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Added value from 576 years of tree-ring records in the prediction of the Great Salt Lake level

Robert R. Gillies [a,b,*], Oi-Yu Chung [a], S.-Y. Simon Wang [a,b], R. Justin DeRose [c], Yan Sun [d]

[a] Utah Climate Center, Utah State University, Logan, UT, USA
[b] Department of Plants, Soils, and Climate, Utah State University, Logan, UT, USA
[c] U.S. Forest Service Rocky Mountain Research Station, Ogden, UT, USA
[d] Department of Mathematics and Statistics, Utah State University, Logan, UT, USA

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SUMMARY

Predicting lake level fluctuations of the Great Salt Lake (GSL) in Utah – the largest terminal salt-water lake in the Western Hemisphere – is critical from many perspectives. The GSL integrates both climate and hydrological variations within the region and is particularly sensitive to low-frequency climate cycles. Since most hydroclimate variable records cover less than a century, forecasting the predominant yet under-represented decadal variability of the GSL level with such relatively short instrumental records poses a challenge. To overcome data limitations, this study assesses two options: (1) developing a model using the observational GSL elevation record of 137 years to predict itself; (2) incorporating the recently reconstructed GSL elevation that utilized 576 years worth of tree-ring records into the predictive model. It was found that the statistical models that combined the tree-ring reconstructed data with the observed data outperformed those that did not, in terms of reducing the root mean squared errors. Such predictive models can serve as a means toward practical water risk management.

1. Introduction

Located in the semi-arid Intermountain West of the U.S.A, the Great Salt Lake (GSL) integrates the region's hydroclimate over its broad watershed (Fig. 1a). The level of the large shallow lake is controlled by direct influx from precipitation and indirect inflow from major rivers, both of which are offset by evaporation primarily during the summer months. Due to its large surface area that is contained within a closed basin, fluctuations in the GSL level duly reflect the hydroclimate conditions of the region: i.e. the highest water mark lags after the peak in the precipitation regime (of the region's prominent wet–dry cycle) while the lowest water mark occurs after the onset of the low point in the precipitation regime (Wang et al., 2010), a condition oftentimes created by persistent drought. The lake level fluctuation (Fig. 1b) therefore records regional hydroclimate variability, especially at low frequencies (Lall and Mann, 1995; Mann et al., 1995; Wang et al., 2010, 2012). Climate forecasts for both the GSL level and volume have been attempted: For example, atmospheric circulation indices have been explored as to their role in controlling the GSL level (Moon and Lall, 1996; Gillies et al., 2011; Wang et al., 2012). Additionally, time-series modeling techniques have been developed in order to predict future GSL levels, though most of the models are only applicable over the short-term of 1–2 years (Lall et al., 1996, 2006).

Focusing on the decadal-scale variability of the GSL level, Wang et al. (2010) discovered that the GSL level is highly coherent with, yet opposite to, the tropical central Pacific sea surface temperature (SST) anomalies at the 10–15 year timescale. The coherency occurs through a unique atmospheric teleconnection excited during the transition phases of this 10–15 year oscillation; this affects precipitation within and around the Great Basin through a trans-Pacific atmospheric wave train (Wang et al., 2011). With regard to the connection that was discovered, Gillies et al. (2011) developed a principal component-lagged regression model that was able to predict the GSL level out as far as 8 years (Fig. 1b). It is also noteworthy that Gillies et al.'s GSL forecast, that began in 2008 and lead up to 2015 (delineated and indicated by arrow in Fig. 1b), was validated with in-situ observations (up to 2013) and showed remarkable consistency, most notably in forecasting the upturn that occurred in 2010–2011 and the downturn thereafter at 2012. At the time of the prediction, the 2010–2011

* Corresponding author at: 4825 Old Main Hill, Logan, UT 84322, USA.
E-mail address: Robert.Gillies@usu.edu (R.R. Gillies).

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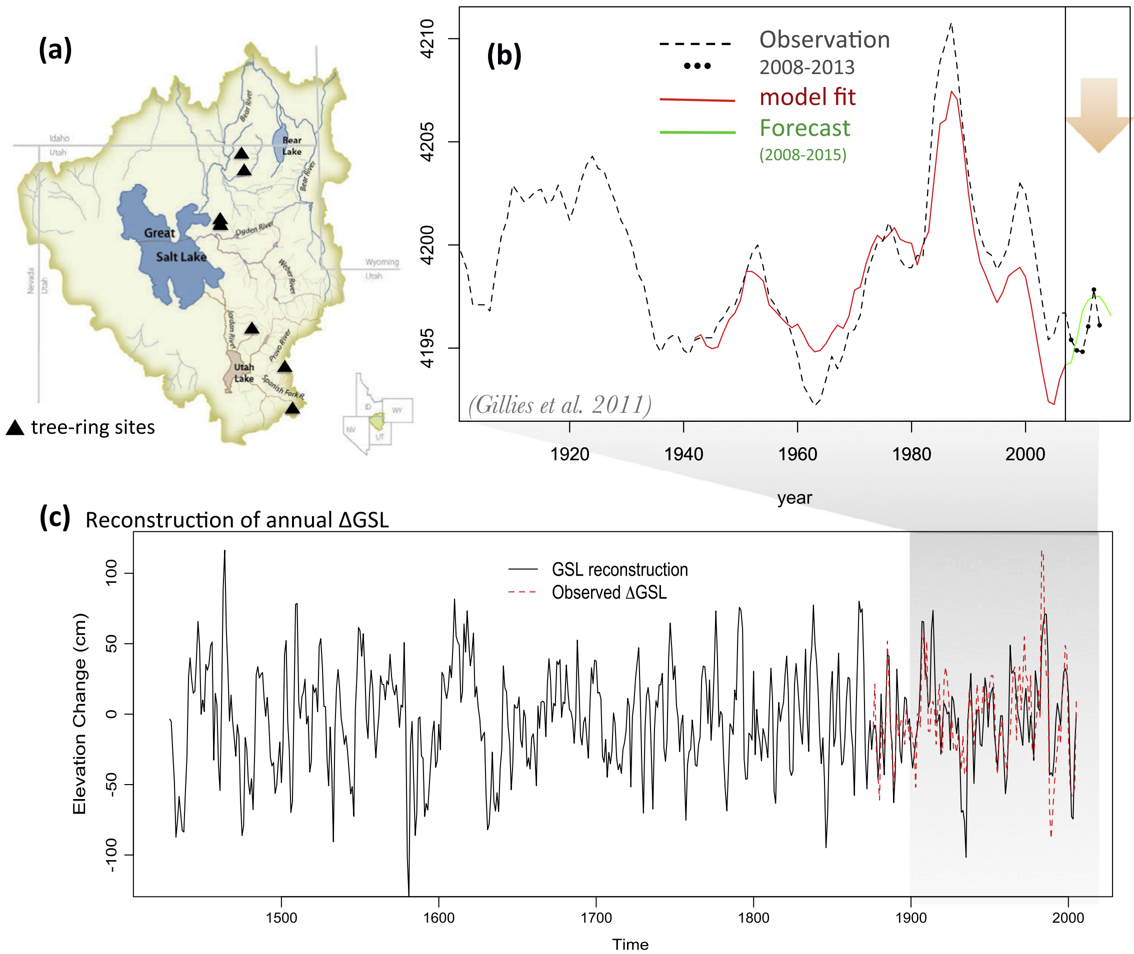

Fig. 1. (a) The locations of tree-ring sites. (b) Gillies et al.'s (2011) principal component-lagged regression model fit and forecast. (c) The observed and the tree-ring reconstructed annual ΔGSL.

increase in the GSL level had yet to occur; this circumstance supported the connection proposed in Wang et al. (2010), i.e. that the so-called Pacific Quasi-Decadal Oscillation (QDO) figured as a dominant climate phenomenon in the Intermountain West and was a strong contemporary driver of the region's hydroclimate.

However, the GSL level forecast, developed by Gillies et al. (2011), exhibited a wet bias that persisted for two decades followed by a dry bias for roughly a similar time span (Fig. 1b). Such biases of prolonged wet/dry apparently are linked to multi-decadal variability, notably a 30–50 year oscillation (Wang et al., 2012), which also influences the hydroclimate in and around the GSL watershed (Gray et al., 2004). At the time, multi-decadal variability was not incorporated within the GSL model of Gillies et al. (2011); this was due to the insufficient length of the historical observational data (~100 years). Noticing the data gap, DeRose et al. (2014) developed a 576-year (1429–2005) reconstruction of the GSL level tendency (water year minus previous water year; Fig. 1c) utilizing tree-ring width data collected from sites within the GSL watershed (Fig. 1a). Just like the GSL level, annual radial increments (i.e. ring widths) in trees respond to and so, reflect such meteorological variables like effective precipitation, air temperature, and vapor pressure deficit (Cook and Kairiukstis, 1990). In vegetation systems that are strongly limited by the release of winter snowpack (i.e., the Intermountain West), ring-width increment also integrates available moisture from the current and previous water years: In this regard, tree-ring chronologies record low frequency hydroclimatology and so, serve as a good proxy for the GSL level. Moreover, robust statistical tests verified the temporal stability of the GSL model over the instrumental period (1876–2005) confirming that the tree-ring-based reconstruction represented about 60% of pre-instrumental variability in the GSL level (DeRose et al., 2014).

Given the aforementioned progress in precipitation reconstructions and the inherent limitation in Gillies et al.'s (2011) technique in predicting the GSL level (i.e. not being able to account for multi-decadal variability), we hypothesized that a much longer period of record of lake level, i.e. one that captures the multi-decadal variability, should in theory improve the former GSL level prediction. Therefore we examined and compared further, the prediction of the GSL level derived from the observed GSL data alone in conjunction with a considerably longer-term tree ring-reconstruction of the GSL. In doing so, we explored the potential of tree-ring reconstructions of lake level enhancing our prior prediction of hydroclimate variability in a closed-basin lake like that of the GSL.

2. Model development

Both the studies of Gillies et al. (2011) and DeRose et al. (2014) focused on the tendency of the GSL level (i.e. the current water year minus the previous one) and used it to reconstruct the actual lake level. Thus, the ensuing analysis focuses on the tendency of the GSL level for both observed and tree-ring reconstructed data, denoted hereafter as ΔGSL. We first examined a prediction model based solely upon the observed ΔGSL, i.e. using ΔGSL to predict ΔGSL itself. We then used a model that combined both the observed and the tree-ring reconstructed ΔGSL to forecast the same time