Wisconsin’s Central Sands Hydroclimatology:
Characterization, Forecasting, and Impacts on Real Estate

by

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Abstract

Hydroclimatological variability often stresses resource and economic conditions locally and globally. The Wisconsin Central Sands, a region in the upper Midwest, has many interests with strong connections to local water resources and is used as a case study to explore capabilities of seasonal forecasts and economic implications of interannual hydrologic conditions.

While seasonal climate forecasts have been posed as a means to anticipate hydroclimatological variability, teleconnections with sea surface temperatures, atmospheric moisture transport, and precipitation become damped and more difficult to model inland over longer distances, such as the upper Midwest of the United States. Currently, dynamical models have exhibited limited performance reproducing the physical processes associated with long distance, continental atmospheric moisture transport. The capabilities of statistical data driven models to identify preseason signals understood to be associated with the mechanisms of atmospheric moisture transport are explored. Results indicate the primary mode of atmospheric moisture transport is accurately captured, primarily during strong La Niña events, and the model produces modest precipitation forecast skill, specifically with respect to forecasting drought conditions.

Negative economic impacts associated with drought and decreased residential property values within the Wisconsin Central Sands are reported by local and regional journalists, but no known formal analyses have been performed. Analyses performed with real estate transactions and hydrologic data indicate non-lakefront residential real estate is relatively insensitive to interannual changes in hydrologic conditions whereas a relatively strong positive relationship exists between interannual changes in hydrologic conditions and lakefront real estate.
CHAPTER 1: Introduction

1.1. Motivation and Research Objectives

Hydroclimatological variability often stresses resource and economic conditions locally and globally. In order to minimize potential losses, farmers are beginning to incorporate seasonal climate forecasts, when skillful, into their decision-making processes. Higher forecast skill often required to motivate use by decision makers in hopes of achieving added value and/or reduce losses is typically achieved in regions proximal to oceans where teleconnections with sea surface temperatures, atmospheric moisture transport, and precipitation are more tightly coupled. These teleconnections become damped and more difficult to model inland over longer distances, such as the upper Midwest of the United States.

Seasonal climate forecast models typically fall into one of two categories: physically based dynamical models and data driven statistical models. Dynamical models attempt to simulate physical processes and often require many assumptions about the future conditions of underlying mechanisms including, but not limited to, sea surface temperatures, pressure systems, and wind vector directions and magnitudes. This presents the possibility of compounding errors when attempting to model atmospheric moisture transport over greater distances at seasonal timescales. Consequently, dynamical models have been shown to have limited performance in areas removed from ocean coastal areas, such as the upper Midwest of the United States. Nonetheless, it is understood these models have been able to accurately identify the mechanisms of atmospheric to the upper Midwest of the United States. On the other hand, statistical models seek to take advantage of empirical relationships between predictors and predictands and do not require the
modelling of every underlying process mechanism. However, atmospheric moisture transport predictor-predictand relationships are typically strongest proximal to coastal ocean areas and become damped over longer teleconnections inland. This provides the context for two research objectives:

- Identify justifiable predictor(s) that may be utilized to produce seasonal precipitation forecasts in the upper Midwest of the United States.
- Using the identified predictor(s), evaluate if statistical models are capable of identifying preseason signals understood to be associated with seasonal atmospheric moisture transport mechanism(s) to the upper Midwest of the United States.

The agricultural community are not the only stakeholders that have experienced negative impacts related to drought. Lakefront property owners and recreationalists have reported concerns [1] of decreased property values and fish populations, respectively. Availability of real estate transaction data and hydrologic data allows for analyses with respect to these stakeholders and provides the foundation for third research objective:

- Evaluate if interannual changes of hydrologic conditions contribute to interannual changes of lakefront real estate property values.

1.2. Case Study: Wisconsin Central Sands

The research objectives are explored within the context of the Wisconsin Central Sands (WCS) located in central Wisconsin (Figure 1). The region is both a highly productive agricultural area and contains many high-value lakefront properties.
Agricultural in the WCS consists of approximately 80,000 hectares of potatoes, carrots, peas, sweet corn, cucumbers and other high-value vegetables contributing an estimated annual economic impact of $6 billion and 130,000 jobs [2, 3]. This production is highly dependent on water, which is supplemented by irrigation, particularly during drought years. Seasonal predications of drought may provide potential benefit to economic interests, agriculture and other, in the region with respect to minimizing loses within their unique planning and management operational strategies.

Local and regional journalists report decreased residential property values associated with lower lake levels within WCS [1, 4]. However, these reports are largely anecdotal, and no known formal analyses have been performed. This study explores the hypothesis that interannual changes in regional hydrologic conditions, specifically lake levels, will evoke a change in residential lakefront real estate value.
CHAPTER 2: Regional Hydrology of the WCS

2.1. WCS Climatology

Monthly precipitation and mean temperature values are readily available via the PRISM dataset [5]. The high-resolution (30-arcsec), gridded PRISM precipitation dataset [5] developed at Oregon State University is used to evaluate the spatiotemporal characteristics of precipitation and develop drought criteria within the WCS. Monthly precipitation and mean temperature data are downloaded and extracted for the study area associated with the WSC with the available R prism package [6]. The spatial extent of the study area includes latitudes 43.5°N - 45°N and longitudes 90.2°W - 88°W and is comprised of 1369 grid points (37 x 37). Monthly values are available from 1895 – present.

It’s reasoned months with higher average precipitation and temperatures during the growing season have the highest potential for supplemental irrigation during drought conditions [7, 8]. Months with higher average precipitation contribute a larger percentage to the necessary crop water requirement, and consequently will require a larger increase in supplemental irrigation during drought conditions. Similarly, higher temperatures have the potential to generate higher evapotranspiration and further increase crop water requirements [9, 10, 11], which has the potential to further increase the amount of required supplemental irrigation during drought conditions. The PRISM dataset [5] is used to evaluate months with these characteristics. The monthly spatial average precipitation and mean temperature climatology of WCS is provided in Figure 2 and Figure 3, respectively.
Figure 2. WCS spatial mean monthly precipitation climatology.

Figure 3. WCS spatial mean monthly temperature climatology.
The season of interest identified in this study is the summertime months of June, July, and August (JJA) and coincides with the highest agricultural irrigation volumes, which comprised approximately 87% of JJA groundwater withdrawals from WCS high-capacity wells during 2011 – 2014 [12, 13]. The average precipitation within this season is approximately 293mm, which contributes 35 percent of the average annual precipitation, 799mm. The mean temperature during these months are 18.7, 21.3, and 20.0°C for the months of June, July, and August, respectively.

2.2. Seasonal Precipitation Spatial Variability

A simple spatial analysis is performed by calculating the mean total JJA precipitation for each of the 1369 grid cells over the time period of 1895 – 2017 (Figure 4). The grid cell mean JJA values range from 273 – 326, a +10 percent difference, which suggests a low potential for spatial variability. However, Zhang et al [14, 15] demonstrate a non-hierarchical clustering analysis may improve forecasting skill in areas of high spatiotemporal variability, and a more thorough analysis is conducted to evaluate potential for spatial variability.
An empirical orthogonal function (EOF) analysis is used to evaluate the spatial variability of precipitation in WCS during JJA [16]. The total precipitation is summed for the months within the season of interest, JJA, for each grid cell. The analysis is performed on 123 years (observations) from 1895 – 2017 with 1369 grid cells (features) in each year. The first two principle components (PC) explain approximately 90 percent of the variance in the data, which is dominated by the first principle component (PC1) explaining 81.5 percent (Figure 5) and correlates with the spatial mean JJA precipitation time series at 0.99.
The first EOF (EOF1) does not exhibit a sign change and appears relatively homogenous (Figure 6). The second EOF (EOF2) does exhibit a sign change and suggests a slight north-south gradient in the spatial behavior of total JJA precipitation (Figure 7), but only explains 8.4 percent of the variance and is not considered to be a significant source of variability when developing the statistical forecasting models. These results are not unexpected because the study area is relatively small and almost entirely within the predefined central Wisconsin climate division [17]. The low spatial variability within the study area suggests clustering is unnecessary.
Figure 6. EOF1 explaining approximately 81.5% of JJA total precipitation spatial variance. Positive (negative) contours in solid (dashed) black lines. WCS aquifer delineation in red.

Figure 7. EOF2 explaining approximately 8.4% of JJA total precipitation spatial variance. Positive (negative) contours in solid (dashed) black lines. WCS aquifer delineation in red.
The relatively low spatial variability with respect to total JJA precipitation across the WCS allows for a simplification, and we proceed using the mean spatial average. However, temporal variability also needs to be considered and is explored in the following section.

2.3. Seasonal Precipitation Temporal Variability

The mean total JJA precipitation time series is provided in Figure 8. Four climate categories – dry, normal-dry, normal-wet, and wet – binned by quartiles are defined. The driest (wettest) years on record received 152mm (495mm) during JJA, and the 25, 50, and 75 percentiles are 243.5, 296, and 332mm, respectively. Forecasting drought within the region is of highest interest and the two categories (dry and normal-dry) which fall below median seasonal precipitation are considered to be two varying intensities of drought conditions.

The period from 1895 – 2017 experiences 32, 30, 30, and 31 years of wet, normal-wet, normal-dry, and dry climate conditions during JJA. The primary objective is to evaluate if statistical models are capable of identifying preseason signals associated with seasonal atmospheric moisture...
transport that may be responsible for this temporal variability in summertime precipitation and whether a skillful statistical forecast can be generated, specifically regarding the two dry climate categories.

2.4. Large-scale Climate Drivers

The relationship with summertime precipitation in the upper Midwest and large-scale climate phenomena has been previously explored [18, 19, 20]. It is believed that large-scale phenomena, such as the Pacific Decadal Oscillation (PDO), Atlantic Multidecadal Oscillation (AMO), and El Niño Southern Oscillation (ENSO), modulate the transport of atmospheric moisture to the basin via increasing or decreasing the strength of the Great Plains Low Level Jet (GPLLJ) [21, 22, 23]. PDO and AMO exhibit inter- and intra-annual variability, but are typically associated with long-term, multidecadal shifts [19, 20]. On the other hand, ENSO exhibits a shorter periodicity and has been shown to influence precipitation over the United States on an inter-annual basis [18]. The relationships between these large-scale climate phenomena and their predictive capability with respect to summertime atmospheric moisture transport to the upper Midwest, specifically the WCS, are explored.

2.5. Statistical Seasonal Forecasting

Sea surface temperatures (SST) are often used to describe and evaluate climate phenomena, exhibit seasonal persistence, and have been shown to modulate regional climate patterns, specifically atmospheric moisture transport [24, 23]. These qualities allow the use of SSTs as a potentially skillful predictive signal for the near-term state of the climate [25, 26, 24].
Empirically based linear-regression models are a simple and efficient method to generate seasonal predictions provided there are meaningful season-ahead predictor(s). However, linear-regression models seek to minimize error and inherently tend to over predict climatic normal and under predict the extremes, which this study is most concerned with forecasting, specifically drought. Therefore, the Niño-index phased based approach (NIPA) developed by Zimmerman et al [27] is used to develop a WCS specific seasonal forecast and examine the ability to identify preseason signals understood to be associated with seasonal atmospheric moisture transport to the region.

2.6. NIPA Model Framework

The modeling framework assumes different SST patterns modulate atmospheric moisture transport during different phases of a given major climatic phenomena, which requires the use of monthly climate index and gridded, global SST anomaly data. The model creates a separate linear regression forecast model with statistically significant (p-value ≤ 0.05) global SST anomalies for each phase of the climate index.

Potential large-scale climate drivers influencing moisture transport to the WCS include ENSO, PDO, and AMO and are evaluated in the NIPA modeling framework. Several indices have been developed to describe the temporal behavior of ENSO. The study uses the MEI index developed by and obtained from the National Oceanic and Atmospheric Administration (NOAA) Earth System Research Laboratory Physical Sciences Division (ESRL) [28, 29] and the AMO and PDO indices developed by and obtained from the National Oceanic and Atmospheric Administration (NOAA) Earth System Research Laboratory Physical Sciences Division (ESRL) [30] and National
Centers for Environmental Information (NCEI) [31], respectively. Climate phases are generated by ranking the climate index data and binning into equal quantiles.

Season-ahead, March-April-May (MAM), SST anomalies that appear to influence atmospheric moisture transport to the WCS are identified via statistically significant (p-value ≤ 0.05) correlation with mean total JJA precipitation in WCS. The Extended Reconstructed Sea Surface Temperature version 3b (ERSST v3b) developed by NOAA NCEI are used in this study [32]. Statistically significant SST grid cells are retained and used to develop a drop-one cross-validated linear-regression model for each climate phase.

2.7. Single Phase Model

An initial linear model using all years, which does not utilize any climate index data, is developed to determine which climate indices may provide the best categorical linear models. Statistically significant (p-value ≤ 0.05) correlation values of MAM global SST anomalies and mean total JJA precipitation for all years from 1895-2017 are presented in Figure 9. These SST grid cells are used to generate a drop-one cross-validated linear regression model. Hindcast values of JJA precipitation are calculated and presented in Figure 10. The linear model (Equation 1) has a coefficient of correlation of 0.16 and exhibits poor performance. However, the SST patterns in the correlation map (Figure 9) suggest which climate indice(s) may produce skillful phase-based linear models, specifically for drought, that capture the mechanism of atmospheric transport.
Figure 9. All years correlation map: Statistically significant (p-value ≤ 0.05) correlation map of MAM global SST anomalies and mean total JJA precipitation.

Figure 10. All years model scatter plot: JJA hindcast and observation values. Red line is the linear model. Coefficient of correlation is 0.16.
\[ JJA \text{ Precipitation Hindcast} = JJA \text{ Precipitation Observation} \times 0.04 + 280 \]

*Equation 1. All years linear model.*

The all years correlation map (Figure 9) displays a pattern similar to ENSO and PDO and are evaluated within the NIPA framework.

2.8. Multi-phase Model

MEI achieves the best performance forecasting drought and only those results are presented. Years are binned by season-ahead MAM MEI index quartiles similar to the in-season JJA precipitation climate categories defined in Section 2.3. Violin plots are generated (Figure 11) as a simple diagnostic of typical JJA precipitation response following MAM MEI index values. Lower (higher) MAM MEI values associated with more La Niña (El Niño) like conditions appear to be associated with lower (higher) JJA precipitation. While there appears to be lower (higher) precipitation observations with lower (higher) MEI values, there are large overlaps between phases of the MEI index. I.e., a low MAM MEI value does not guarantee dry or even normal-dry JJA precipitation.
Statistically significant correlation values of MAM global SST anomalies and mean total JJA precipitation for each MEI phase are generated and presented in Figure 12. These SST grid cells are used to generate a drop-one cross-validated linear regression model for each MEI phase. The models are aggregated and hindcast values of JJA precipitation are calculated and presented in Figure 13. The linear model (Equation 2) has a coefficient of correlation of 0.44 and shows marked improvement over the all years model (Figure 10). However, only the most negative MEI phase (Figure 12 d) exhibits large areas of SST anomalies that are statistically significant. This phase exhibits the strongest association with lower JJA precipitation (Figure 11) and is further explored.
Figure 12. MEI phase-based correlation maps: Statistically significant (p-value ≤ 0.05) correlation map of MAM global SST anomalies and mean total JJA precipitation. 
a) years with MEI values <25th percentile, 
b) years with MEI values within 25-50th percentile, 
c) years with MEI values within 50-75th percentile, 
d) years with MEI values >75th percentile.
Equation 2. MEI phased-based linear model.

\[ JJA \text{ Precipitation Hindcast} = JJA \text{ Precipitation Observation} \times 0.23 + 227 \]

2.9. Mechanism of Atmospheric Moisture Transport

The phase has strong positive correlation with SST anomalies in the tropical Atlantic associated with the Caribbean Low Level Jet (CLLJ) and Great Plains Low Level Jet (GPLLJ). These LLJs are believed to be the primary mechanism of atmospheric moisture transport to the upper Midwest [33, 34]. Increased (decreased) GPLLJ intensity results in more (less) zonal atmospheric moisture transport to higher latitudes and consequently results in higher (lower) summertime precipitation across the upper Midwest [33, 34]. However, there is a high degree of uncertainty with respect to
the meridional component of the transport, and a strong GPPLJ does not necessarily guarantee increased summertime precipitation in the WCS. On the other hand, a weaker GPPLJ typically results in lower summertime precipitation across the upper Midwest, including WCS. This relationship associated with a weaker GPPLJ during stronger La Niña events, negative MEI values, appears to be captured by the negative phase model (Figure 15, Equation 3).

Figure 14. MAM MEI negative phase. CLLJ represented by meridional arrow, GPPLJ represented by zonal arrow, atmospheric moisture transport uncertainty is represented by the cone extending from the zonal arrow.
Figure 15. MEI negative phase model scatter plot: JJA hindcast and observation values. Red line is the linear model. Coefficient of correlation is 0.54.

\[ JJA \text{ Precipitation Hindcast} = JJA \text{ Precipitation Observation} \times 0.31 + 187 \]

*Equation 3. MEI negative phase linear model.*

The MEI phased-based approach obtains better performance than the all years model and appears to capture the mode of atmospheric transport to the WCS. This is particularly true during drier JJA climatic conditions associated with drought, which are of special concern to the WCS. However, there are still some still years where the model fails to capture the correct climatic category, for example dry versus normal-dry.
CHAPTER 3: Interannual Hydrologic Conditions Impact on Real Estate

3.1. Overview

Local and regional journalists report decreased residential property values associated with lower lake levels within the WCS [4]. However, these reports are largely anecdotal, and no known formal analyses have been performed. This study explores the hypothesis that interannual changes in regional hydrologic conditions, specifically lake levels, will evoke a change in residential lakefront real estate value. The analyses are performed on an annual basis and use non-lakefront residential real estate to provide a regional baseline and limit false causation conclusions. The subsequent sections discuss the regional hydrology, real estate data, and the relationship between the data.

3.2. Lake Levels

The region has over 300 lakes, but lake level data is limited both spatially and temporally. Many lakes are seepage lakes supplied by surface runoff and groundwater, and local geology results in a tightly coupled relationship between ground and surface water [35]. The unique hydrology of the WCS is a product of relatively shallow groundwater, high aquifer transmissivity, and high soil hydraulic conductivity, where shallow groundwater exhibits a tightly coupled relationship with area surface waters and high transmissivity allows quick groundwater response from external forcings, such as precipitation and groundwater withdrawals [35]. Therefore, the gridded PRISM precipitation data may potentially be used to model interannual lake level changes in the WCS.

Two seepage lakes (Figure 16 and Table 1) are identified within the WCS with a minimum of 7 consecutive years of United State Geological Survey (USGS) lake level data [36].
Figure 16. Locations of available USGS lake level data in the WCS: WCS delineation (red polygon), NHD waterbodies (blue polygons), USGS lake level gage locations (inverted pink triangles).

<table>
<thead>
<tr>
<th>Lake</th>
<th>USGS Gage</th>
<th>Location (Latitude, Longitude)</th>
<th>Period of Record (Years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lake Huron</td>
<td>05401063</td>
<td>44.195639, -89.417472</td>
<td>2001 – 2017</td>
</tr>
<tr>
<td>Long Lake</td>
<td>441257089071500</td>
<td>44.215722, -89.120722</td>
<td>2010 – 2017</td>
</tr>
</tbody>
</table>

Table 1. WCS Seepage Lake Summary.

Total annual precipitation values are calculated for the period of 2000 – 2017, which spans the period of record for the two identified seepage lakes. The mean annual total precipitation for this period is approximately 868 mm. The precipitation anomalies from the mean annual total precipitation are reasoned to be one of the primary drivers affecting lake levels in the WCS and are used to model the estimated interannual hydrologic changes (Equation 4).
(Hydrologic Change)ₜ = (Total Annual Precipitation)ₜ − (Mean Annual Precipitation)

Equation 4. Estimated interannual hydrologic changes. This change is estimated with the precipitation anomaly and represents the approximate change in storage, which affects lake levels in the region.

(Mean Lake Level Change)ₜ = (Mean Lake Level)ₜ − (Mean Lake Level)ₜ₋₁

Equation 5. Change in mean annual lake level.

A linear regression is performed for each identified seepage lake (Figure 17) with the estimated interannual changes in hydrologic conditions (Equation 4) and interannual changes in lake levels (Equation 5). Lake Huron exhibits a much stronger lake level response compared to Long Lake. This is likely due to the hydrologic properties of each lake, which includes the lake surface area to depth ratio and the location in the aquifer. The magnitude of individual lake level response may be different throughout the WCS, but it’s reasoned lakes within the region experience a positive lake level response with respect to modeled hydrologic change. This suggests annual precipitation anomalies may be used as a reasonable surrogate for changes in interannual regional lake levels in the WCS.
3.3. Residential Real Estate

These analyses utilize the Zillow Transaction and Assessment Data (ZTRAX) [37] to develop lakefront and non-lakefront real estate transactions data within the WCS. Transaction data from 2005 to 2017 is available for the region except for Wood County, Wisconsin, and includes various attribute information. The transaction data are filtered for the following: located within the delineated WCS, residential property, sales price greater than zero dollars, and not flagged for intrafamily transaction.

The Zillow ZTRAX data does not include attribute data differentiating lakefront and non-lakefront real estate and a metric must be developed. The data includes latitude and longitude coordinates and two populations, lakefront and non-lakefront, are established on proximity to lakes identified.
in the USGS National Hydrography Dataset (NHD) [38]. The threshold for the lakefront properties is 100 meters.

Annual transaction sales prices exhibit interannual variability for the two populations (Figure 18). The average number of annual lakefront and non-lakefront residential property sales are 375 and 2125, respectively. While the average number of annual non-lakefront transactions are approximately 5.7 times greater than annual lakefront transactions; the mean lakefront sales prices are approximately 1.9 times greater than non-lakefront transactions. The average total annual sales are $72.5 million and $220 million for lakefront and non-lakefront, respectively, in the WCS.

![Figure 18. Annual sales of lakefront and non-lakefront residential real estate within the WCS from 2005 to 2017.](image)

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3.4. Hydrologic – Real Estate Interannual Change Relationships

This study evaluates the potential impacts of changing hydrologic conditions, specifically lake levels, on residential real estate on an annual basis. The interannual changes in WCS regional hydrologic conditions are estimated with the precipitation anomalies from the mean annual total precipitation (Equation 4). The interannual changes in lakefront and non-lakefront property in the WCS are estimated with the change in median sales price for each population (Equation 6). The median population value is used to control for individual property positive or negative price changes, which could result from remodeling, building a new addition, letting the property fall into disrepair, and a wide variety of other activities.

\[
(Real \text{ Estate \ Population \ Change})_t = (Median \ Sales \ Price)_t - (Median \ Sales \ Price)_{t-1}
\]

*Equation 6. Estimated change in annual real estate conditions in the WCS. Annual changes are calculated for year (t) 2006 to 2017.*

A linear regression is performed for each residential real estate population, lakefront and non-lakefront, with the annual change in hydrologic conditions (Figure 19). The analysis is performed under two conditions: a) all years and b) excluding sales in 2008 for both populations. The second analysis excludes sales in 2008 in an attempt to limit large external economic effects on the real estate market associated with the subprime lending crisis, which is an outlier in the dataset and may mask the potential relationship between real estate and hydrologic conditions.
Figure 19. Linear regression of two real estate populations, lakefront (blue dots) and non-lakefront (orange crosses) with change in annual hydrologic change, which is estimated via the change in total annual precipitation. Shaded areas indicate the 95% confidence interval. Figure a) includes all years between 2006 – 2017. Figure b) excludes data for 2008 associated with the subprime lending crisis.

The data in both scenarios suggest annual changes in hydrologic conditions have little, to no effect the year to year sales prices of non-lakefront residential real estate, and a positive relationship appears to exist between increased (decreased) annual sales prices of lakefront real estate when the annual change in hydrologic conditions are wetter (drier). Furthermore, the removal of 2008 data result in a more statistically significant relationship between median lakefront property sales prices and changing hydrologic conditions, reducing the p-value from 0.27 to 0.13 and increasing the coefficient of correlation from 0.34 to 0.48. The change in non-lakefront property sales with respect to changing hydrologic conditions results in a non-statistically significant slope near zero, which suggests the population is not affected by interannual variability in hydrologic conditions.
3.5. Lakefront Real Estate and Hydrologic Conditions

An apparent positive relationship exists between the interannual change in hydrologic conditions and change in median lakefront property sales in the WCS. However, this does not address the state of the hydrologic conditions, which includes a hydrologic storage component, and corresponding state of lakefront property real estate. The state of the hydrologic conditions in the WCS is modeled with the cumulative sum of annual precipitation anomalies (Equation 7), which represent the interannual change in hydrologic conditions. The state of annual lakefront property is represented by the median sales price.

\[
\text{Hydrologic Condition} = \sum_{t=2000}^{2017} (\text{Annual Precipitation}_t) - (\text{Mean Annual Precipitation})
\]

*Equation 7. Modeled annual hydrologic condition from year (t) 2000 to 20017. The sum of the annual changes in hydrologic conditions is used to estimate the hydrologic conditions in each year.*

A linear regression is performed for the state of hydrologic conditions and lakefront real estate in the WCS (Figure 20). A statistically significant positive slope at the 95% confidence interval (p-value \( \leq 0.05 \)) exists for the relationship between hydrologic conditions and lakefront real estate. At a regional scale, this suggests a 20% (174 mm) increase (decrease) in hydrologic conditions will elicit a 5% ($7,300) increase (decrease) in median lakefront property sales price values within the WCS. This response may increase (decrease) for lakes with higher (lower) hydraulic sensitivity.
Figure 20. Hydrologic condition and lakefront real estate in the WCS. The shaded area indicate the 95% confidence interval.
CHAPTER 4: Discussion

4.1. Seasonal Forecasting and Atmospheric Moisture Transport

The seasonal precipitation forecast appears to have modest skill with respect to forecasting drought conditions, especially when the MAM MEI index value falls in the lowest quartile indicative of La Niña conditions. This phase of ENSO reduces the intensity of the GPLLJ, which is the primary mechanism of moisture transport from the Gulf of Mexico across the Great Plains and upper Midwest, is damped, resulting in decreased summertime precipitation. The statistical model appears to identify the preseason signal associated with this phenomenon well and provides modest predictive capabilities. However, this empirical relationship deteriorates as the MAM MEI index values and GPLLJ intensity increases. While the increased jet activity does provide increased poleward moisture transport over the Great Plains and upper Midwest; both the meridional and zonal variability of precipitation increases, making a basin specific forecast less predictable.

The modeled JJA precipitation forecast is issued on June 1st, which is after farmers have made cropping decisions and planted. However, it may still provide value in terms of intraseasonal supplemental irrigation requirements and potential crop yields. A skillful forecast with a longer lead would potentially be able to provide additional value. However, maintaining forecast skill becomes increasingly difficult, especially when considering the large uncertainty associated with the ENSO spring barrier. Insight into upcoming seasonal climatic conditions with a longer lead time may be partially achieved with long-term projections.
4.2. Long-term Seasonal Projection

The AMO and PDO climate indices do not appear to capture interannual variability, but their multidecadal patterns may provide beneficial information within a long-term projection framework. These long-term projections may not provide information if drought conditions are going to occur in any given year, but they may provide information of increased or decreased likelihood of a drought occurring. This information can be provided for the next several years and may be used to develop long-term water management plans due to the decadal variability of the predictors: PDO and AMO. Additionally, it can provide a second line of evidence supporting a drought forecast if strong MAM La Niña conditions are present.

McCabe et al propose that over half of all temporal variance in multidecadal drought frequency can be explained by the state of AMO and PDO [39]. They identify four phases of the 20-year rolling average of these indices that contribute to drought frequency across the contiguous United States (CONUS): AMO positive (+) PDO+, AMO negative (-) PDO+, AMO+ PDO-, and AMO-PDO- (Figure 21).

*Figure 21. Mean annual AMO (red) and PDO (blue) index values.*
Identified years for AMO PDO conditions are the following:


The frequency of normal-dry and dry JJA precipitation is calculated for each AMO-PDO category. A frequency higher (lower) than 25 percent suggests a higher (lower) probability of the climate quantile occurring during the given AMO PDO condition. The AMO and PDO climate patterns exhibit 60 – 80 and 40 – 60 year periods, respectively [19, 20]. This longer periodicity may provide useful information 5, 10, or more years.

The calculated values for each AMO PDO climate condition are provided in Table 2. A frequency higher (lower) than 25 percent suggests a higher (lower) probability of the climate quantile occurring during the given AMO PDO condition. The frequency of either dry or normal-dry climate conditions are also reported.

<table>
<thead>
<tr>
<th>Phase of Climate Indices</th>
<th>Probability of JJA Precipitation Climate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dry</td>
</tr>
<tr>
<td>AMO+ PDO+</td>
<td>31.0</td>
</tr>
<tr>
<td>AMO+ PDO-</td>
<td>15.4</td>
</tr>
<tr>
<td>AMO- PDO+</td>
<td>20.0</td>
</tr>
<tr>
<td>AMO- PDO-</td>
<td>33.3</td>
</tr>
</tbody>
</table>

*Table 2. Frequency of dry and normal-dry precipitation climate conditions given the phase of AMO and PDO climate indices.*
The results suggest an increased probability of dry conditions when AMO and PDO are in-phase with the highest frequency associated with negative-negative conditions. The lowest frequency of dry conditions is observed during AMO+ PDO-, and this increased probability continues for normal-dry conditions as well. It’s worth noting there also exists a large reduction in probability of dry conditions when the two climate indices are out of phase, especially for AMO+ PDO-.

4.3. Lakefront Real Estate

The results of the real estate analysis indicate year to year non-lakefront real estate transactions are relatively insensitive to changes in area hydrologic conditions and provides a regional baseline for real estate transactions in the WCS. The near zero slope of non-lakefront sales has an y-intercept of approximately $2,035, which is interpreted to be associated with regional inflation. On the other hand, there is strong evidence for interannual changes in the value of lakefront real estate with respect to changing hydrologic conditions. The data suggest annual lakefront real estate sales prices will experience an increase (decrease) when the annual change in hydrologic conditions, represented by the annual precipitation anomaly, is greater (less) than approximately 100 mm. It is also worth noting the intersection between the non-lakefront and lakefront linear regressions occur around 0 mm, which may suggest similar regional inflationary pressures affecting lakefront and non-lakefront properties. The relationship is strengthened when the interannual changes in hydrologic conditions are used to model the annual state of hydrologic conditions, which attempts to account for the current relative storage in the system. At a regional scale, a 20% (174 mm) increase (decrease) in hydrologic conditions appears to elicit a 5% ($7,300)
increase (decrease) in median lakefront property sales price values within the WCS. This response may increase (decrease) for lakes with higher (lower) hydraulic sensitivity.

Insights into hydraulic sensitivity could be performed with additional sales data at a sub-regional, lake category, or even for individual lakes in the future. It’s reasoned WCS lakefront property in areas of higher hydraulic sensitivity would experience a stronger response from interannual changes in hydrologic conditions. Hydraulic sensitivity refers to the hydraulic response of individual lake levels from inputs and outputs of the local water balance, such as precipitation and evapotranspiration, and is believed to be largely affected by the relative position of the lake within the aquifer with respect to the groundwater mounding profile, the local transmissivity, and the lake type: seepage, drainage, or spring fed. It’s reasoned that seepage lakes located in areas of high hydraulic conductivity and in upland areas closer to hydraulic divides would exhibit higher hydraulic sensitivity and consequently experience larger decreases in lake levels during periods of drought. Modelling conducted by Kraft et al indicate the presence of a north-south hydraulic divide (Figure 22) located approximately in the middle of the WCS delineated aquifer with higher rates of hydraulic conductivity in the western half [10].
Figure 22. Map figure groundwater equipotential contour lines, which represent lines of equal hydraulic head. A north-south hydraulic divide is located approximately in the middle of the WCS. This data was developed by Kraft et al [10].

A preliminary sub-regional hydrologic sensitivity analysis is performed with the methods used for the regional analysis. The WCS region is subdivided into a 3 by 3 grid (Figure 24) and linear regressions between annual hydrologic conditions and median lakefront property sales prices are
developed for each sub-regional area (Figure 24). However, annual transaction data is limited at the sub-regional level and analyses are only performed if a minimum of 10 lakefront property transactions exist for each year during the period of record: 2005 – 20017. The limited transaction data does not allow for statistically significant conclusions, but the data does appear to partially coincide with assumptions of higher hydraulic sensitivity along the hydraulic divide and western half of the aquifer.

Figure 23. WCS sub-regional divisions: a), b), c), d), e), f), g), h), and i). Sub-regional longitude boundaries are located at -90.0°W, -89.7°W, -89.3°W, and -88.9°W. Sub-regional latitude boundaries are located at 44.9°N, 44.5°N, 44.0°N, and 43.6°N. Spatial coverage of sub-regions a) and i) are primarily outside of the delineated WCS aquifer.
Figure 24. Linear regressions of annual hydrologic condition and median lakefront population sales price for WCS sub-regional divisions a), b), c), d), e), f), g), h), and i). Sub-regions a) and i) have less than 10 lakefront property transactions for at least one year during the period of record: 2005 – 2017. Shaded areas indicate the 95% confidence interval.
Data at present may be too limited for sub-regional analyses, but additional analyses with currently available data may include cross-regional comparisons in nearby areas and/or throughout the United States. Considerable attention has been given to high-capacity wells within the WCS and the relationship to lake levels, but there have also been concerns about lake levels in northern Wisconsin [1] where there are a limited number of high-capacity wells and lower lake levels are presumed to be primarily associated with drought. There has also been growing interest in groundwater-surface water interactions in the Minnesota Central Sands, a region that shares many of the same characteristics of the WCS. The analyses performed in this study could be replicated for these regions and compared to those obtained in the WCS.

4.4. Conclusions

The ENSO climate phenomenon is identified as the primary large-scale climate phenomena affecting interannual variability of summertime precipitation in the WCS. However, it should be noted that AMO and PDO, which exhibit multi-decadal frequencies, also modulate summertime precipitation. The MEI is one of the available indices used to describe the temporal behavior of the ENSO climate phenomena and indicates drier conditions are more likely during the negative phase, which is associated with La Niña conditions. The MEI is used within the NIPA statistical model, which utilizes sea surface temperature anomalies, to develop a four-phase model and results indicate the negative phase, associated with drier conditions, is capable of identifying preseason signals of atmospheric moisture transport.

Interannual changes in lake levels within the WCS can reasonably be modeled with annual precipitation anomalies and are used to estimate the change in hydrologic conditions within the
region. Interannual changes in hydrologic conditions within the WCS appear to elicit a positive response in median lakefront property sales prices, and non-lakefront property do not exhibit any sensitivity to changing hydrologic conditions. The cumulative sum of interannual hydrologic conditions are used to account for storage in the system and model the annual state of hydrologic conditions in the WCS. A statistically significant positive slope at the 95% confidence interval (p-value \(\leq 0.05\)) exists for the relationship between hydrologic conditions and lakefront real estate. The analyses, at a regional scale, suggest a 20% (174 mm) increase (decrease) in hydrologic conditions will elicit a 5% ($7,300) increase (decrease) in median lakefront property sales price values within the WCS.
References


