Geophysical Research Letters

RESEARCH LETTER
10.1029/2019GL082289

Key Points:
- Oceanographic hydrodynamic models are evaluated for use in large lake water balance accounting
- Operational configurations of Great Lakes FVCOM models provide robust real-time simulations of evaporation

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Citation:
Gronewold, A. D., Anderson, E. J., & Smith, J. (2019). Evaluating operational hydrodynamic models for real-time simulation of evaporation from large lakes. *Geophysical Research Letters*, *46*, 3263–3269. https://doi.org/10.1029/2019GL082289

Received 30 JAN 2019
Accepted 11 MAR 2019
Accepted article online 15 MAR 2019
Published online 28 MAR 2019

Evaluating Operational Hydrodynamic Models for Real-time Simulation of Evaporation From Large Lakes

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Abstract Methods for simulating evaporative water loss from Earth's large lakes have lagged behind advances in hydrodynamic modeling. Here we explore use of oceanographic models to simulate lake evaporation from a long-term water balance perspective. More specifically, we compare long-term monthly simulations of latent heat flux from two configurations of a current operational hydrodynamic forecasting system (based on the Finite Volume Community Ocean Model, or FVCOM) for the Laurentian Great Lakes. We then compare these simulations to comparable simulations from a legacy conventional lake thermodynamics model, and from a recently developed statistical water balance model. We find that one of the FVCOM configurations that is currently used in operations for short-term hydrodynamic forecast guidance is also suitable for real-time simulation of evaporation from very large lakes. The operational versions of FVCOM should therefore be considered a readily available tool for supporting regional water supply management and, pending further research, extended water supply forecasting.

1. Introduction

Using numerical models to accurately simulate turbulent heat fluxes from Earth's surface waters is a critical stepping stone toward successfully forecasting regional and continental-scale hydrological and meteorological processes (Deacu et al., 2012; Ghanbari & Bravo, 2008; Notaro et al., 2015). Accurately simulating these processes is also critical to resolving heat and mass fluxes from oceans and large lakes (Assel et al., 2004; Gronewold & Stow, 2014). While the state of the art in ocean flux modeling has advanced steadily over recent decades, evaluations of flux algorithms from an evaporative water loss perspective, particularly for large freshwater systems, have lagged behind, primarily due to sparse or unavailable validation data. We find, more specifically, that lake evaporation is commonly inferred through simple water balance accounting in which evaporation is calculated as a residual from other more readily measurable water balance components such as lake inflow, outflow, and precipitation (Gianniou & Antonopoulos, 2007; Hostetler & Bartlein, 1990; Quinn, 1979). Satellite-based measurements have also been successfully applied to studies on the water balance of large lakes but typically cannot differentiate lake evaporation from other water balance components without local in situ meteorological and hydrological data (Alsdorf et al., 2001; Swenson & Wahr, 2009; Wahr et al., 1998).

On the Laurentian Great Lakes (hereafter referred to simply as “the Great Lakes”), which includes the largest lake on Earth by surface area (Lake Superior), historical studies indicate that evaporation is roughly equivalent on annual time scales to over-lake precipitation and lateral tributary runoff (Gronewold et al., 2013; Lenters, 2001; Quinn, 2002; Spence et al., 2013). Nearly all of these studies, however, were based on a legacy data set (Hunter et al., 2015) of simulated monthly total lakewide evaporation derived from a relatively outdated, conceptual one-dimensional thermodynamics model (Croley, 1989, 1992). Importantly, the boundary conditions for this legacy evaporation model were defined through coarse spatiotemporal interpolation of land-based meteorological measurements (including cloud cover and air temperature) that were quality controlled over a period lasting from days to weeks (Hunter et al., 2015). Model calibration, furthermore, was based solely on lakewide average surface water temperature data; in situ flux measurements, which would have provided a more robust basis for calibration and verification, were not available when the above-referenced historical water balance studies were published.

Consequently, there are significant but unacknowledged uncertainties in Great Lakes water balance estimates that have served as the basis for historical studies and regional water management planning decisions. These uncertainties, in addition to posing a challenge to water management agencies, have led to confusion and even misinformation about the drivers of water level variability across the Great Lakes region (Moulton & Cuthbert, 2000). The urgency of resolving these uncertainties was underscored during dramatic declines in Great Lakes water levels in the late 1990s and the unprecedented period of persistent low water levels that followed (Sellinger et al., 2007). In public discourse, the low water level conditions during this period were misattributed to historical dredging operations and interbasin water diversions (Gronewold & Stow, 2014). Scientists and practitioners, despite an understanding of how increased evaporation likely led directly to water level declines (Assel et al., 2004), were not able to use state-of-the-art operational oceanographic models or data sets to support their work and to guide public perceptions. Important advancements were being made in regional operational oceanographic numerical modeling at that time (Deacu et al., 2012; Pietroniro et al., 2007; Schwab & Bedford, 1994), but the modeling systems were used predominantly for simulating and forecasting meteorological-scale events (including storm surge) over relatively short time horizons (out to 5 days), and they had not been verified from a turbulent heat flux or water mass balance perspective.

To use these state-of-the-art operational oceanographic models in regional water balance and water level accounting, two important advancements were needed. First, in situ eddy-covariance stations needed to be deployed across the Great Lakes to (among other objectives) assess and refine the intrinsic flux algorithms in the models. To date, this step has been achieved; a small network of in situ eddy-covariance stations was deployed across the Great Lakes through an initiative launched by the International Joint Commission (Blanken et al., 2011; Spence et al., 2011) in the mid- to late-2000s, and the measurements have been used to validate the algorithms encoded in the operational models (Charusombat et al., 2018; Deacu et al., 2012; Fujisaki-Manome et al., 2017).

The second advancement, which we address in this study, is the testing of lakewide simulations of evaporation from these models from a mass balance perspective. More specifically, we use existing operational oceanographic models within the National Oceanic and Atmospheric Administration (NOAA) to simulate evaporation from the Great Lakes and test them according to criteria relevant to water resources management agencies, including those that issue water supply forecasts. Our approach represents a rare evaluation of a community ocean model and its underlying heat flux algorithms from a domain-scale evaporation perspective. Successfully demonstrating the capability of simulating lakewide evaporation rates would justify immediate use of these models in their new operational settings while supporting not only a broader understanding of drivers of water level change throughout the region (Assel et al., 2004; Gronewold & Stow, 2014) but also the potential for using state-of-the-art oceanographic models to reconcile uncertainties in the water balance of large freshwater systems around the world.

2. Methods

To better understand the potential utility of state-of-the-art oceanographic models for simulating and forecasting the water balance of large lake systems, we generate and assess results from two configurations of a modeling system currently deployed in operational hydrodynamic forecasting (Anderson et al., 2018; Kelley et al., 2018) for Lake Erie (one of the five Great Lakes). We then compare these results to those from a legacy lake evaporation model, and a recently developed statistical lake water balance model.

2.1. Model Simulations

The Finite Volume Community Ocean Model (FVCOM; Chen et al., 2006) is an unstructured-grid, three-dimensional ocean model that is being systematically customized and implemented into an update of the Great Lakes Operational Forecast System (GLOFS). GLOFS is a set of short-term hydrodynamic forecast models maintained by NOAA's National Ocean Service for operational forecast guidance and support of navigation, spill response, search and rescue operations, and recreational safety (Anderson et al., 2018; Kelley et al., 2018; Schwab & Bedford, 1994). FVCOM has been successfully implemented in several ocean and Great Lakes studies (Anderson et al., 2015; Fujisaki-Manome et al., 2013, 2017; Rowe et al., 2017), including simulation of ice conditions using the Los Alamos Sea Ice Model (CICE; Hunke et al., 2010), which is internally coupled with FVCOM. Further details about model setup for the Lake Erie Operational Forecast System (LEOFS), a subset of GLOFS, can be found in Anderson et al. (2018). In this study, evaporation from LEOFS is evaluated using two available heat flux algorithms native to FVCOM-CICE.

The first configuration of FVCOM-CICE employs the SOLAR flux algorithm, which is the existing operational setup of LEOFS. The SOLAR algorithm, developed at the NOAA Great Lakes Environmental Research Laboratory (GLERL) for application to the Great Lakes, solves standard bulk flux expressions for latent and sensible heat based on Monin-Obukhov Similarity Theory (Foken, 2006; Kantha & Clayson, 2004). SOLAR has served as the legacy flux algorithm for Great Lakes operational hydrodynamic forecasting following the initial implementation of GLOFS and has subsequently been applied to other research projects (Anderson & Schwab, 2013; Beletsky & Schwab, 2001).

Our second configuration of FVCOM-CICE employs the Coupled Ocean Atmosphere Response Experiment (COARE) flux algorithm (Fairall et al., 1996, 2003). The COARE algorithm currently represents the state of the art in ocean flux modeling but, because it was developed after initial development of GLOFS, is being considered for flux models on the Great Lakes for the first time in this study. A freshwater parameterization of COARE is included within FVCOM and uses Monin-Obukhov Similarity Theory with minor differences in stability functions relative to SOLAR. Our study therefore represents a unique opportunity to evaluate potential improvements to the flux algorithm within LEOFS from not only a water balance perspective but a meteorological and hydrodynamic perspective as well. Both configurations utilize native GLOFS meteorological forcings as boundary conditions (for details, see Kelley et al., 2018; Schwab & Bedford, 1994).

We ran the two FVCOM configurations over a historical period from January 2004 through December 2016 (Anderson et al., 2018), with the 2004 calendar year set aside as a spin-up period. We extracted gridded values for latent heat flux and converted them to evaporation (in units of mm over the surface of Lake Erie). We then aggregated these variables across the entire surface of Lake Erie to obtain an estimate of total lakewide evaporation at each time step.

Similarly, we extracted simulated evaporation from the Large Lakes Thermodynamics Model (LLTM). The LLTM is the previously referenced legacy model developed at NOAA GLERL for Great Lakes water balance modeling (Croley & Hartmann, 1987; Croley, 1989, 1992) and employed operationally by regional water resources management agencies in seasonal water supply forecasting (Gronewold et al., 2011). For this study, we extracted daily lakewide evaporation for Lake Erie from 2005 through 2016 (coinciding with the period used for the FVCOM runs) from the experimental configuration of LLTM maintained at NOAA GLERL as part of a research-oriented long-term hydrometeorological database (Hunter et al., 2015).

2.2. Model Verification

Verifying modeled evaporation is a challenge for any freshwater body, and it is particularly challenging for the Great Lakes given their vast surface areas, the intrinsic spatiotemporal variability of fluxes across those surfaces (Blanken et al., 2000), and the spatial coverage of the valuable (but relatively sparse) in situ flux monitoring network (Blanken et al., 2011; Spence et al., 2011, 2013). While the recent model evaluation studies utilizing this monitoring network (Charusombat et al., 2018; Fujisaki-Manome et al., 2017) indicate that the flux algorithms in FVCOM-COARE and FVCOM-SOLAR provide reasonable simulations of sensible and latent heat fluxes at discrete monitoring points, we know of no previous study that has explicitly verified lakewide simulations of evaporation for any configuration of FVCOM.

We therefore take two approaches to verifying the FVCOM and LLTM models from a lake water balance perspective. First, we compare simulated lakewide average surface water temperatures across Lake Erie from each model to satellite-derived temperatures from the Great Lakes Surface Environmental Analysis (GLSEA; Leshkevich et al., 1996; Schwab et al., 1999). The GLSEA is commonly employed in Great Lakes regional hydrodynamics and lake physics studies as a basis of comparison for surface water temperature and other variables (Dupong et al., 2012; Holman et al., 2012; Notaro et al., 2013).

We then compare simulated lakewide evaporation from each model to monthly total lakewide evaporation estimates from a recently developed statistical water balance model. This model, commonly referred to as the large lake statistical water balance model, or L2SWBM (Gronewold et al., 2016), employs a Bayesian modeling framework (Press, 2003; Van Dongen, 2006) to infer posterior probability distributions for monthly total values of major water balance components of the Great Lakes. The L2SWBM reconciles each lake's long-term water balance using historical water levels and readily available historical data sets of the water balance. For this study, we ran the L2SWBM across all of the Great Lakes from 2005 to 2016 and assimilated estimates of precipitation, evaporation, runoff, and connecting channel flows from multiple existing sources (described in Gronewold et al., 2016). We also, specifically for this study, included the estimates of Lake Erie

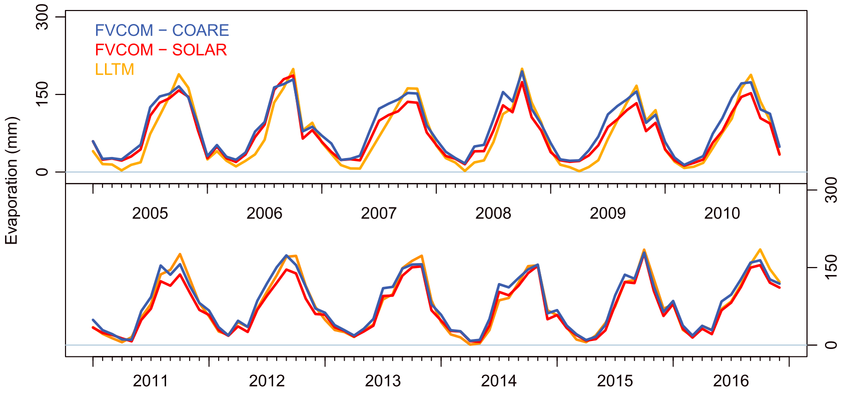

Figure 1. Time series of monthly total evaporation from Lake Erie based on two configurations of Finite Volume Community Ocean Model (FVCOM) and the legacy Large Lakes Thermodynamics Model (LLTM).

evaporation from FVCOM-COARE, FVCOM-SOLAR, and LLTM. This approach leads to L2SWBM estimates of Lake Erie monthly evaporation that reconcile the water balance of the entire Great Lakes basin over multiple time periods, while also identifying the relative bias of each historical data source (including the two configurations of FVCOM, and the LLTM).

3. Results

A comparison between model simulations of lakewide evaporation (Figure 1) indicates that from 2005 through 2011, the LLTM typically has lower evaporation rates in the spring months and higher seasonal peak evaporation in the fall months (2005, 2007, and 2009 are particularly profound examples) when compared to the two configurations of FVCOM. Also during this period, we find that summer evaporation rates in the

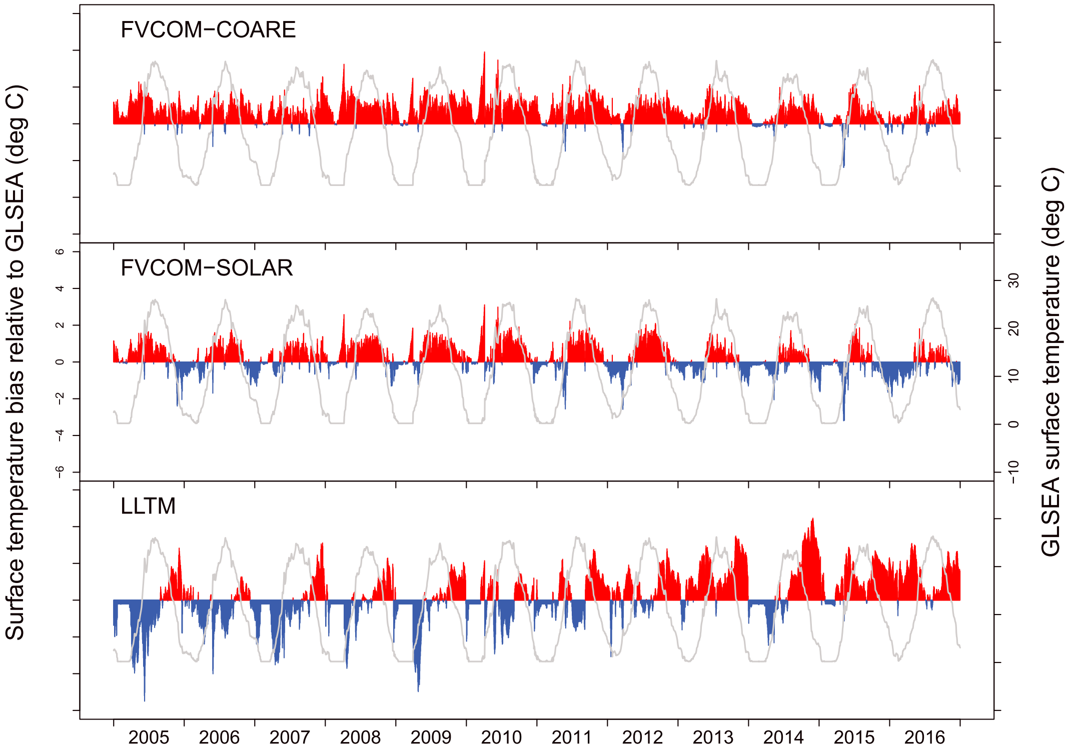

Figure 2. Time series of bias in simulated daily Lake Erie average surface water temperature from each model relative to GLSEA. GLSEA surface temperatures are also presented (gray line) in each panel for reference. GLSEA = Great Lakes Surface Environmental Analysis; FVCOM = Finite Volume Community Ocean Model; LLTM = Large Lakes Thermodynamics Model.

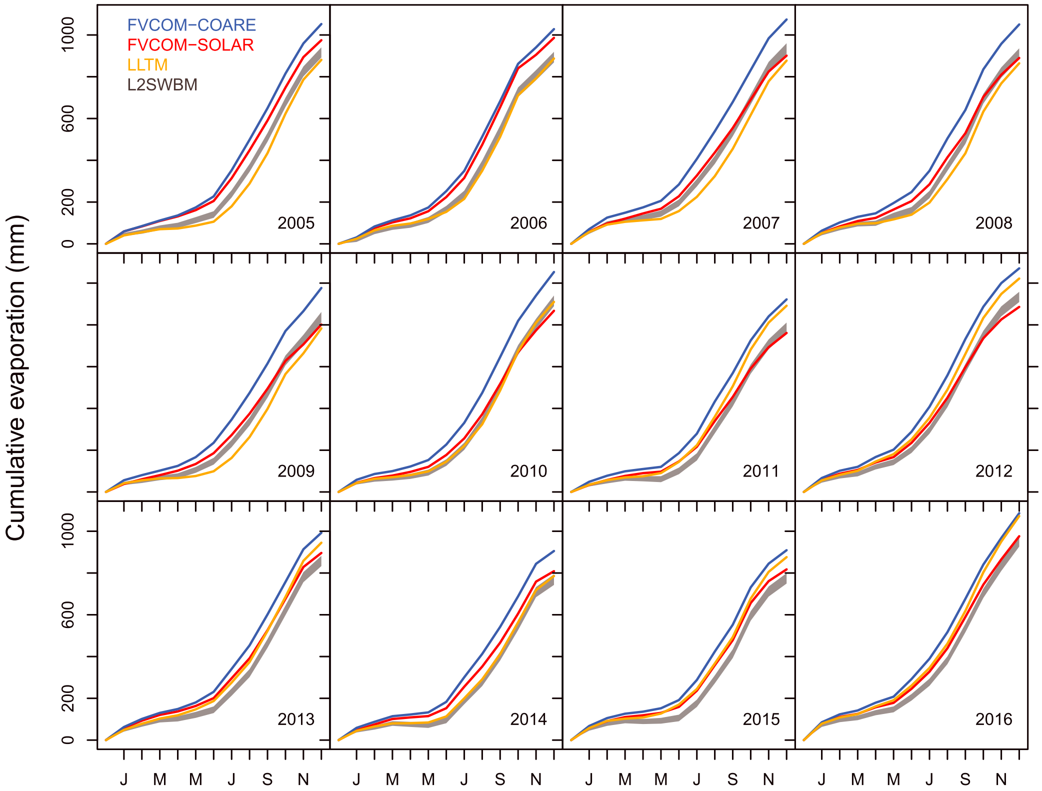

Figure 3. Cumulative annual (calendar year) lakewide total evaporation from Lake Erie based on two configurations of FVCOM, the LLTM, and the L2SWBM (L2SWBM results represented by 95% credible intervals). FVCOM = Finite Volume Community Ocean Model; LLTM = Large Lakes Thermodynamics Model; L2SWBM = large lake statistical water balance model.

LLTM are typically lower than those in the FVCOM simulations. The time series also indicates that FVCOM evaporation simulations using the COARE algorithm have a chronic positive bias relative to FVCOM simulations using the SOLAR algorithm throughout most of the study period. This bias is typically pronounced in summer months and is most noticeable as (in the FVCOM simulations) interruptions in the otherwise gradual increase in summer and fall evaporation (see, e.g., summer months in 2008 and 2013 through 2015).

Interestingly, with the exception of the noted differences in the rate of increasing evaporation in the summer months, LLTM and the two configurations of FVCOM are quite similar starting in early 2012 through early 2016. During this latter period, hydrologic and hydrodynamic conditions across the Great Lakes were characterized by an abrupt record-setting rise in Lake Superior and Lake Michigan-Huron water levels. This surge has been attributed to a combination of persistent above-average precipitation across the Great Lakes region, and below-average evaporation (Gronewold et al., 2016).

A time series of surface temperature bias for each of the models (blue and red vertical lines, Figure 2) relative to GLSEA temperatures (superimposed in each panel as gray lines in Figure 2) provides insight into the origins of intermodel discrepancies in simulated evaporation. More specifically, we find that the tendency for FVCOM-COARE to provide relatively high evaporation estimates can be partially explained by a chronic positive bias in simulated surface water temperature and that the bias (while persistently positive) has a strong seasonal pattern. Surface temperature bias in FVCOM-SOLAR also follows a strong seasonal pattern, albeit one in which bias is low near the end of each calendar year, negative through winter and early spring, and positive in the summer and early fall. LLTM surface temperature has a strong seasonal bias as well, but one that is out of phase with the bias in the FVCOM configurations. Interestingly, over time, the bias in LLTM surface temperature increases while the strength of the seasonal signature decreases.

Our analysis of cumulative evaporation during each calendar year (Figure 3) indicates that over our period of study, the FVCOM-SOLAR model is most consistent with the long-term water balance of the entire Great Lakes system. More specifically, we find that cumulative annual evaporation from the FVCOM-SOLAR model is closest to evaporation estimated by the L2SWBM for 8 of the 12 years of study, while the LLTM is closest for the other 4 years. Furthermore, cumulative evaporation from the FVCOM-SOLAR model was very close to cumulative evaporation from the L2SWBM in nearly every year of our study (with the exception of 2016), while the LLTM was substantially different from L2SWBM cumulative evaporation in five of our study years (2011, 2012, 2013, 2015, and 2016). Simulations from FVCOM-COARE were consistently positively biased and, among the three models, departed most from evaporation estimates in the L2SWBM. Nonetheless, simulations from FVCOM-COARE could still be useful to the regional water supply modeling and forecasting community, particularly if used as an input to the L2SWBM.

Despite the strong association between cumulative annual evaporation from FVCOM-SOLAR and L2SWBM, we find there are discrepancies between the two at subannual time scales reminiscent of seasonal biases in FVCOM surface water temperature simulations. The graphical depictions of cumulative annual evaporation, for example, underscore the extent to which FVCOM-SOLAR overestimates evaporation on Lake Erie in May, June, and July and underestimates Lake Erie evaporation in Autumn. While we expect to further explore (and potentially remedy) these biases in future research, we find that for now, they are not much more severe (if at all) than the intermonthly biases in the legacy model (i.e., the LLTM).

4. Summary and Conclusions

We have demonstrated the potential utility of applying state-of-the art numerical ocean models to large lake water balance accounting. Our representative application is based on an assessment of lakewide evaporation simulations from two configurations of FVCOM for Lake Erie, a legacy evaporation model (the LLTM), and a statistical water balance model (the L2SWBM).

More specifically, we have found that the SOLAR configuration of FVCOM, which is currently employed by NOAA in operational forecasting, is suitable for real-time simulation of Lake Erie evaporation and could be used alongside (or as a substitute for) the LLTM and other legacy lake models. In other words, the results presented here support the notion that model-simulated latent heat flux within LEOFS is suitable for translation into a lakewide total estimate of evaporation, and for public dissemination from within its existing operational platform. Based on these findings, we further recommend that FVCOM simulations be included in current applications of the L2SWBM that support operational water management by U.S. and Canadian federal agencies, including the United States Army Corps of Engineers and Environment and Climate Change Canada.

Acknowledgments
The authors are grateful for funding from the NOAA Coastal Storms Program, the IJC International Watersheds Initiative (IWI), and the NOAA Research Transition Acceleration Program (RTAP), all of which were administered by NOAA GLERL in partnership with the University of Michigan Cooperative Institute for Great Lakes Research (CIGLR). Funding was awarded to Cooperative Institute for Great Lakes Research (CIGLR) through the NOAA Cooperative Agreement with the University of Michigan (NA17OAR4320152). Greg Lang provided technical support. Data used in this study are freely available through NOAA GLERL (www.glerl.noaa.gov) and through specific product web pages (identified as subdirectories within the NOAA GLERL page) including those for the L2SWBM (… /data/WaterBalanceModel/), the GLCFS (… /res/glcfs/), and the LLTM (… /ahps/mnth-hydro.html). This is NOAA-GLERL publication 1916 and UM-CIGLR publication 1140.

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