low flows, and baseflow were implemented in R (R Core Team 2015) on a WY basis. The magnitude and distribution of streamflow discharge were described by the minimum (min), maximum (max), mean, and median 1-day mean daily discharge statistics and by total annual discharge (discharge). Three statistics were used to describe high flows: timing of the center of mass of the annual flow (CT), peak flow (peak), and water year day of the peak flow (peak day). CT was calculated from mean daily streamflow data as described by (Stewart et al. 2005) as follows:

\[ CT = \frac{\sum(t_i q_i)}{\sum(q_i)} \]

where \( t_i \) is time in days corresponding to the WY day (October 1 is day one of the WY), and \( q_i \) is the corresponding mean daily flow measurement. As snowmelt runoff is the largest contribution to streamflow in snow-dominated watersheds, CT may be used as a proxy for the timing of the snowmelt pulse (Stewart et al. 2005). Peak flow and peak day were determined from the peak instantaneous flow dataset. For the purposes of this study, peak day is defined as the water year day during which the instantaneous peak flow occurred. Low flows were described by the annual minimum of the 7-day moving average of the mean daily discharge (7-day min). Summer-fall baseflow (BF) was calculated from the mean daily streamflow dataset following Nathan and McMahon (1990) using the EcoHydRology package (Fuka et al. 2014) in R. A filter parameter of 0.925 and three filter passes were employed for this study, following the recommendations of Nathan and McMahon (1990). Summer-fall baseflow index (BFI) was calculated by dividing the summer-fall baseflow by the total streamflow for the same period. Annual and seasonal climate statistics were calculated for comparison to the streamflow statistics. Total precipitation and mean temperature were calculated on a seasonal and WY basis from the climate datasets for each watershed. In addition, annual runoff ratio was calculated for each watershed.
2.2.6 Change and Trend Detection

The Wilcoxon rank-sum test and Mann-Kendall trend test were used to test for significant differences and trends in streamflow and climate statistics prior to and during the bark beetle outbreaks. These tests are nonparametric and do not require that the data conform to the normal distribution. For this study, \( p \) values <0.05 were considered statistically significant. The Mann-Kendall test was used to test for monotonic increasing or decreasing trends in the streamflow and climate statistics over the entire time series. The Wilcoxon rank-sum test was applied to streamflow and climate statistics for the red/mixed phase and early gray phase periods to test for evidence of significant differences compared to those for the pre-outbreak period. The pre-outbreak period included available climate and streamflow data from WY 1970 until the first year of the bark beetle attack (green phase). No correction for multiple comparisons was made in determining significance due to the conservative nature of these corrections for large numbers of samples.

The Durbin-Watson test found some evidence of serial correlation in the climate and streamflow statistics. Serial correlation increases the probability that the test detects a significant trend (using the Mann-Kendall test) or significant difference (using the Wilcoxon rank sum test) when a one is not actually present (type I error). No correction for serial autocorrelation was made because few significant trends or differences were detected in the hydrologic times series data, as discussed further in the next section. Prewhitening the data following Von Storch (1995) prior to statistical analysis was attempted and found to have little effect on the study findings. Prewhitening resulted in fewer significant differences, but with increased type II error rates (the probability of detecting a significant trends or difference when one is actually present).

2.3 Results and Discussion

Precipitation and temperature data were analyzed for trends over the 35 year period of record and for significant changes after onset of bark beetle outbreak. Wilcoxon rank sum test results (table 1) for mean annual precipitation indicate that there were no significant differences in precipitation in the red/mixed phase and early gray phase periods compared to pre-outbreak years. This is consistent with Chapman et al (2012), who found that the MPB epidemic was triggered during a short, intense drought from 2002-2003 but that rainfall returned to normal levels after 2003. The Mann-Kendall test results (table 1) indicate that a significant decreasing
monotonic precipitation trend over the 35 year period of record (1970-2014) is present in only four of the 33 watersheds. No significant increasing trends were identified. Insignificant trends in precipitation largely follow regional patterns. Total annual precipitation in watersheds located in the Rocky Mountain range decreased over the 35 year record, except for basins in Colorado, while precipitation in the Colorado, Cascadian, and western South Dakota watersheds increased. Similar to other studies (Kunkel et al 2013b, 2013a), a warming trend was observed over the study area. Mann Kendall test results indicate that 26 of the 33 watersheds show evidence of a significant increasing trend in temperature over the 35 year study period. Wilcoxon rank sum test results indicate that mean annual temperature is higher in nearly all watersheds after onset of bark beetle. The increases were significant in seven watersheds for the red/mix phase and in 19 watersheds for the early gray phase.

The Wilcoxon rank sum test results (table 1) indicate that there are few significant changes to discharge statistics following bark beetle outbreak. Changes to daily streamflow statistics (mean, median, min, max, and total discharge) are split nearly evenly between those with higher discharge statistics after onset of bark beetle infestation and those with lower

<table>
<thead>
<tr>
<th>Wilcoxon Rank Sum Test</th>
<th>Wilcoxon Rank Sum Test</th>
<th>Mann-Kendall Trend Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red/Mixed Phase vs. Pre-Onset</td>
<td>Early Gray Phase vs. Pre-Onset</td>
<td>Full Record</td>
</tr>
<tr>
<td>Lower</td>
<td>No Change</td>
<td>Higher</td>
</tr>
<tr>
<td>BF</td>
<td>14</td>
<td>1</td>
</tr>
<tr>
<td>BFI</td>
<td>13 (1)</td>
<td>2</td>
</tr>
<tr>
<td>CT</td>
<td>18</td>
<td>1</td>
</tr>
<tr>
<td>Discharge</td>
<td>15</td>
<td>1</td>
</tr>
<tr>
<td>Peak Day</td>
<td>17 (1)</td>
<td>1</td>
</tr>
<tr>
<td>Max</td>
<td>13</td>
<td>1</td>
</tr>
<tr>
<td>Mean</td>
<td>15</td>
<td>1</td>
</tr>
<tr>
<td>Median</td>
<td>15 (1)</td>
<td>2</td>
</tr>
<tr>
<td>Min</td>
<td>16</td>
<td>--</td>
</tr>
<tr>
<td>7-Day Min</td>
<td>13</td>
<td>1</td>
</tr>
<tr>
<td>Peak</td>
<td>14</td>
<td>1</td>
</tr>
<tr>
<td>Precipitation</td>
<td>20</td>
<td>3</td>
</tr>
<tr>
<td>Runoff Ratio</td>
<td>16</td>
<td>--</td>
</tr>
<tr>
<td>Temp.</td>
<td>--</td>
<td>1</td>
</tr>
</tbody>
</table>
statistics. Results for runoff ratio are also split, generally following the changes to discharge and mean streamflow with few statistically significant changes. The low flow (7-day min) and baseflow (BF and BFI) streamflow statistics do not show consistent patterns of higher or lower values after onset of bark beetle infestation. While our study shows significant trends in earlier peak day in seven watersheds and earlier CT in four watersheds over the 35-year period of record, the Wilcoxon rank sum tests found few significant changes in the high flow (peak day, peak, and CT) streamflow statistics after onset of bark beetle infestation. The insignificant changes in spring melt timing do not suggest a consistent pattern of higher or lower values following bark beetle infestation, and, in some cases, do not follow the 35-year trend.

While forest cover type, percent of watershed area impacted, and percent of precipitation that falls as snow result in a distributional change in the outcome, there are few statistically significant differences in the outcome. The majority of significant changes were detected in watersheds with smaller catchment areas (table 2). The two watersheds with significantly higher discharge, mean, and min statistics during the red/mixed phase concurrently experienced higher precipitation with \( p \)-values around 0.10. Higher precipitation can increase snowpack, which could be further influenced by canopy loss (Boon 2007, 2012, Pugh and Small 2012, 2013). The majority of the significantly higher daily streamflow, low flow, and baseflow statistics are associated with periods of higher precipitation and significantly lower statistics are associated with lower precipitation (table 3). Further, significantly higher peak flows are associated with periods with higher spring precipitation (table 4), significantly higher CT and peak day are associated with periods of lower spring temperature, and significantly lower CT and peak day area associated with periods of higher spring temperature (table 5). This is not surprising, as earlier snowmelt have been linked to increasing temperature trends in the Western US (Stewart et al 2005, Barnett et al 2004, Harpold et al 2012, Clow 2010). These results suggest that the most significant changes in streamflow statistics are likely climate related, rather than due to bark beetle impacts and that these changes are more pronounced in watersheds with smaller catchment areas.

The autocorrelation in the data and the absence of a correction for multiple comparisons in determining significance, discussed in Section 2.6, reinforce this result, as they serve to overestimate the number of significant results in table 1. Similar to results reported by Stednick and Jenson (2007), Somor (2010), and Biedeman et al (2015), this study does not find evidence
Table 2.2 Number of watersheds with lower, higher, and no change in streamflow, as indicated by the Wilcoxon rank sum test results, for two time period comparisons: i) red/mixed phase compared to the pre-onset period (n=33) and ii) early gray phase compared to the pre-onset period (n=32). Results are grouped by total watershed area using the Jenks natural breaks classification method. Numbers of watersheds with significant change ($\alpha=0.05$) are indicated in parentheses.

<table>
<thead>
<tr>
<th>Change in Total Annual Precipitation</th>
<th>15.5-275 km$^2$</th>
<th>315-851 km$^2$</th>
<th>2,120-3,350 km$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Red/Mixed</td>
<td>Early Gray</td>
<td>Red/Mixed</td>
</tr>
<tr>
<td></td>
<td>Lower</td>
<td>No Change</td>
<td>Higher</td>
</tr>
<tr>
<td>CT</td>
<td>11 (0)</td>
<td>--</td>
<td>9 (1)</td>
</tr>
<tr>
<td>Discharge</td>
<td>8 (0)</td>
<td>--</td>
<td>12 (2)</td>
</tr>
<tr>
<td>Peak Day</td>
<td>11 (1)</td>
<td>--</td>
<td>9 (0)</td>
</tr>
<tr>
<td>Max</td>
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<td>--</td>
<td>13 (1)</td>
</tr>
<tr>
<td>Mean</td>
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<td>--</td>
<td>12 (2)</td>
</tr>
<tr>
<td>Median</td>
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<td>1 (0)</td>
<td>10 (2)</td>
</tr>
<tr>
<td>Min</td>
<td>7 (1)</td>
<td>--</td>
<td>9 (1)</td>
</tr>
<tr>
<td>7-Day Min</td>
<td>8 (0)</td>
<td>--</td>
<td>10 (1)</td>
</tr>
<tr>
<td>Runoff Ratio</td>
<td>9 (0)</td>
<td>--</td>
<td>11 (2)</td>
</tr>
</tbody>
</table>

Table 2.3 Number of watersheds with lower, higher, and no change in daily streamflow statistics, as indicated by the Wilcoxon rank sum test results, for two time period comparisons: i) red/mixed phase compared to the pre-onset period (n=33) and ii) early gray phase compared to the pre-onset period (n=32). Results are grouped by change in total annual precipitation over the same period. Numbers of watersheds with significant change ($\alpha=0.05$) are indicated in parentheses.

<table>
<thead>
<tr>
<th>Change in Precipitation</th>
<th>Lower Precipitation</th>
<th>No Change in Precipitation</th>
<th>Higher Precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Red/Mixed</td>
<td>Early Gray</td>
<td>Red/Mixed</td>
</tr>
<tr>
<td></td>
<td>Lower</td>
<td>No Change</td>
<td>Higher</td>
</tr>
<tr>
<td>Discharge</td>
<td>14 (0)</td>
<td>1 (0)</td>
<td>5 (0)</td>
</tr>
<tr>
<td>Max</td>
<td>9 (0)</td>
<td>--</td>
<td>11 (0)</td>
</tr>
<tr>
<td>Mean</td>
<td>14 (0)</td>
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<td>5 (0)</td>
</tr>
<tr>
<td>Median</td>
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<td>1 (0)</td>
<td>7 (0)</td>
</tr>
<tr>
<td>Min</td>
<td>14 (0)</td>
<td>--</td>
<td>6 (0)</td>
</tr>
<tr>
<td>7-Day Min</td>
<td>9 (0)</td>
<td>1 (0)</td>
<td>10 (0)</td>
</tr>
<tr>
<td>Runoff Ratio</td>
<td>13 (0)</td>
<td>--</td>
<td>7 (1)</td>
</tr>
<tr>
<td>BF</td>
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<td>--</td>
<td>9 (0)</td>
</tr>
<tr>
<td>BFI</td>
<td>6 (0)</td>
<td>1 (0)</td>
<td>13 (1)</td>
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</table>
Table 2.4  Number of watersheds with lower, higher, and no change annual instantaneous peak flow, as indicated by the Wilcoxon rank sum test results, for two time period comparisons: i) red/mixed phase compared to the pre-onset period (n=33) and ii) early gray phase compared to the pre-onset period (n=32). Results are grouped by change in spring precipitation over the same period. Numbers of watersheds with significant change ($\alpha=0.05$) are indicated in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Lower Spring Precipitation</th>
<th>No Change in Spring Precipitation</th>
<th>Higher Spring Precipitation</th>
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</thead>
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<td>Red/Mixed</td>
<td>Early Gray</td>
<td>Red/Mixed</td>
</tr>
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<td>No Change</td>
<td>Higher</td>
</tr>
<tr>
<td>Peak</td>
<td>8 (0)</td>
<td>1 (0)</td>
<td>8 (0)</td>
</tr>
</tbody>
</table>

Table 2.5 Number of watersheds with lower, higher, and no change in annual instantaneous peak flow timing, as indicated by the Wilcoxon rank sum test results, for two time period comparisons: i) red/mixed phase compared to the pre-onset period (n=33) and ii) early gray phase compared to the pre-onset period (n=32). Results are grouped by change in spring temperature over the same period. Numbers of watersheds with significant change ($\alpha=0.05$) are indicated in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Lower Spring Temperature</th>
<th>No Change in Spring Temperature</th>
<th>Higher Spring Temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Red/Mixed</td>
<td>Early Gray</td>
<td>Red/Mixed</td>
</tr>
<tr>
<td></td>
<td>Lower</td>
<td>No Change</td>
<td>Higher</td>
</tr>
<tr>
<td>CT</td>
<td>3 (0)</td>
<td>1 (0)</td>
<td>6 (1)</td>
</tr>
<tr>
<td>Peak Day</td>
<td>4 (0)</td>
<td>--</td>
<td>6 (1)</td>
</tr>
<tr>
<td></td>
<td>11 (1)</td>
<td>1 (0)</td>
<td>9 (0)</td>
</tr>
</tbody>
</table>
of consistent increased streamflow or baseflow following bark beetle disturbance. Instead, the results suggest that the post-outbreak streamflow statistics generally fall within the range of the pre-outbreak variability.

2.4 Conclusions

The current bark beetle infestations in the Western US were predicted to modify watershed hydrology, assuming the reduced transpiration and interception of the attacked trees would increase stream discharge and the reduction in forest canopy would lead to higher peak flows and earlier snowmelt timing (Edburg et al 2012, Mikkelson et al 2013). While bark beetles immediately and severely reduce the transpiration of the attacked tree, there is a growing body of empirical evidence indicating that the excess moisture is utilized by the ecosystem response, resulting in little net impact to discharge (Biederman et al 2014b, Brown et al 2014, Reed et al 2014). In addition, canopy reduction has been shown to have inconsistent impact on snow water equivalent in the snow pack and on snowmelt timing (Boon 2012, Harpold et al 2015). Our results show no significant change in daily streamflow statistics, peak flow, or snowmelt timing relative to the current bark beetle outbreaks. Climate variability may be a stronger driver of streamflow patterns and snowmelt timing than chronic forest disturbance, as post-outbreak flows generally fall within the range of the pre-outbreak variability. The impact of bark beetles on water quality, however, remains an open question (Mikkelson et al 2013). This work expands upon previous stand- and plot-scale findings to the watershed scale, providing more evidence that the current bark beetle outbreak is not significantly altering streamflow hydrology across western US watersheds.

Acknowledgements

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CHAPTER 3
ACTIVE-PASSIVE SURFACE WATER CLASSIFICATION: A NEW METHOD FOR HIGH RESOLUTION MONITORING OF SURFACE WATER DYNAMICS

Modified from a manuscript in preparation for publication
Kimberly M. Slinski\textsuperscript{5,6}, Terri S. Hogue\textsuperscript{5}, and John E. McCray\textsuperscript{5}

Abstract

This study develops a new method to produce accurate, high-resolution maps of waterbody dynamics. Cloud-based computing resources and machine learning techniques are used to merge Sentinel 1 synthetic aperture radar and Landsat observations to generate monthly waterbody maps at a 10-meter resolution. Merging data from two sensor types reduces the impact of errors associated with each individual sensor. The accuracy of this method is shown to be comparable to waterbody map products generated by high performance computing resources. The technique is demonstrated by mapping surface water change over the Awash River basin in Ethiopia during the 2015 regional drought. Results indicate that the downstream sub-catchments were most strongly impacted by drought and that surface water in all catchments recovered to pre-drought surface water area after the 2016 summer rains. The mapping illustrates the acute impact the drought had on surface water area, but this study could not determine surface water volume because measurements of the change in water body depth are not available. The upcoming Surface Water and Ocean Topography (SWOT) mission will provide global satellite altimetry measurements of water levels. The APWC technique combined with SWOT measurements of water elevation will be a powerful tool for monitoring changes in surface water volume in data-sparse regions. To our knowledge, our study is the first to merge passive and active sensors to generate waterbody maps and the first to create waterbody maps at a 10-meter resolution. This technique will help earth scientists better monitor and understand the impact of environmental changes on global freshwater ecosystems.

3.1 Introduction

Surface water is essential for human wellbeing and ecosystem function. Inland surface water is critical for human health and livelihoods (Costanza et al 1997, Finlayson et al 2005) as

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well as high-level biodiversity (Gardner et al 2015). Surface water is also important to climate regulation via the land-atmosphere interactions in the water, energy, and carbon cycles (Raymond et al 2013, Tranvik et al 2009). Small waterbodies, in particular, provide critical ecological habitat and are important to buffer climate variability; they provide habitat for highly specialized plant and animal communities (Zedler 2003, Leibowitz 2003), as well as nesting for migratory waterbirds (Dodman and Diagana 2006). Carbon dioxide and methane emissions from small lakes and ponds also play a disproportionately important role in the global carbon cycle (Holgerson and Raymond 2016, Downing 2010). Climate change, land-use change, and other environmental changes affect the extent of inland water bodies. High resolution monitoring of surface water occurrence and persistence is critical to understanding the impact of environmental changes on freshwater ecosystems and modeling future change. However, only a very small proportion of global lakes and ponds are systematically monitored (Palmer et al 2015).

Satellite remote sensing techniques using passive and active sensors have long been recognized as a viable approach to monitoring surface water dynamics, particularly in data-sparse regions (Palmer et al 2015, Bukata 2013). Multispectral data from NASA’s Landsat and Moderate Resolution Imaging Spectoradiometer (MODIS) missions and the commercial Satellite Pour l’Observation de la Terre (SPOT) mission have been used to create global and continental-scale maps of surface waterbodies (e.g., Yamazaki et al 2015, Mueller et al 2016, Pekel et al 2016, Carroll et al 2016, Haas et al 2009). Synthetic aperture radar (SAR) data from active microwave sensors have been used to generate high temporal and spatial resolution time series of flood extent (e.g., Schumann et al 2011, Pulvirenti et al 2011) and wetlands inundation (e.g., Rebelo et al 2012, Lang et al 2008, Bourgeau-Chavez et al 2005). These remotely-sensed datasets provide critical information for earth science studies. However, sensor and methodological limitations as well as data storage and processing capacity hinder the automated generation of high resolution single sensor waterbody maps.

Passive sensors are limited by their daylight-only application and inability to penetrate cloud cover and vegetation. In addition, Landsat 7 data collected since May, 2003 is affected by the failure of the scan-line corrector (SLC), which results in approximately 22% of each scene to be lost (Scaramuzza and Barsi 2005). Shadows from clouds, terrain features, and infrastructure maybe incorrectly classified as water. Differences in the spectral properties of water bodies caused by turbidity, chlorophyll concentration, as well as waterbody depth and bottom material
further complicate water classification (Grimaldi et al 2016, Bhardwaj et al 2015, Anon 1995). Complex water classification algorithms have been developed in an effort to overcome these limitations (notably, Mueller et al 2016, Pekel et al 2016), however these algorithms require large amounts of data storage and computational time (e.g., Pekel et al (2016) reports storing 1,823 terabytes of data). Further, these algorithms were unable to overcome sensor limitations that cause missing data (i.e., clouds and the SLC error) or to resolve waterbodies at a sub-pixel resolution.

SAR instruments have several advantages over passive sensors: they are substantially less impacted by atmospheric conditions; collect data during the day and night; and penetrate clouds (Grimaldi et al 2016, Schumann and Moller 2015, Oliver 2004). SAR data is also available at higher spatial resolution than Landsat imagery. SAR methods classify water based on phase coherence and/or return amplitude (Refice et al 2018, Zhou et al 2009). Amplitude methods are the simpler of the two methods. However, roads, sand, and other highly reflective surfaces may be incorrectly classified as water. Further, waterbody surfaces roughened by wind, floating vegetation, or other factors will scatter the signal and may be incorrectly identified as non-water. Speckle is also a major source of error in SAR images (Grimaldi et al 2016, Schumann and Moller 2015, Oliver 2004, Refice et al 2018). Coherence-based methods are not subject to these errors, except for speckle, but require substantial data storage and computation time and, to-date, have not been implemented over large areas and time periods (Refice et al 2018). Mapping surface water by merging data from SAR and Landsat acquisitions reduces the impact of errors associated with each individual sensor.

The current study was motivated by the need to develop accurate, high resolution maps of waterbody dynamics using methods that do not require substantial data storage and computation time. The overall objective is to generate a time series of accurate, high resolution waterbody maps using simple automated methods that are reproducible using publicly available tools. We leverage Google Earth Engine (GEE; Google Earth Engine Team 2015) cloud-based computing resources and machine learning techniques to merge observations from SAR and Landsat acquisitions and generate monthly waterbody maps at a 10-meter resolution. This active-passive surface water classification (APWC) method is tested by generating a monthly waterbody maps over the Awash River basin (Figure 3.1) depicting basin surface water dynamics from October 2014 to March 2017. The current work answers the following research questions: 1) What was
the impact of the 2015 drought on surface water resources in the Awash Basin? and 2) Has surface water recovered to pre-drought conditions? To our knowledge, this study is the first to merge passive and active sensors to generate waterbody maps, and the first to create waterbody maps at a 10-meter resolution.

3.2 Study Area

The APWC method was applied across the drought-prone Awash River basin (Figure 3.1), an 110,000 square kilometer endorheic basin located in northeastern Ethiopia. The headwaters of the Awash River are in the Ethiopian highlands at an elevation of approximately 3000 meters (m) above mean sea level (msl). The Awash River flows through the Rift Valley and terminates in Lake Abhe (Figure 3.1), a saltwater lake on Ethiopia-Djibouti border at approximately 250 m above msl. The basin is commonly divided into the six catchments shown on Figure 3.1 (e.g., Awash Basin Authority 2017). Major fresh water features in the basin include reservoirs in the Koko, Helledebi, and Terminal catchments; as well as Lake Caddabass and the Gewane Lake/Swamp complex, located in the Hellidebi and Aditu catchments (Figure 3.1; Hughes and Hughes 1992, FAO 2016). Characteristic of the Rift Valley, the Awash River basin contains several saltwater lakes. The largest are located in the Terminal and Eastern catchments (Schagerl 2016, Hughes and Hughes 1992). This study focuses on changes to freshwater resources, thus major saltwater bodies (shown on Figure 3.1) were excluded from the analysis.

The Awash River basin is characterized by a humid climate at its headwaters and an arid and semi-arid climate in the Rift Valley and lower basin. The region is subject to recurring droughts (Belayneh et al 2014, Edossa et al 2010, Hailemariam 1999). Tropical Rainfall Measurement Mission (TRMM) observations of mean annual precipitation range from approximately 1,500 mm in the highland areas to trace amounts in the desert areas in the northeastern parts of the basin (TRMM 2011). The rainfall pattern is bimodal with two rainy seasons and two dry seasons. The most important rainy season is in July-August-September, during the summer, and the second is in March-April-May, during the spring (Nicholson 2016, Liebmann et al 2014) (Figure 3.2.A). Rainfall in East Africa is influenced by the El Niño-Southern Oscillation (ENSO) and Indian Ocean dipole (IOD) large-scale climate modes. El Niño conditions are associated with failure of summer rains (Lyon 2014). Drought has been
Figure 3.1 This map shows the Awash study area and catchments, with saltwater areas excluded from the study in green. Surface water occurrence is shown by the color key. 100% occurrence indicates that surface water was detected for all study months. Basemap source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community.

more prevalent during the last 15 years in the Awash River basin than in previous years (Figure 3.2.B), similar to conditions reported across East Africa (e.g., Nicholson 2016, Lyon 2014)). The 2015/2016 drought conditions over the Awash River basin correspond with lower than average spring and summer rains during 2015 (Figure 3.2.C). Higher than average spring rains in 2016 (Figure 3.2.C) correspond to a short recovery from drought conditions during mid-2016 (Figure 3.2.B). Our analysis covers the 30-month period from October 2014 to March 2017, covering the 2015 drought and 2016 recovery.

Prior to the 1960s, the Awash River basin was used by seminomadic pastoralists as rangeland, and for small-scale, rainfed agriculture. Dam construction during the 1960s led to the transition of riverine areas to irrigation agriculture and the establishment of sugar and cotton plantations (Kloos 1982, Behnke and Kerven 2011). Major dams include the Koko hydroelectric dam and Tendaho irrigation dam (FAO 2016). Though the Awash basin is considered one of the
most developed in Ethiopia (Mersha et al 2015), with an estimated 78% of the total surface water diverted for irrigation (Berhe et al 2013), rainfed agriculture and pastoralism are still important, particularly in region below the Koko hydroelectric dam (Behnke and Kerven 2011, Abule et al 2005, Ola-Adams and Okali 2008, Kloos 1982). The 2015 drought in Ethiopia had severe impacts on agriculture, health, and livelihoods in the Awash River Basin (Government of Ethiopia and Humanitarian Partners 2016). The reduction of water in rivers and lakes greatly reduced irrigation levels during 2015, with irrigation-based crops failing completely in some areas (Government of Ethiopia and Humanitarian Partners 2015). The drought severely impacted water availability leading to shortages for household use and for watering livestock (Government of Ethiopia and Humanitarian Partners 2015). Accurate mapping of surface water resources during drought and drought-recovery enables water resource managers and policy makers to better mitigate the impact of water shortages across drought-prone areas such as the Awash River Basin. In-situ measurements of surface water extent are sparse across this region; mapping generated by the APWC technique is one way to provide these critical data.

3.3 Data

High resolution (10-meter) Sentinel 1A and 1B ground range detected (GRD) data were obtained from the GEE data collections (Google Earth Engine Team 2015) across the study area from October 1, 2014 to March 31, 2017. The satellites are in a sun-synchronous, near-polar orbit, with a 12-day repeat cycle. GRD images are focused SAR data that have been detected, multi-looked, orthorectified, and geo-referenced. Pixel values represent the amplitude of the detected SAR signal (Torres et al 2012, Google Earth Engine Team 2015). VV polarization data was used because it has been shown to perform slightly better at detecting water than VH polarization (Twele et al 2016) and because substantially more VV scenes are available for the study area. The SAR dataset includes 1,389 GRD scenes from 14 orbital paths (descending and ascending orbits), covering the entire study area at least once each month.

Landsat 7 Enhances Thematic Mapper-plus and Landsat 8 Operational Land Imager data were obtained from the GEE data collections (Google Earth Engine Team 2015). The satellites are in a sun-synchronous, near-polar orbit, with a 16-day repeat cycle and provide 30-meter resolution data. Calibrated, orthorectified Landsat 7 and 8 surface reflectance scenes were utilized. These data are calibrated to top of atmosphere radiance and atmospherically corrected
Figure 3.2 Historical precipitation observed over the Awash River basin from the Global Precipitation Climatology Project (GPCP) version 2.3 mean monthly precipitation dataset (Adler et al. 2003) for January 1979 through March 2017. Panel A shows boxplots of the mean monthly precipitation intensity over the Awash River basin. Panel B shows the 12-month standard precipitation index calculated following AghaKouchak (2015). Panel C shows departures from mean monthly precipitation over the time period covered by this study. GPCP Precipitation and ENSO data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from the web site at http://www.esrl.noaa.gov/psd/.
to surface radiance using Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS; Landsat 7) and Landsat Surface Reflectance Code (LsSRC; Landsat 8) (Google Earth Engine Team 2015, USGS 2017a, 2017b). Landsat 7 data collected since May, 2003 are affected by the failure of the SLC, which caused approximately 22% of each scene to be lost (Scaramuzza and Barsi 2005). Clouds and cloud shadows were masked from each image using the CFMask band (USGS 2017a, 2017b). The Landsat dataset includes all available acquisitions from August 1, 2014 to March 31, 2017, a total of 1429 scenes from six orbital paths. The dataset covers the entire study area at least once each month, but includes some gaps due to clouds, cloud shadows, and the SLC error.

3.4 The Active-Passive Surface Water Classification Method

The following steps were used to delineate surface water and non-surface water areas: 1) calculation of a water index image for each Landsat scene; 2) generation of a 30-day median composite SAR and Landsat images; and 3) merging of the SAR and Landsat images and perform k-means cluster analysis to water and non-water zones. This process generated time series of 10-meter resolution monthly maps with zones given one of three possible labels: water, non-water, and no data (included in Appendix A).

The modified normalized difference water index (MNDWI; Xu 2006) was used to index water in the Landsat. The MNDWI is calculated as: $\text{MNDWI} = (G - \text{SWIR1})/(G + \text{SWIR1})$; where G is the green band and SWIR1 is the shortwave-infrared 1 spectral band. This index ranges from -1 to 1. Positive values are associated with surface water areas and negative values with terrestrial areas. The MNDWI was selected over the normalized difference water index (NDWI; McFeeters 1996) and the automated water extraction index (AWEI; Feyisa et al 2014) due to its performance (described further in Section 3.5).

Image compositing was used to generate a single image for each month that best represents the ensemble of acquisitions over that month. The median composite approach was selected because it is computationally efficient and the median is a robust estimator with well-understood behavior (Huber 2011). A median composite SAR image was generated for each month by selecting all Sentinel 1 SAR scenes collected +/- 15 days of the 15th of each month and calculating the median GRD value at each pixel. The same method was used to generate median composite MNDWI image was generated for each month. However, no-data pixels were present.
in many MNDWI composites due to cloud cover and other errors present in the Landsat images. A conservative, sequential approach was used to fill these gaps while minimizing the impact of artifacts introduced by the process. First, an attempt was made to fill the gaps using the median composite of all images collected during the same month for 2014-2017. In most areas, this was sufficient to fill missing data. An attempt was made to fill the remaining gaps using the median composite of all images collected during a three-month period for 2014-2017. This filled in the missing data in nearly all areas. The remaining gaps were labeled as no-data pixels.

The monthly SAR and MNDWI composite images were combined in GEE and classified using K-means clustering (Caliński and Harabasz 1974), an unsupervised classification method. K-means clustering partitions data into clusters by minimizing the variance within each cluster. The SAR and MNDWI composite images were projected to a 10-meter resolution grid in the maps Mercator (EPSG: 3857) coordinate system and combined to generate a single image with two bands for each month (band 1 is the SAR composite and band 2 is the MNDWI composite). Raster cells were resampled using the nearest-neighbor method. The raster cells for each monthly image were partitioned into 20 clusters using the K-means clustering method, with one cluster corresponding to surface water bodies. The zones corresponding with the cluster ID water were labeled as water. The remaining unlabeled areas were identified as non-water. Results of each classification step over an example waterbody, and the final classification output are shown in Figure 3.3. This process resulted in a monthly time series of 10-meter resolution maps, where study area zones were given one of three labels: water, non-water, or no data (these maps are included in Appendix A). In addition, a freshwater occurrence map was generated by calculating the percent of total time steps that water was detected in each pixel (Figure 3.1.A).

3.5 Classification Accuracy Assessment Results

Stratified random sampling methods were used to assess errors of omission (areas with water incorrectly classified as non-water) and errors of commission (areas without water incorrectly classified as water). The accuracy assessment was conducted in two phases. The first phase consisted of an automated screen of the NDWI, MNDWI, and AWEI APWC results to determine which index performed best at classifying water and non-water areas. The global surface water occurrence maps recently generated by Pekel et al. (2016) were used to identify
Figure 3.3  Illustration of the steps for classifying a small lake in the Awash River basin using K-means clustering. Panels A and B show the MNDWI and SAR composite images, respectively. The dark zone in the two images represents the surface water body. Panel C depicts the cluster results, with the waterbody cluster in dark blue. Panel D shows the final extracted waterbody area in pink overlaid on the MNDWI composite.

Table 3.1  This table lists the results of the water index classification accuracy test. APWC using the AWEI water index has lowest error omission (water areas incorrectly classified as non-water) while APWC using the MNDWI has the lowest error of commission (non-water areas incorrectly classified as water).

<table>
<thead>
<tr>
<th>True Classification</th>
<th>Number of Points</th>
<th>MNDWI</th>
<th>NDWI</th>
<th>AWEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>95% Occurrence</td>
<td>20,000</td>
<td>94.70%</td>
<td>95.40%</td>
<td>98.47%</td>
</tr>
<tr>
<td>0% Occurrence</td>
<td>64,250</td>
<td>0.03%</td>
<td>0.52%</td>
<td>0.14%</td>
</tr>
</tbody>
</table>
study area zones with a high probability of perennial water and zones where there is a high probability that water is never present. Ten thousand random points were selected from freshwater zones where Pekel et al (2016) reported water in 95% of the images (i.e., 95% occurrence) and 64,250 random points were selected from area Pekel et al (2016) reported that water was never detected. Performance of the NDWI, MNDWI, and AWEI APWC results relative to the control points is summarized in Table 3.1. Although the AWEI water index results have the lowest error of omission, the MNDWI water index has the lowest error of commission. The MNDWI was selected based on these results.

The second phase compared the APWC results using the MNDWI to manually classified control points. Because the study area containing surface water is substantially smaller than the non-water zones of the study area, this accuracy assessment focused on surface water-containing areas. The approach follows the accuracy assessment of Pekel et al (2016). A 0.25 degree grid was placed over the study area and random points were selected from each grid cell as follows: one random point was selected in a zone where Pekel et al (2016) detected water in 95% of the images (i.e., 95% occurrence) and one random control point was selected from each grid cell in a pixel that the K-means clustering results classified as water. Landsat, Sentinel 1, and high resolution satellite imagery were used to manually classify each of these control points as “true water” or “true non-water”. A total of 2,456 control points were manually classified. The APWC method errors of omission and commission were found to be 5.98% and 4.38%, respectively.

Classification accuracy assessment methods are not consistent between waterbody map products, making it difficult to compare the reported accuracy between products. However, the APWC accuracy assessment method is similar to that used by Pekel et al (2016). Pekel et al (2016) reports errors of omission and errors of commission as <5% and <1%, respectively. The errors of omission using the merged method are similar to that reported by Pekel et al (2016) while errors of commission are slightly higher. Inspection of these zones show that the primary cause of the errors of commission is the concurrence of layover effects in the SAR image and terrain shadows in the Landsat image.
3.6 Awash River Basin Results

The APWC method was used to generate ten-meter resolution waterbody maps over the Awash River basin for each month from October 2014 through March 2017. A time series of total freshwater area over each catchment was extracted from these maps (Figure 3.4.A). As expected, surface water area was found to be strongly related to basin precipitation and drought status. Surface water area follows seasonal precipitation, with increases in surface water after the spring and summer rainy seasons and declines between these events (Figure 3.4.A). Comparing total monthly surface water to the two-year monthly mean (January 2015 to December 2016; Figure 3.4.B) indicates that total surface water was below average over the 2015/2016 drought period shown previously (Figure 3.3.B), except for a short period after the 2015 summer rains. The recovery of basin surface water area to pre-drought levels corresponds with the heavy rains during spring 2016 and average rains during summer 2016. Surface water area in the lower Awash River catchments (Terminal and Aditu) and the Eastern catchment were more strongly impacted by drought than the upriver catchments. Separating percent average reservoir and non-reservoir surface water (shown on Figures 3.4.C and 3.4.D, respectively) indicates that the Tendaho reservoir (located in the Terminal catchment) was much more impacted by the drought than the upriver reservoirs. This is also seen by comparing surface water occurrence over the Koka and Tendaho reservoirs (Figures 3.5.A and 3.5.B, respectively). The period of maximum non-reservoir freshwater surface area shown on Figure 3.4.C corresponds to the above average 2016 summer rains and the short period of drought recovery shown previously (Figure 3.3.B). As these high surface water periods are generally only present for a single month, they are interpreted as flood inundation events. These areas are shown in yellow on the freshwater occurrence maps in Figures 3.1 and 3.5. Although a two year mean is a limited period for generating percent average surface water for climate impact studies, it is used for this study because a longer time period cannot be generated given data limitations and it covers both drought and inundation events over the study area.
Figure 3.4 This figure shows the evolution of surface water area in the Awash River basin over the study period. Panel A shows precipitation and total surface water area over the basin, separated by catchment. Precipitation is from the Global Precipitation Measurement IMERG monthly precipitation dataset (Huffman et al 2015). Panels B, C, and D show total surface water area, reservoir surface water area, and non-reservoir surface water area, respectively, normalized by mean surface water area for the catchment from January 2015 to December 2016.

Figure 3.5 Surface water occurrence over for the Koka and Tendaho dam reservoirs (Panel A and B, respectively). 100% occurrence indicates that surface water was detected for all study months. Basemap source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community.
3.7 Conclusions and Discussion

The current study presents a novel, automated process that merges Landsat and SAR observations to generate accurate, high-resolution maps of inland freshwater dynamics. The combination of active and passive satellite data reduces the impact of errors associated with classification methods that typically employ a single type of data. The GEE cloud computing and machine learning techniques allow the rapid generation of surface water maps without the high performance computing resources used in other mapping efforts (e.g., Pekel et al 2016, Mueller et al 2016).

The APWC method was used to map surface water change over the Awash River basin over the course of the 2015 regional drought and recovery. The basin was severely impacted by water shortages during the drought. Results indicate that the Terminal, Aditu, and Eastern catchments were most strongly impacted by drought, and that surface water in all catchments recovered to pre-drought surface water area after the 2016 summer rains. The mapping illustrates the acute impact the drought had on surface water area. The change on surface water volume over the course of the drought could not be determined because measurements of the change in water body depth were not available. Measurements of water volume change are critical to developing hydrologic models and monitoring the state of water resources, but are not widely available in data-poor, drought-prone areas like East Africa. The upcoming Surface Water and Ocean Topography (SWOT) mission will provide global satellite altimetry measurements of water levels. The APWC technique combined with SWOT measurements of water elevation could be a powerful tool for measuring changes in surface water volume, providing water managers with the data necessary to monitor the drought impacts on water resources in these regions.

High resolution maps of surface water dynamics will allow water managers and other actors to better target humanitarian response efforts mitigating the impact of the water shortages over the course of the drought and drought recovery. Further, these data may be used to better understand the effects of climate, land-use, and other environmental changes on freshwater ecosystems and the consequent impact on human health and environment. To our knowledge, this study is the first to merge passive and active sensors to generate waterbody maps, and the first to create waterbody maps at a 10-meter resolution. It is anticipated that the APWC
technique will help earth scientists better understand the impact of environmental changes on freshwater ecosystems and inform policy decisions affecting the water, energy, agriculture and other sectors reliant on water resources.

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CHAPTER 4

SEASONAL DYNAMICS OF SURFACE DEFORMATION INDUCED BY THE WEST AFRICAN MONSOON IN SUDANIAN WEST AFRICA

Modified from a manuscript in preparation for publication
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Abstract

West Africa is undergoing unprecedented growth and development. Its population is increasing by 2.75% each year and is expected to double in 25 years. This growth is intensifying pressure on regional and local land water resources while changes in climate and land use are modifying the regional hydrology. The consequential changes to water availability are not fully understood, due in part to the scarcity of in situ data across the region. Satellite remote sensing techniques are increasingly being used to better understand hydrology in data-sparse regions. This study uses interferometry of synthetic aperture radar (InSAR) techniques to map the dynamics of seasonal deformation across the Ara Watershed, a small catchment located in the Sudanian ecoregion in northern Benin. Seasonal deformation was found to be closely linked precipitation from the West African Monsoon. Riparian areas and the seasonally water-logged areas in the headwaters of small streams called bas-fonds in French-speaking West Africa experience larger and more rapid deformations than adjacent upland areas, regions of lateritic covers, and areas where quartzite/quartz dykes have been identified. Two mechanisms are proposed to explain these patterns of deformation. This result may be due to the larger seasonal changes in water mass in the bas-fond and riparian regions as the monsoon precipitation accumulates as perched water and streamflow in these areas and is subsequently removed by evapotranspiration during the dry season. The anomalies could also be explained by shrinkage of the deeper clay layers as the permanent groundwater table continues to recede through the early part of the monsoon. Our results indicate that InSAR methods show promise for being able to identify relative changes in water mass in areas with sparse data coverage. This study is one of the first to study spatial and temporal patterns of surface deformation in the Sudanian ecoregion under the West African Monsoon. It is anticipated that the new methods developed by

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this study may be extended to other areas to better understand the dynamics of water availability in West Africa under changing climate and land use conditions and increasing water demand.

4.1 Introduction

4.1.1 Background

West Africa is undergoing unprecedented growth and development. Its population is growing by 2.75% each year and is expected to double in 25 years (UN Population Division 2015), with a consequential increase in demand for water, food, and energy. Concurrent changes in climate and land use are modifying regional hydrology and the water available to meet this new demand (Descroix et al 2009, Mahé et al 2013). However, data is sparse across the region and its hydrology is not fully understood (Descroix et al 2009). This creates a substantial challenge to policy makers, who must balance finite water resources with the needs of the water, energy, agriculture, fisheries, transport, and other sectors.

Changing land use and climate conditions are modifying the distribution of surface and underground water storage in West Africa (Descroix et al 2009, Mahé et al 2013). The region experienced a severe drought from 1970 to 1990 (Mahé et al 2001, Nicholson 1980, Hunt 2000). The hydrological response to the drought varied by ecoregion. Despite experiencing a 30% precipitation deficit during the drought, streamflow increased in West African Sahelian rivers (Leblanc et al 2008, Mahé and Paturel 2009, Mahé et al 2013, Gardelle et al 2009). Sahelian streamflow is driven by overland flow (Séguis et al 2004, Casenave and Valentin 1992). Land clearance from agricultural development has caused soil crusting, resulting in less pervious surfaces and increased runoff in the Sahelian region, and explaining the paradox of increased streamflow during a period of drought (Leblanc et al 2008, Mahé and Paturel 2009, Mahé et al 2013, Gardelle et al 2009). Conversely, runoff in the West African Sudanian region substantially decreased during the drought (Mahé et al 2013). For example, the upper Ouémé catchment in Benin experienced a 40% deficit in streamflow under 15-20% rainfall deficits (Lebel and Ali 2009). Other areas experienced up to 60% streamflow deficits (Mahé and Olivry 1999). Infiltration-driven subsurface flow is important to streamflow in Sudanian rivers (Séguis et al 2011b, Hector et al 2015). Reduced baseflow due to the lower groundwater table under drought conditions partially explains the reduction in streamflow (Mahé 2009). Seasonal perched water has also shown to be an important contribution to streamflow in Sudanian rivers.
(Séguis et al 2011b, Hector et al 2015). However, the hydrology of Sudanian ecoregion is not yet fully understood (Descroix et al 2009).

Displacement at the ground surface can signify changes in hydrology. One cause of surface displacement is the modification of vertical effective stress. Vertical effective stress is the vertical component of the forces at solid-to-solid contact points (Das 1995). Changes to the distribution of atmospheric, hydrological, and oceanic mass loads cause crustal deformation. Water mass variation is a substantial driver of changes in vertical effective stress. For example, crustal deformations due water mass change have been measured by Global Positioning System (GPS) studies in the Amazon (Moreira et al 2016, Davis 2004), the California Central Valley (Amos et al 2014), and the High Plains Aquifer (Chew and Small 2014). Hydraulic deformation estimated from the Gravity Recovery and Climate Experiment (GRACE) observations are well correlated with GPS in areas with large water mass changes (Tesmer et al 2011, Kusche and Schrama 2005, Tregoning et al 2009). However, hydrologic, atmospheric, and ocean loading models do not explain all of the variability in the GPS data. Small-scale, local hydrologic changes are increasingly being shown to be important drivers of surface displacement (e.g, Nahmani et al 2012). These may be due to small-scale variations in water mass loads, aquifer fluid pressure, moisture content of clays, and/or soil freeze/thaw.

Surface displacement may also be induced by pressure and moisture content changes due to the compressibility of the soil structure, particularly in clays and silts. Pumping lowers fluid-pressure in the aquifer, causing sediments to compact, while recharge increases fluid-pressure, causing aquifer sediments to swell (Fetter 2001). Changes in moisture content induce pressure changes in the unsaturated zone that also cause soils to shrink and swell. Increased moisture content will cause compressible soils to swell and decreased moisture content will cause soils to compact (Fetter 2001, Lu and Likos 2004). Displacement measured at the ground surface may be due to the integrated compaction or swelling of soils resulting from pressure changes in the underlying saturate and unsaturated zones. The relationship between surface deformation and pressure change in the subsurface has been widely used to estimate storage changes in confined aquifers (e.g., Galloway et al 1998, Galloway and Burbey 2011, Chen et al 2016, Castellazzi et al 2016b, Miller and Shirzaei 2015) and, to a lesser extent, to estimate changes in the moisture content of the unsaturated zone (te Brake et al 2013, Kirby et al 2003).
Interferometry of synthetic aperture radar (InSAR) using satellite data is increasingly being used to measure surface deformation because of its precision, spatial coverage, and cost efficiency (Castellazzi et al 2016a). InSAR interprets the phase shift between multiple synthetic aperture radar (SAR) images of the same scene taken at different times. Contributions due to atmospheric effects and the perspective changes from the difference in satellite position between images are removed from the phase analysis. The resulting phase shift map, called an interferogram, represents changes in the line of sight distance between image acquisitions. The interferogram is converted to a map of the change in ground surface elevation (Massonnet and Feigl 1998, Berardino et al 2002). Small baseline subset (SBAS) interferometry techniques estimate the deformation time series by inverting a stack of overlapping interferograms. Deformation is estimated at each time step on a pixel-by-pixel basis (Doin et al 2011, Berardino et al 2002). InSAR methods have been used to detect millimeter to centimeter precision changes in elevation between image acquisitions (Galloway and Hoffmann 2007).

InSAR-derived surface deformation was used to identify spatiotemporal patterns of groundwater depletion and subsequent recovery in Tucson, Arizona from 1993 to 2006 (Kim et al 2015) and in Las Vegas, Nevada from 1992 to 1997 (Amelung et al 1999). Co-located InSAR and hydraulic head measurements have been used to estimate aquifer storage properties including the elastic storage and inelastic skeletal storage coefficients (Miller and Shirzaei 2015, Chen et al 2016). Chen et al (2016) estimated hydraulic head across the San Luis Valley in Colorado using InSAR-derived surface deformation. Recently, InSAR has been combined with mass change observations from the Gravity Recovery and Climate Experiment (GRACE) to estimate groundwater storage loss in Central Mexico (Castellazzi et al 2016b). InSAR has also been used to study surface deformation due changes in clay volume and frost heave in agricultural fields (Brake et al 2013), permafrost thawing (Liu et al 2010), and local hydrologic loading (Doin et al 2015). However, these are among the few studies to use InSAR methods to study seasonal deformation.

The overarching goal of this study is to better understand hydrologic processes in the Ara Watershed (study area, Figure 4.1), located in the Sudanian ecoregion in northern Benin, under changing climate and land use conditions. The study area has been studied by the African Monsoon Multidisciplinary Analysis - Coupling the Tropical Atmosphere and the Hydrological Cycle (AMMA-CATCH) observatory (AMMA-CATCH 1990) since 2002. However, only small
portions have been extensively instrumented. InSAR methods were developed to map the
dynamics of seasonal deformation across the Ara Watershed and determine if small seasonal
surface displacements at the ground surface detectable in the study area using InSAR techniques.
The deformation anomaly dataset was analyzed in the context of the in-situ data collected by the
AMMA-CATCH observatory and previous work at the study area (e.g., Séguis et al 2011b,
Descloitres et al 2011, Hector et al 2015, Vouillamoz et al 2015) to answer the research
questions: 1) What are the physical processes driving the spatial and temporal trends in surface
deformation? and 2) How does the new data augment the existing site data to refine the current
understanding of site geology and hydrology?

This study is one of the first to study spatial and temporal patterns of surface deformation
in the Sudanian ecoregion under the West African Monsoon. The InSAR methods developed by
this study provide new data on the distribution of water storage change across the study area and
site geological structure. It is anticipated that the new methods developed by this study may be
extended to other West African areas to better understand the dynamics of water availability
under changing climate and land use conditions and increasing water demand.

4.2 Study Area

The Ara Watershed (Figure 4.1) is a 12 km² subcatchment of the AMMA-CATCH upper
Ouémé mesoscale site. AMMA-CATCH Observatory (AMMA-CATCH 1990) has collected
critical zone data from stations in this study area since 2002. The watershed is located in the
humid Sudanian ecoregion of northern Benin. The primary land cover is fallow and crop land,
with trees only present along the fringes of the bas-fonds and the riparian areas adjacent to the
Ara River. The bas-fonds are seasonally water-logged areas in the headwaters of first order
streams common to the Sudanian ecoregion. These areas are used for small scale rice or yam
cultivation. The primary geological units are shallow high permeability surficial soil, underlain
by a weathered mantle containing lateritic, saprolite, and low-permeability clayey layers. In
some areas, the mantle is covered by a ferricrete layer (hardpan, or lateritic covers). Basement
rocks are metamorphic, containing gneiss, micaschists, and quartzites
Figure 4.1 Panel A shows the location of the Ara Watershed. Basemap source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community. Panel B shows the Ara watershed features, including the stream network and AMMA-CATCH Observatory monitoring stations. Digital elevation model is from the NASA Shuttle Radar Topography Mission (NASA JPL 2014).

(Hector et al 2015, Vouillamoz et al 2015, Descloitres et al 2011, Séguis et al 2011b). Figures 4.2 and 4.3 show the primary geological units and electrical conductivity of the regolith, respectively, determined by geological and geophysical surveys conducted by Descloitres et al. (2011).

Precipitation follows the West African Monsoon, with a distinct rainy season during the summer through early fall (Figure 4.4). Rainwater percolates quickly through the soil during monsoonal precipitation events due to the high soil permeability (Séguis et al 2011a). This also limits infiltration excess overland flow. The groundwater system consists of a permanent unconfined aquifer in the weathered mantle and temporary perched water (Séguis et al 2011b). The permanent aquifer is fed by direct recharge from rainwater and is thought to be depleted by evapotranspiration processes in riparian zones and forested areas during the dry season (Guyot et al 2012, Descloitres et al 2011, Mamadou et al 2016). The Ara is an ephemeral stream. It is a tributary of the Donga, itself a tributary to the Ouémé. Perched water and the bas-fonds are the main contributors to baseflow (Hector et al 2015, Séguis et al 2011b), with some evidence that the permanent water table contributes to baseflow during high precipitation years (Hector et al 2015).
Figure 4.2 Primary geological units of the Ara watershed (Descloitres et al 2011).

Figure 4.3 Electrical conductivity of the regolith in the Ara watershed estimated from measurements taken along the east-west transects shown in gray (Descloitres et al 2011).
Figure 4.4 Panel A shows monthly precipitation measured at the NALOHOU_1, NALOHOU_2, and NALOHOU_3 gage stations. Panel B shows streamflow by month measured at the PARSHALL station. Panel C shows 20 cm soil moisture by month measured at the NALOHOU_040B, NALOHOU_200M, and NALOHOU_500H stations. Panel D shows groundwater surface elevation by month measured at the NAHP2 station. Station locations are shown on Figure 4.1. Data is from the AMMA-CATCH regional observing system (AMMA-CATCH 1990).
Monthly soil moisture, streamflow, and groundwater levels measured at the AMMA-CATCH Observatory monitoring stations (AMMA-CATCH 1990) located at the study area are shown on Figure 4.4. As shown by these plots, soil moisture and streamflow increase rapidly after the onset of West African Monsoon precipitation. The deeper, permanent groundwater table does not start to rise until a couple of months after onset of the monsoon (Figure 4.8).

4.3 Methods

4.3.1 SAR Data

The study obtained all available single look complex (SLC) images acquired by the Sentinel 1 mission (Torres et al. 2012, ESA 2015) over the study area from May 2015 through December 2017 from the Alaska Satellite Facility (ASF) Distributed Active Archive Centers (DAAC; http://www.asf.alaska.edu/). The Sentinel 1 mission is a two satellite constellation providing global C-band SAR imaging. Sentinel 1A was launched by the European Space Agency (ESA) in April 2014 and Sentinel 1B was launched in April 2016. The satellites are in a sun-synchronous, near-polar orbit, with a 12-day repeat cycle. Sentinel 1B images were not available over the study area. All images were acquired by the Sentinel 1A satellite during its ascending pass. Earlier acquisitions were not used due to inconsistencies in their geographical extent. Later acquisitions were not used because the precise orbit data necessary for InSAR processing were not available at the time of study. The SAR dataset has a 12-day time step, corresponding to the 12-day repeat cycle of the Sentinel 1A orbit. However, acquisitions for some dates are not available due to gaps in the SAR archive. Additional acquisitions were discarded from the study dataset because phase noise caused poor quality interferograms (as described in the next section). The final study dataset consisted of images corresponding to 69 acquisitions (Figure 4.5) over the study area. VV and VH polarization images are available. VV polarization was selected for this study because it is less sensitive to volume backscatter by vegetation.

4.3.2 Interferogram Generation

This study generated Interferograms using the open source (GNU General Public License) Generic Mapping Tools 5 Synthetic Aperture Radar (GMT5SAR) processing system (Sandwell et al. 2016, Massonnet and Feigl 1998). GMT5SAR geometrically aligns Sentinel TOPSAR images to a single master image with centimeter accuracy, maps topography into
Figure 4.5  Network plot of SAR acquisition date verses perpendicular baseline relative to the January 22, 2016 SAR acquisition. Interferogram pairs are linked.

phase, and forms a stack of complex interferograms (Sandwell et al 2016). The Generic Mapping Tools- (GMT-) (Wessel et al 2013) based GMT5SAR postprocesser filters the interferogram and generates phase, coherence, and phase gradient products. GMT5SAR unwraps the interferograms using the well-known snaphu algorithm (Chen and Zebker 2000).

Interferograms may be generated by pairing each geometrically aligned SAR image in the stack with every other image in the stack with the dataset. However, temporal decorrelation increases as the time between SAR acquisitions increases, reducing the quality of the resulting interferogram. Temporal decorrelation is caused by pixel noise created by small-scale disturbances in the scattering surface between the master and slave images, i.e., due to snow, vegetation, farming, construction, etc. The maximum number of days between pairs of SAR acquisitions was chosen to reduce pixel noise, which can be assessed by evaluating local coherence and pixel closure error (Ferretti et al 2007). Local coherence is the cross-correlation coefficient of the interferogram estimated over a small window (i.e., a few pixels in range and azimuth) (Ferretti et al 2007). Closure errors can be assessed by summing the unwrapped interferograms generated for a cycle of SAR acquisition dates (i.e., interferogram [date 1:date 2] + interferogram [date 2:date 3] - interferogram [date 1:date 3]). Figure 4.6 presents the mean coherence and closure error associated with each SAR acquisition date. This figure and the maps of mean local coherence by month and number of days between SAR acquisitions (Appendix C)
show that pixel noise varies by location and time of the year. Coherence during the rainy/growing season (approximately mid-March through October) is substantially lower than the dry season coherence (approximately November through mid-March). Figure 4.6 shows that mean coherence has an inverse relationship with normalized difference vegetation index (NDVI), indicating that vegetation is strong contributor to pixel noise over the Ara study area. The maximum time between interferogram pairs was chosen based on these results as follows: 24 days for the rainy/growing season for the Ara study area; and 36 days for the dry season for the Ara study area.

Small-scale differences in atmospheric conditions (temperature, pressure, water content, etc.) between SAR acquisitions also cause phase noise. In some cases, this produces interferograms with high RMSE closure error outside of the rainy/growing season. These interferograms were also discarded. The final datasets are comprised of 104 interferograms. Network plots showing the interferogram pairs and their perpendicular baseline are presented on Figure 4.5.

Filter and decimation parameters for the InSAR processing were chosen to produce relatively high resolution interferograms, considering the computational cost of phase unwrapping. Lighter filtering and decimation improves interferogram resolution, but increases the computational time for phase unwrapping. Pixels were decimated by a factor of 8 in the range and 2 in the azimuth directions, generating interferograms with a pixel size of approximately 18.4 x 28.2 meters (range x azimuth). A 100 meter Gaussian filter was selected for the Ara study area. Enhances spectral diversity was used to reduce phase mismatch at the burst boundary (Sandwell et al 2016).

4.3.3 Time Series Generation

The new small baseline subset (NSBAS) technique (Doin et al 2011) was used to generate a time series analysis of deformation across the study area. The NSBAS algorithm was applied using the Generic InSAR Analysis Toolbox (GIAnT; Agram et al 2012, 2013). The GIAnT tool box stacked the geometrically-aligned phase-unwrapped interferograms, estimated and applied corrections for residual long-wavelength errors due to imprecise orbits, and estimated line-of-sight displacements using the NSBAS technique. Acquisition dates without redundancy and short networks of interferograms were discarded from the analysis. The final
Figure 4.6 Panel A presents the mean root mean square (RMS) closure error in radians by SAR acquisition date over the Ara Watershed from March 1, 2015 to October 15, 2017. Mean RMS closure error is the average error for all interferograms generated using the SAR acquisition at the indicated date. Panel B presents mean coherence by SAR acquisition date using the same dataset. Mean coherence is the average coherence of all interferograms generated using the SAR acquisition at the indicated date. Panel C presents mean NDVI over the Ara study area SAR processing area. Mean NDVI is inversely related to mean coherence. Mean NDVI is calculated from MOD13A1 V6 (Didan 2015), accessed from the GEE data catalog (Google Earth Engine Team 2015).
time series analysis used the interferograms generated from 36 SAR acquisitions that form two interferogram networks: the first network consists of 16 acquisitions 11/1/2015 through 6/13/2016 and the second network consists of 20 acquisitions 11/6/2016 through 6/20/2017.

The two networks were treated as unconnected time series and processed separately. Average bias was subtracted from each interferogram to correct for large-scale atmospheric affects. Differential interferometry generates relative displacement. Subtracting average bias generated a displacement time series of relative to the mean elevation at each time step. Corrections for tropospheric stratifications were not applied because the topography over the study area is relatively flat. The mean displacement of each pixel over the time series was subtracted by pixel to reduce the impact of errors at each individual time step. This was done separately for each network. The final time series estimates the displacement anomaly relative to the mean elevation of the study area at each time step. All time series processing steps were conducted in radar coordinates, with the outputs projected to latitude/longitude coordinates for display purposes only.

4.3.4 Kmeans Clustering and EOF Analysis

Kmeans clustering and empirical orthogonal (EOF) analysis were used to find the spatial patterns of the seasonal deformation anomalies estimated by the NSBAS analysis. These analyses were performed simultaneously for all time steps (i.e., not separately by network). Pixels with a mean RMS closure error greater than 0.002 m were masked from the statistical analyses to reduce the impact of phase noise on the statistical analyses. The clustering and EOF analysis were performed using R (R Core Team 2015).

Kmeans clustering groups pixels into clusters where the within-cluster variance of the time series is minimized and the between-cluster variance is maximized (Caliński and Harabasz 1974); i.e., the pixels are divided into groups with similar temporal patterns of deformation. Cluster solutions for the seasonal deformation anomalies were generated for two through ten clusters. The three-cluster model was selected based on a review of the incremental increase in variance explained by increasing the number of clusters (i.e., when increasing from two to three clusters, see Appendix C for details). Further increases in the number of clusters generate relatively small gains in the percent variance explained by the cluster solution.
EOF analysis was performed to identify the principle patterns in the deformation anomaly dataset and to confirm that the pixels are clustered according to these patterns. EOFs (also called principle component analysis) decomposes the pixel time series in terms of orthogonal basis functions (Cressie and Wikle 2011). This analysis generates EOFs representing the spatial patterns of the deformation anomalies and their associated expansion coefficients. EOFs are ranked by amount of variance explained. The expansion coefficients represent how each EOF evolves in time.

4.4 Results and Discussion

4.4.1 Spatial and Temporal Patterns of the Seasonal Deformation Anomalies

The spatial pattern of the three clusters and the distribution of the line of sight (LOS) pixel displacements for each cluster are presented on Figure 4.7. Comparing the spatial distribution of the cluster (Figure 4.7.A) to the elevations shown on Figure 4.1, the clusters 2 and 3 generally encompasses bas-fond and riparian areas while cluster 1 includes higher elevation areas including the watershed divide. Cluster 3 pixels are generally downstream of cluster 2. Comparing the spatial distribution of the clusters to the geologic and geophysical maps shown on Figures 4.3 and 4.4, respectively, cluster 1 generally encompasses areas with lower conductivity where lateritic covers and quartzite/quartz dykes have been identified while clusters 2 and 3 generally encompasses areas with higher conductivity or where the amphibolite and gneiss/micaschists units have been identified. Cluster 1 also includes village areas located to the north and south of the Ara watershed. Figure 4.7.B depicts the temporal evolution of the deformation anomalies by cluster. As explained previously, the deformation anomalies represent LOS displacement relative to the mean LOS displacement of the processing area (i.e., positive displacements indicates larger than average displacement towards the satellite and negative displacements indicate smaller than average displacement towards the satellite).

As shown by Panel B of Figure 4.7, the temporal pattern of deformation anomalies for clusters 1 and 3 diverge, while the cluster 2 anomalies is generally neutral (indicating displacement close to the mean displacement of the processing area). The temporal patterns of displacement repeat annually. The cluster 2 and 3 anomalies are more positive than the cluster 1 anomalies prior to April and more negative than the cluster 1 anomalies after April. The maximum difference in relative displacement occurs in during mid-March, suggesting a
relationship with the seasonal monsoon (which begins in April; Figure 4.4.A). Soil moisture (Figure 4.4.C) and Ara River stream flow (Figure 4.4.B) also increase starting in April. These results indicate that seasonal displacement anomalies approach zero and cross a second time between mid-June and late October. However, the timing cannot be determined because InSAR measurements could not be made during these months.

The first EOF (Figure 4.8.A) captures the seasonal behavior of the dataset. The expansion coefficients of the first EOF (Figure 4.8.B) represent how this pattern evolves in time. Subsequent EOFs explain less variance in the data and may represent phase noise and/or random errors in the data (see Appendix C for further details). EOF 1 is consistent with the spatial pattern of the kmeans clustering model. EOF 1 is negative in the areas corresponding to cluster 3, indicating a negative LOS displacement relative to the mean displacement of the processing area. EOF 1 is positive in areas corresponding to cluster 1, indicating a negative positive LOS displacement relative to the mean displacement of the processing area. The EOF for Cluster 2 areas is close to zero indicating displacement that is close to the mean displacement of the processing area. As shown by Figure 4.8.B, the temporal pattern of the expansion coefficients for EOF 1 repeats annually. The negative expansion coefficients prior to April indicate that the sign of the LOS displacements is the inverse of Figure 4.8.A during these months. This is follows the distribution of displacement anomalies by cluster shown on Figure 4.7.B (i.e., cluster 1 pixel displacement anomalies are negative prior to April in both the EOF and the cluster analysis, and so forth). The consistency between the EOF and cluster analyses results indicates that the clustering model groups the deformation anomaly dataset based its principal components.

These data models explain approximately one-third of the variance in the deformation anomalies dataset. The three cluster solution explains 29.3% of the dataset variance and the first EOF explains 32.1% of the dataset variance. While SBAS inversion and the application of the data models improve the signal to noise ratio in the dataset, phase noise from vegetation growth and atmospheric affects generate variance that cannot be explained by the cluster or EOF 1 data models. However, the temporal patterns of displacement anomalies are consistent across two seasons and their spatial patterns reflect geological structure present at the study area. Thus, the temporal and spatial patterns of the two data models are thought to be meaningful, despite explaining only about one third of the variance..
Figure 4.7 Panel A shows the spatial distribution of the clustering result for three clusters. Panel B shows the distribution of the line of sight displacement at each time step by cluster. Points represent the median value and error bars are drawn to the 25th and 75th percentile. A smooth line is drawn through the median values using LOESS local regression.
Figure 4.8 Panel A presents the spatial pattern of EOF 1. Panel B presents the expansion coefficients for EOF 1. A smooth line is drawn through the expansion coefficients using LOESS local regression.
4.4.2 Comparison of the Seasonal Deformation Anomalies to GPS and Hydrologic Loading Model Deformation Estimates

GPS data and loading model data help to interpret the deformation anomaly data set. The NALO GPS station is located at the edge of the study area (Figure 4.1) in a region associated with cluster 1 (Figure 4.7). Vertical displacement observations for 2013-2015 without correction for atmospheric or hydrological loading are shown Figure 4.9. Seasonal decomposition of the data indicates that the station has an annual harmonic displacement with 15 mm amplitude. The displacement corresponds to the timing of monsoonal precipitation loadings. The maximum station elevation is measured during April/May and the minimum elevation is September/October. Nahmani et al. (2012) reported near identical mean annual station displacements for 2005-2008 at the DJOU GPS station, located approximately 7 km southeast of the study area in Djougou, Benin. Nahmani et al. (2012) showed that the vertical displacements in the DJOU station data are largely explained by regional-scale deformation estimates from GRACE observations and that hydrologic loading is the dominant contributor to the signal. Similar to DJOU, the NALO station seasonal displacements follow estimates from hydraulic loading models, with the GRACE loading model explaining 78% of the variance of the GPS station seasonal signal (Figure 4.9).

Nahmani et al. (2012) detected a semi-annual deformation signal between September and March at six West African GPS stations that could not be explained by regional-scale hydrologic loading models. The signal was strongest in the Sahel stations, but was present in the Sudanian stations as well. At the DJOU station, the semi-annual signal peaks in January and has a trough in February/March. A similar oscillation is seen in the NALO station data (Figure 4.9), but it is not as pronounced as for the DJOU and other stations in Nahmani et al. (2012). Nahmani et al. (2012) hypothesized that the semi-annual oscillation is due to the local effect of swelling/shrinking of clays underlying the GPS station.

Comparing the deformation anomaly dataset to the NALO GPS data, cluster 2 and 3 anomalies are more negative than the cluster 1 anomalies during the rising part of the deformation seasonal trend and more positive than the cluster 1 anomalies during the falling portion of the deformation seasonal trend.
Figure 4.9 This figure presents vertical displacement data from the NALO station (location shown on Figure 4.1) without corrections for atmospheric, ocean, or hydraulic loading. Panel A presents GPS data for January 1, 2013 through December 31, 2015 (Boy 2017). A 10-day boxcar filter was applied to the GPS measurements. Panel B presents the long term in the data estimated using LOESS local regression with a one year window. Panel C presents the estimated seasonal trend, repeated for each year of data. Panel D presents a one-year close-up of the seasonal trend plotted with detrended hydrologic displacements estimated using from loading models that use GRACE observations and model outputs from GLADAS and MERA (Gegout et al. 2010, Petrov 2004, MacMillan and Boy 2004).
4.4.3 Hydrological Implications of the InSAR Results

These results suggest two possible hydrologic mechanisms to explain the deformation anomalies. The deformation anomalies may be due to larger changes in water mass in the bas-fond and riparian regions than in the upland zones along the watershed divide, towns areas, and regions where lateritic covers and quartzite/quartz dykes have been identified. Hector et al. (2015) found higher amplitude seasonal water mass fluctuations in the bas-fonds than in areas with lateritic covers. The water mass increases in the bas-fond and riparian regions as monsoon precipitation infiltrates the soil and accumulates as perched groundwater and surface water. Water mass decreases during the dry season as the surface water and perched groundwater dries up. The higher water mass upon onset of the monsoon would cause downward deformation, which would be reversed during the dry season. The anomalies could also be explained by shrinkage of the deeper clay layers as the permanent groundwater table continues to recede through the early part of the monsoon. Both affects could occur simultaneously or one process could be dominant at the site. The portion of the deformation anomalies attributed to changes in water mass across the site may be estimated using an elastic loading model. The analysis is suggested as future work.

This study was unable to generate InSAR measurements between mid-June and the end of October because of poor interferogram quality. Phase noise from vegetation growth and harvest is the primary source of phase noise during this period. Therefore, it was not possible to determine the spatial or temporal pattern of relative deformation during the period of maximum hydrologic loading. This limits the understanding of the total magnitude of the deformations and the timing of the maximum negative deformations. Interferometry with L-band SAR data may allow the generation of interferograms covering the growing/rainy season and increase their spatial coverage, as higher wavelength radar signals are less impacted by vegetation (Ferretti et al 2007). Global L-band SAR acquisitions are expected from the upcoming NASA/Indian Space Agency NISAR mission, which has a 2020 launch date.

4.5 Conclusions

InSAR-derived displacement measurements were used to map the dynamics of small, seasonal deformation in the Ara Watershed under hydraulic loading from the West African Monsoon. Cluster and EOF analyses separated the study area into zones with similar
displacement patterns. The resulting deformation anomaly dataset indicates that *bas-fond* and riparian regions of the study area have more negative deformation following the onset of the West African Monsoon than the upland zones along the watershed divide, towns areas, and regions where lateritic covers and quartzite/quartz dykes have been identified. The dataset indicates that the *bas-fond* and riparian regions of the study area have more positive deformations during the dry season. Two mechanisms are proposed to explain these patterns of deformation. This result may be due to the larger seasonal changes in water mass in the *bas-fond* and riparian regions as the monsoon precipitation accumulates as perched water and streamflow in these areas and is subsequently removed by evapotranspiration during the dry season. The higher water mass upon onset of the monsoon would cause downward deformation, which would be reversed during the dry season. The anomalies could also be explained by shrinkage of the deeper clay layers as the permanent groundwater table continues to recede through the early part of the monsoon. Both affects could occur simultaneously or one process could be dominant at the site. There is some uncertainty in the timing and magnitude of the deformations due to gaps in the InSAR dataset during the growing/rainy season and the inconsistent temporal coverage of the study precipitation, GPS, and InSAR datasets.

Despite some gaps in the spatial coverage of the InSAR data, the spatial pattern of deformation follows geological units previously identified at the site, including the regions where of lateritic covers and quartzite/quartz dykes have been identified. The spatial patterns identified in this study augment previous geological and geophysical data, and may be used to refine the boundaries of the primary geological units present at the site. The spatial patterns may be used to better understand the geology in off-site areas where in-situ observations are not available.

This study is one of the first to study spatial and temporal patterns of surface deformation in the Sudanian ecoregion under the West African Monsoon. The InSAR methods developed by this study provide new data on the geological structure of the Ara Watershed. The study results show that InSAR methods may identify relative changes in water mass under the West African Monsoon, providing a new tool for understanding the distribution of water resources in areas with sparse data coverage. This is especially important in regions such as West Africa, where population growth and development are putting increasing pressure on water resources while changes climate and land use are modifying the regional hydrology. It is anticipated that the new
methods developed by this study may be extended to other areas to better understand the
dynamics of water availability in West Africa under changing climate and land use conditions
and increasing water demand.

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CHAPTER 5
CONCLUDING REMARKS

The overarching objective of this dissertation was to better understand how changing patterns of land use and climate conditions impact the distribution and availability of freshwater resources. Warmer temperatures and low annual precipitation during the mid-1990’s are linked to the onset of the MPB outbreak in the western United States in 1996 (Chapman et al 2012, Meddens et al 2012). The second chapter of this dissertation examines the impact of the bark beetle infestation on water resources in the West. The third and fourth chapters of this dissertation examine the impact of drought and land use changes on the distribution of water resources in East and West Africa. Novel remote sensing techniques are required to answer these questions because of the scarcity of in-situ data in these regions. A fused SAR/Landsat waterbody classification method is developed in CHAPTER 3 and used to evaluate the impact of the 2015 regional drought on surface water in the Awash River basin, in Ethiopia. Chapter 4 uses InSAR measurements to better refine the conceptual model of site hydrology in the Ara Watershed, an AMMA-CATCH critical zone research site located in northern Benin, an area where changes to land use and the recent drought has modified the distribution of surface and underground water (Descroix et al 2009, Mahé et al 2013).

5.1 Research Questions Addressed

The results from each study answer the following research questions:

To what degree is the timing and amount of watershed discharge across the Western US modified by bark beetle infestation?

Chapter 2 evaluates the streamflow and baseflow response of 33 watersheds in seven western states using hydrologic metrics that include timing and amount of peak flows and daily streamflow statistics. Watershed statistics after bark beetle outbreak were compared to pre-infestation conditions to evaluate the change in streamflow statistics, peak flow, and snowmelt timing in the years following the infestation. Previous studies have predicted that the current bark beetle infestations in the Western US would modify watershed hydrology, assuming the reduced transpiration and interception of the attacked trees would increase stream discharge and the reduction in forest canopy would lead to higher peak flows and earlier snowmelt timing.
(Edburg et al 2012, Mikkelson et al 2013). While bark beetles immediately and severely reduce the transpiration of the attacked tree, there is a growing body of empirical evidence indicating that the excess moisture is utilized by the ecosystem response, resulting in little net impact to discharge (Biederman et al 2014b, Brown et al 2014, Reed et al 2014). In addition, canopy reduction has been shown to have inconsistent impact on snow water equivalent in the snow pack and on snowmelt timing (Boon 2012, Harpold et al 2015). The study results show no significant change in daily streamflow statistics, peak flow, or snowmelt timing relative to the current bark beetle outbreaks. Climate variability may be a stronger driver of streamflow patterns and snowmelt timing than chronic forest disturbance, as post-outbreak flows generally fall within the range of the pre-outbreak variability. The impact of bark beetles on water quality, however, remains an open question (Mikkelson et al 2013). This work expands upon previous stand- and plot-scale findings to the watershed scale, providing more evidence that the current bark beetle outbreak is not significantly altering streamflow hydrology across western US watersheds.

What was the impact of the 2015 drought on surface water resources in the Awash Basin in Ethiopia? Has surface water recovered to pre-drought conditions?

Chapter 3 develops a new technique called the APWC method to generate accurate, high resolution waterbody maps using simple automated methods that are reproducible using publicly available tools. GEE (Google Earth Engine Team 2015) cloud-based computing resources and machine learning techniques are leveraged to merge observations from Sentinel 1 SAR and Landsat acquisitions and generate monthly waterbody maps at a 10-meter resolution. The accuracy of this method is shown to be comparable to waterbody map products that required high performance computing resources to generate [e.g., Pekel et al (2016)].

Monthly waterbody maps over the Awash River basin are generated to depict basin surface water dynamics from October 2014 to March 2017, corresponding to the 2015 regional drought and recovery. The basin was severely impacted by water shortages during the drought. The mapping illustrates the acute impact the drought had on surface water area. The results indicate that the Terminal, Aditu, and Eastern sub-catchments were most strongly impacted by drought and that surface water in all catchments recovered to pre-drought surface water area after the 2016 summer rains. However, the change in surface water volume over the course of the
drought could not be determined because measurements of the change in water body depth were not available. The upcoming Surface Water and Ocean Topography (SWOT) mission will provide global satellite altimetry measurements of water levels. The APWC technique combined with SWOT measurements of water elevation will be a powerful tool for monitoring changes in surface water volume under changing climate conditions.

High resolution maps of surface water dynamics allow water managers and other actors to better target humanitarian response efforts mitigating the impact of the water shortages over the course of the drought and drought recovery. Further, these data may be used to better understand the effects of climate, land-use, and other environmental changes on freshwater ecosystems and the consequent impact on human health and environment. To our knowledge, this study is the first to merge passive and active sensors to generate waterbody maps, and the first to create waterbody maps at a 10-meter resolution. It is anticipated that the APWC technique will help earth scientists better understand the impact of environmental changes on freshwater ecosystems and inform policy decisions affecting the water, energy, agriculture and other sectors reliant on water resources.

Are small, seasonal surface displacements at the ground surface detectable in the Ara Catchment using InSAR techniques? What are the physical processes driving the spatial and temporal trends in surface deformation? How does the new data augment the existing site data to refine the current understanding of site geology and hydrology?

Chapter 4 uses InSAR methods to map the dynamics of seasonal deformation across the Ara Watershed. Interferograms were generated from Sentinel 1 SAR scenes acquired over the watershed from November 1, 2015 to June 20, 2017. The poor signal-to-noise ratio in the InSAR measurements was improved by: 1) limiting the analysis to November to mid-June, the time period less affected by phase noise; 2) the application of the NSBAS method (Doin et al 2011) to invert the data and estimate deformation at each time step, and 3) masking the inversion results to remove pixels still affected by phase noise and applying kmeans cluster and EOF data models to identify the spatial and temporal deformation patterns present across the site.

Despite the high variance still present in the data, the cluster and EOF results identified meaningful spatial and temporal displacement patterns across the site. The deformation anomaly dataset indicates that bas-fond and riparian regions of the study area have more negative
deformation following the onset of the West African Monsoon than the upland zones along the watershed divide, towns areas, and regions where lateritic covers and quartzite/quartz dykes have been identified. The dataset indicates that the bas-fond and riparian regions of the study area have more positive deformations during the dry season. Two mechanisms are proposed to explain these patterns of deformation. This result may be due to the larger seasonal changes in water mass in the bas-fond and riparian regions as the monsoon precipitation accumulates as perched water and streamflow in these areas and is subsequently removed by evapotranspiration during the dry season. The higher water mass upon onset of the monsoon would cause downward deformation, which would be reversed during the dry season. The anomalies could also be explained by shrinkage of the deeper clay layers as the permanent groundwater table continues to recede through the early part of the monsoon. Both affects could occur together or one process could be dominate at the site. There is some uncertainty in the timing and magnitude of the deformations due to gaps in the InSAR dataset during the growing/rainy season and the inconsistent temporal coverage of the study precipitation, GPS, and InSAR datasets.

Despite some gaps in the spatial coverage of the InSAR data, the spatial pattern of deformation follows geological units previously identified at the site, including the regions where of lateritic covers and quartzite/quartz dykes have been identified. The spatial patterns identified in this study augment previous geological and geophysical data, and may be used to refine the boundaries of the primary geological units present at the site. The spatial patterns may be used to better understand the geology in off-site areas where in-situ observations are not available.

This study is one of the first to study spatial and temporal patterns of surface deformation in the Sudanian ecoregion under the West African Monsoon. The InSAR methods developed by this study provide new data on the geological structure of the Ara Watershed. The study results show that InSAR methods may identify relative changes in water mass under the West African Monsoon, providing a new tool for understanding the distribution of water resources in areas with sparse data coverage. This is especially important in regions such as West Africa, where population growth and development are putting increasing pressure on water resources while changes climate and land use are modifying the regional hydrology. It is anticipated that the new methods developed by this study may be extended to other areas in West Africa to better
understand the dynamics of water availability under changing climate and land use conditions and increasing water demand.

5.2 Future Work

The waterbody mapping results generated by the APWC method and the seasonal and temporal deformation anomaly results generated using InSAR techniques demonstrate the value of using satellite remote sensing observations to better understand hydrologic processes in data-sparse regions. Several future research directions arise from this work. As mentioned above, the upcoming SWOT mission will provide satellite radar altimeter data that will monitor water levels in global freshwater resources. The first proposal for future work is to combine the APWC method with the SWOT data to monitor surface water volume changes. This will provide data necessary to develop hydrologic models in data-poor regions and assist water managers in monitoring the state of surface water resources.

Further work is necessary understand the physical processes driving the spatial and temporal trends in surface deformation identified at the Ara Watershed. Two processes are proposed: 1) difference in water mass due to the distribution of monsoonal precipitation across the site and 2) clay swelling and shrinking. These processes may be occurring together or one may be dominant at the site. The portion of the deformation anomalies attributed to changes in water mass across the site may be estimated using an elastic loading model. The analysis is proposed as future work. In addition, a field campaign is proposed to collect precipitation, gravimetric, and GPS measurements at the watershed. Comparing these measurements to concurrent InSAR-derived deformation anomalies will reduce the uncertainty regarding the dominant processe(s) causing deformation at the site.
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Figure A.1 Locations where surface water (in black) was detected in the Awash River basin for 2014 images. Maps prior to October, 2014 are blank because Sentinel 1 data were not available for these dates.
Figure A.2 Locations where surface water (in black) was detected in the Awash River basin for 2015 images.
Figure A.3 Locations where surface water (in black) was detected in the Awash River basin for 2016 images.
Figure A.4 Locations where surface water (in black) was detected in the Awash River basin for 2017 images. Maps after March, 2017 are blank because Landsat data were not available for these dates at the time of study.
This appendix presents Figures C.1 through C.5, which show average pixel coherence by month for interferograms generated using synthetic aperture radar (SAR) imagery acquired over the Ara Watershed. The SAR imagery was acquired by the Sentinel 1A satellite between March 1, 2015 and December 31, 2017. The interferograms were generated by the Generic Mapping Tools 5 Synthetic Aperture Radar (GMT5SAR) processing system (Sandwell et al 2016, Massonnet and Feigl 1998). As shown by these figures, the average coherence of the interferogram pairs decreases as the number of days between the pairs increases, particularly during the March through October rainy/growing season. This is due to phase noise.
Figure B.1 This figure presents the average pixel coherence of interferograms generated by SAR images acquired 12 days apart over the Ara ROI. Images in the first row depict the coherence for all pixels by month. The lower rows present the same sequence of images with a mask applied; pixels with a mean coherence lower than the indicated threshold are masked.
Figure B.2 This figure presents the average pixel coherence of interferograms generated by SAR images acquired 24 days apart over the Ara ROI. Images in the first row depict the coherence for all pixels by month. The lower rows present the same sequence of images with a mask applied; pixels with a mean coherence lower than the indicated threshold are masked.
Figure B.3 This figure presents the average pixel coherence of interferograms generated by SAR images acquired 36 days apart over the Ara ROI. Images in the first row depict the coherence for all pixels by month. The lower rows present the same sequence of images with a mask applied; pixels with a mean coherence lower than the indicated threshold are masked.
Figure B.4 This figure presents the average pixel coherence of interferograms generated by SAR images acquired 48 days apart over the Ara ROI. Images in the first row depict the coherence for all pixels by month. The lower rows present the same sequence of images with a mask applied; pixels with a mean coherence lower than the indicated threshold are masked.
Figure B.5 This figure presents the average pixel coherence of interferograms generated by SAR images acquired one year apart over the Ara ROI. Images in the first row depict the coherence for all pixels by month. The lower rows present the same sequence of images with a mask applied; pixels with a mean coherence lower than the indicated threshold are masked.
APPENDIX C
FULL RESULTS OF THE CLUSTER AND EOF ANALYSIS

Clustering and empirical orthogonal (EOF) analysis techniques were used to find the spatial patterns of seasonal deformation estimated for the Ara study area. The clustering and EOF analysis were performed using R (R Core Team 2015). Pixels with an average root mean square (RMS) closure error greater than 0.002 m were masked from the statistical analyses to reduce the impact of phase noise on the statistical analyses. This appendix presents the results of the clustering and EOF analyses.

Cluster analysis is a statistical method that defines groups of pixels where the within-group variance of the time series is minimized and the between group variance is maximized (Caliński and Harabasz 1974). This appendix presents the results for the solution for two through ten clusters. Figure A.1 shows the amount of variance in the dataset explained by each cluster model. The three-cluster solution was chosen because it generates a largest increase in dataset variance explained, with additional increases in the number of clusters generating smaller increases in percent variance explained. The three-cluster model explains 29.3% of the dataset variance. This is low due to the amount of noise in the deformation time series. Figures B.2 through B.11 show the spatial pattern of each clustering solution and the pixel distribution by cluster.

EOF analysis decomposes the pixel time series in terms of orthogonal basis functions (Cressie and Wikle 2011). Figure A.12 presents the cumulative sum of the percent variance in the dataset explained by each EOF. The first EOF explains the most dataset variability (32.1%). As with the cluster solution, the amount of variance explained is low due to the amount of noise in the time series. Figures B.13 through B.16 present the spatial distribution and associated eigenvector for EOFs 1 through 4.
Figure C.1 This figure presents the amount of dataset variance explained by each cluster model.
Figure C.2 Panel A presents the spatial pattern of the one-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn in gray through the pixel distribution using LOESS local regression.
Figure C.3 Panel A presents the spatial pattern of the two-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn through the pixel distribution using LOESS local regression.
Figure C.4 Panel A presents the spatial pattern of the three-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn through the pixel distribution using LOESS local regression.
Figure C.5 Panel A presents the spatial pattern of the four-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn through the pixel distribution using LOESS local regression.
Figure C.6 Panel A presents the spatial pattern of the five-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn through the pixel distribution using LOESS local regression.
Figure C.7 Panel A presents the spatial pattern of the six-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn through the pixel distribution using LOESS local regression.
Figure C.8 Panel A presents the spatial pattern of the seven-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn through the pixel distribution using LOESS local regression.
Figure C.9 Panel A presents the spatial pattern of the eight-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn through the pixel distribution using LOESS local regression.
Panel A presents the spatial pattern of the nine-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn through the pixel distribution using LOESS local regression.
Figure C.11 Panel A presents the spatial pattern of the ten-cluster solution. Panel B presents the distribution by cluster of a random sample of 10,000 pixels. A smooth line is drawn through the pixel distribution using LOESS local regression.
Figure C.12 This figure presents the cumulative sum of the variance explained by each EOF.
Figure C.13 Panel A presents the spatial pattern of EOF 1. Panel B presents the eigenvector associated with EOF 1. A smooth line is drawn through the eigenvector using LOESS local regression.
Figure C.14 Panel A presents the spatial pattern of EOF 2. Panel B presents the eigenvector associated with EOF 1. A smooth line is drawn through the eigenvector using LOESS local regression.
Figure C.15 Panel A presents the spatial pattern of EOF 3. Panel B presents the eigenvector associated with EOF 1. A smooth line is drawn through the eigenvector using LOESS local regression.
Figure C.16 Panel A presents the spatial pattern of EOF 4. Panel B presents the eigenvector associated with EOF 1. A smooth line is drawn through the eigenvector using LOESS local regression.