Energy Budget Considerations for Hydro-climatic Impact Assessment in Great Lakes
Watersheds

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Abstract

Given the large share of the water budget contributed by evapotranspiration (ET), accurately estimating ET is critical for hydro-climate change studies. Routinely, hydrologic models use temperature proxy relationships to estimate potential evapotranspiration (PET) when forced using GCM/RCM projections of precipitation and temperature. A limitation of this approach is that the temperature proxy relationships do not account for the conservation of energy needed to estimate ET consistently in climate change scenarios. In particular, PET methods using temperature as a proxy fail to account for the negative feedback of ET on surface temperature. Using several GCM projections and a hydrologic model developed for the Great Lakes basin watersheds, the NOAA Large Basin Runoff Model (LBRM), the importance of maintaining a consistent energy budget in hydrologic and climate models is demonstrated by comparing runoff projections from temperature proxy and energy conservation methods. Differences in hydrologic responses are related to watershed characteristics, hydrologic model parameters and climate variables. It is shown that the temperature proxy approach consistently leads to prediction of relatively large and potentially unrealistic reductions in runoff. Therefore, hydrologic projections adhering to energy conservation principles are recommended for use in climate change impact studies.

Keywords: Climate change, Evapotranspiration, Watershed Characteristics, Hydrologic models

Introduction

In the upper midwestern United States, annual evapotranspiration (ET) is approximately 30-50% of annual rainfall (Sanford and Selnick, 2013). Given this large proportion of the water budget, accurately estimating ET is critical for hydro-climate change studies. As direct measurements of ET (e.g. using pans, eddy covariance flux towers, and weighing lysimeters) are expensive and not frequently available, ET is commonly estimated as a function of moisture storages and potential evapotranspiration (PET), i.e., the evaporative potential given unlimited moisture availability. PET, in turn, is often estimated only as a function of daylight hours (season) and temperature (Hamon, 1963), and sometimes as a function of humidity, wind speed, and surface radiative fluxes as well (Penman, 1948; Priestley and Taylor 1972). Full energy budget approximations are seldom used due to intensive data requirements.

Contrary to the expectation that increased air temperature would lead to increased evaporation, pan evaporation measurements around the world show a steady decrease over the last 50 years (Peterson et al., 1995; Golubev et al., 2001). An explanation of this ‘pan evaporation paradox’ is that increased land surface evaporation alters the humidity regime, causing air over the pan to be more saturated (Brutsaert and Parlange, 1998). Another explanation is that increased cloudiness and decreased solar irradiance due to aerosol deposition have in fact resulted in reduced land surface evaporation, as reflected in pan evaporation records (Stanhill and Cohen, 2001; Ramanathan et al., 2001). Further, it is claimed that large-scale groundwater depletion has accelerated significantly since the mid-twentieth century, affecting the terrestrial evaporative budget, as well as increasing runoff that contributes to sea level rise (Aeschbach-Hertig and Gleeson, 2012; Konikow, 2013; Pokhrel et al., 2012; Wada et al., 2010). This limited understanding and agreement in historical evaporation trends have complicated

accurate actual ET quantification (Barnett et al., 2005), and it has been suggested that the components of the hydrological cycle be considered together to interpret inter-relationships of pan, potential, and actual evapotranspiration when estimating the net evaporative budget (Sumner and Jacobs, 2005).

A general method to estimate ET uses a water balance equation given by $\Delta S = P - Q - ET$, where ΔS is the change in water storage over the basin and P, Q and ET are precipitation, runoff and evapotranspiration, respectively. For water budget analyses on annual or longer time scales, the net change in annual storage may be assumed zero. In order to estimate runoff at finer timescales, using precipitation and temperature as inputs to hydrologic models, ET is typically estimated as a function of PET. PET may be an exogenous input to hydrologic models, as in HEC-HMS (USACE, 2010), or it may be computed internally, as in LBRM (Croley, 2002) which uses a temperature proxy method conceptually similar to Thornthwaite (1948).

As climate model outputs other than precipitation and temperature have received relatively little attention among hydrologists, hydrologic projections have continued to use empirical temperature proxy relationships to estimate PET (e.g. Croley, 2002; Hartmann, 1990; Chao, 1999; Lofgren et al., 2002; Angel and Kunkel, 2010). Recent findings have shown that the temperature proxy methods fail to account for the surface radiation balance within the GCMs (Lofgren et al., 2011; Milly and Dunne, 2011; Shaw and Riha, 2011), including the negative feedback of increased ET on surface temperature (Lofgren et al., 2013). A potential artifact of the temperature proxy approach is that reduced runoff is projected into the future as a result of an inconsistent energy budget between climate and hydrologic models. Among other studies describing limitations of temperature-based PET estimation, Shaw and Riha (2011) argue that

temperature-based equations will shift with climate change and likely exaggerate PET in a warmer climate. Wild and Liepert (2010) illustrate that the improved knowledge of surface radiation balance is the key to better understanding variations in the hydrologic cycle, and shortcomings in the simulation of the surface radiation balance in climate models may contribute to the poor simulation of decadal variations in precipitation during the 20th century. Haddeland et al. (2012) demonstrate that radiation, humidity and wind speed estimates have potentially large effects on simulated water fluxes, and that using these values directly from climate models can result in very different evapotranspiration and runoff estimates than when using values based on reanalysis and observational data.

Lofgren et al. (2011) show how ET responses in the Great Lakes region can be exaggerated when the watershed models are forced only by air temperature and precipitation from GCMs, as opposed to when ET is directly simulated from the same GCMs with integrated land surface-atmosphere models. In a similar experiment conducted by Milly and Dunne (2011), it was shown that the air temperature-based modified Jensen–Haise formula, used in the hydrologic model Precipitation Runoff Modeling System (Leavesley et al., 1983), estimates a change in PET that is typically three times the change implied by the climate models with surface energy budget considerations. These findings warrant caution when projecting changes in PET using hydrologic models to evaluate climate change impacts on water resources.

This study compares hydrologic projections from temperature proxy and energy conservation methods in the Great Lakes basin at a watershed scale. The flow responses across the Great Lakes watersheds are further evaluated in relation to climate projections, hydrologic model parameters and watershed characteristics. The following “Methods” section describes the overall radiative energy budget, including latent and sensible heat fluxes, used to estimate PET

from respective GCMs for input to LBRM; the selection of representative future climate scenarios; and the LBRM simulations using either the temperature proxy method or the energy conservation approach. The “Results” section discusses the ET and PET projections; streamflow projections and relationship to watershed characteristics; and identified streamflow regimes and snow water equivalent (SWE) projections from LBRM simulations across the Great Lakes watersheds. Finally, the “Conclusion” section includes a discussion of seasonal and regional variability of flow regimes, along with future directions of research to look more closely at the sensitivity of evaporative responses using additional climate model outputs and PET estimation methods in the Great Lakes basin.

Methods

This section focuses on the energy conservation PET formulation and inputs to the LBRM. The temperature-proxy PET formulation (which does not consider energy conservation) and the model structure of LBRM are described in greater detail in Lofgren et al. (2011). The ET estimation method herein is also similar to Lofgren et al. (2011), but a larger array of GCM projections is included to inform a multi-model ensemble approach to climate change impact assessment. Furthermore, unlike the aggregated lake level responses evaluated by Lofgren et al. (2011), watershed-specific responses are evaluated by comparing PET, runoff, and snow water equivalent (SWE) projections from the temperature proxy and energy conservation approaches for 14 Great Lakes watersheds (Figure 1), selected based on their nutrient loading to the lakes (LaBeau et al., 2013).

Radiative energy budget

In order to maintain a balance between incoming and outgoing energy at the surface, the following equation must be satisfied:

$$SW - LW - SH - LH - G - SM = 0 \quad (1)$$

where SW is net shortwave radiation; LW is net long-wave radiation; SH is sensible heat flux; LH is latent heat flux of evapotranspiration and sublimation; G is heat flux into the ground; and SM is latent heat of snowmelt. As discussed in Lofgren et al. (2011) and Milly and Dunne (2011), PET is explicitly dependent on the quantity $(SW - LW - G - SM)$. For estimation of PET as input to LBRM using the energy conservation approach, this quantity is equated to the sum of latent and sensible heat fluxes $(LH + SH)$ as derived from the respective GCMs. Latent heat flux is the energy required for the separation of attractive intermolecular forces to vaporize water to a gaseous phase. Sensible heat flux is the portion of radiant energy intercepted at the Earth's surface not used for evaporation, but used in warming the air in contact with the ground. The direction of sensible heat energy is upward from the ground during the day and downward at night (Maidment, 1993). The net radiative heat fluxes at the surface area are major drivers of PET.

Climate scenario selection

Climate scenarios are selected from an ensemble of 53 projections archived in World Climate Research Programme's Coupled Model Inter-comparison Project phase 3 (WCRP CMIP3) database (Meehl et al., 2007). These 53 projections come from 16 GCMs combined with four emissions scenarios (a1, a2, a1b, and b1) and different initial conditions. Daily GCM outputs (precipitation and temperature) are downscaled using the bias-corrected construction analog (BCCA) method, which uses a quantile mapping bias correction on large scale data prior to using a constructed analogues (CA) approach at finer scales. The CA method is based on the premise that an analogue for a given coarse-scale daily weather pattern for a given GCM simulation can be constructed by combining the weather patterns from a library of historic

patterns (Hidalgo et al. 2008). The BCCA CMIP3 projections include maximum air temperature, minimum air temperature and precipitation downscaled at 1/8th of a degree (~12 km resolution) at a daily time step. Although the downscaled data are already bias-corrected, residual precipitation biases were found to exist in the U.S Great Lakes region (Gyawali, 2013). These biases were corrected using the change factor method (e.g. Rasmussen et al., 2012) prior to input to LBRM.

Selection of a representative set of climate scenarios is based on percent changes in precipitation and absolute changes in air temperature between the historical baseline period (1980-1999) and a future period (2046-2065), as shown in Figure 2. The quadrants are divided according to median changes in precipitation and temperature. A total of nine scenarios were selected to be representative of the entire ensemble. A few scenarios which reported outlier future radiative fluxes were not included in the analysis. A similar scenario selection approach based on precipitation and air temperature changes is employed in Brekke et al. (2009). Table 1 summarizes the selected scenarios, including the GCM runs, corresponding grid sizes and representative future climates.

LBRM simulation using temperature and energy adjustment approaches

LBRM is used to simulate future flows of selected Great Lakes watersheds using outputs from GCMs. This model has been regarded as a ‘cornerstone’ in understanding the hydrology of the Great Lakes watersheds (Fry et al., 2013). In the Great Lakes region, LBRM has been extensively used for simulating flows under historic and current climate (e.g., Angel and Kunkel, 2010; Croley et al., 2005; DeMarchi et al., 2010). Currently, LBRM is used to generate seasonal forecasts of Great Lakes water levels as a component of the Advanced Hydrologic Projection System (AHPS), maintained by NOAA GLERL and NWS. For the watersheds evaluated herein,

the goodness of fit (R squared) between the modeled and observed monthly flows in the 1980-1999 period ranged from 0.51 to 0.82.

The distinction between the temperature adjustment (TA) and energy adjustment (EA) methods for simulating hydrologic impacts of climate change with LBRM is based on potential evapotranspiration (PET) inputs to the model. In LBRM, PET is given by:

$$PET = A * e^{(T/T_b)} \quad (2);$$

where A is an evapotranspiration parameter with units of cm/day, T is mean daily air temperature in ° Celsius, and T_b is a base temperature parameter with units of ° Celsius. The parameters A and T_b are fitted by a constraint imposed in the calibration process requiring that the sum of PET over the year, multiplied by latent heat per unit mass, must be equal to the incident solar radiation summed over the year, even though this constraint no longer holds in simulations of future climate (Lofgren et al., 2011). Given the non-stationary nature of streamflows in the future, assuming the calibrated parameters would remain unchanged is a common limitation for hydrologic models, including this effort. Further, a high correlation ($R^2 = 0.87$) between the calibrated parameters A and T_b indicates the non-uniqueness of the calibration process. In this case, higher values of A are offset by higher values of T_b , indicating that there is not much variation in historic PET across the region (Gyawali, 2013).

The TA approach uses a temperature proxy relationship (strictly a function of air temperature) to estimate PET directly from Eq. (2) using the bias-corrected air temperature inputs from the GCMs. An assembly of boundary conditions, parameter and meteorological inputs, based on the GCM and observed climatology, is then used to simulate LBRM in historic and future periods.

In contrast, the EA method is based on monthly latent plus sensible heat flux values from the GCMs, which are physically consistent with temperature values in the GCM land surface energy budget. To compute monthly PET in LBRM, the EA method first calculates PET based on the historical air temperatures. The future monthly PET is then adjusted by the ratio of future to historical latent plus sensible heat fluxes output by the GCMs, instead of being adjusted using the temperature change factor as in the TA method.

Results

The hydrology of 14 selected Great Lakes watersheds, roughly corresponding to the hydrologic unit code 8 (HUC8) scale, is simulated using both TA and EA methods to evaluate projections for climate change impact assessment. It is found in all 14 watersheds that the TA approach leads to more severe decreases in simulated runoff than the EA method. Also, the variability in TA PET is much larger, which leads to more uncertainty in future flow estimates. The EA method, on the other hand, projects more moderate runoff changes and wider seasonal and regional variations with respect to precipitation, air temperature and PET changes (details provided in Electronic Supplementary Material Fig. S1-S9 and Tables S1 and S2). Further, the EA method also accounts for heat fluxes and feedback processes within the climate models, as PET is directly estimated from the climate model outputs. Thus, the EA-based hydrologic responses are further evaluated in relation to watershed characteristics, hydrologic model parameters and climate projections. The results are presented in terms of impacts on PET, streamflow and snow water equivalent (SWE) in the historic period (1981-1999) and two future periods (2046-2065 and 2081-2100).

PET projections

Figure 3 shows an example of EA and TA PET estimates for the Maumee River watershed developed using the 9 selected climate scenarios. Other comparisons of TA and EA method projections were similar in nature and are provided in the supplementary materials. The TA method results in a significantly increased PET in the future periods, whereas the PET estimates from the EA method indicate a more moderate increase. Change in PET estimated by the TA method is based on the multiplication factor $e^{(\Delta T/T_b)}$, derived using equation 2. As a result, the estimated change in PET is highly sensitive to the parameter value (T_b), estimated in calibration of LBRM. For the Maumee River basin, T_b was estimated as 6.6 °C, which means that a 1 °C increase in temperature leads to a 16% increase in PET using this method.

In terms of latent plus sensible heat fluxes, there was a large discrepancy in the fluxes computed from the GCMs and those implied by the TA method. The average annual flux implied by the TA method was 112.9 W/m², about 31% greater than that directly estimated by GCMs (86 W/m²) for Maumee River basin in the near future (2046-2065) period. Discrepancies were much larger in the late spring and summer months, with May through September fluxes accounting for 85% of the total annual difference. The evaporation equivalent of the fluxes is such that in months when mean temperature is above 0 °C, 1 mm/day of evaporation equals 29.07 W/m² of heat flux; and when mean monthly temperatures are less than 0 °C, 1 mm/day of evaporation equals 32.95 W/m². Hence, a discrepancy of 26.9 W/m² roughly corresponds to a difference of 89 cm/year of PET.

Streamflow projections and relationship with watershed characteristics

Model results indicate that Great Lakes watersheds will respond differently to climate change. Results for the 14 watersheds considered in the study are presented in Figure 4, ordered by the latitude of basin centroids from south to north. Shown are the mean annual percent changes in runoff, precipitation and PET between the historic baseline (1980-1999) and the ensemble mean of the near-future period (2046-2065), based on simulations using the EA method. The ranges of projected streamflow changes across the 9 selected scenarios are presented in Table 2. Analysis of the far-future period (2081-2100) yielded qualitatively similar results, with larger differences as expected, and are not shown due to space limitations.

EA-based projections of the Great Lakes watersheds yield variable average annual runoff changes for similar precipitation and PET changes. From Figure 4, it can be inferred that in addition to the precipitation and PET differences, runoff changes may be affected by other watershed characteristics such as physiographic factors, storage and stream density, aridity or future climate projections. For example, Cattaraugus, St. Louis and Saginaw projections show significantly increased runoff, although PET change is not large relative to other watersheds. To evaluate the role of specific watershed characteristics resulting in varied flow responses, selected watershed characteristics based on the GAGESII dataset (Falcone et al., 2012) and the baseflow coefficients from the LBRM are reviewed (see Table 3).

Among the southernmost watersheds, Sandusky, Maumee, Cuyahoga and St. Joseph, which experience relatively high temperatures and PET in the baseline period, the largest flow reductions are projected for the Maumee River watershed. This could be a consequence of its dominant surface flow regime (i.e., low baseflow contribution), resulting in a higher potential for evaporative losses. Table 3 shows the LBRM baseflow-related coefficients, indicating lower

percolation and interflow coefficients in the Maumee River watershed compared to other watersheds. Similarly, Cattaraugus, Cuyahoga, St. Joseph, Clinton, Bad and Milwaukee are found to have relatively large percolation and inter-flow coefficients, indicating more sustained baseflow regimes, consistent with the estimates of baseflow index (BFI) of the Great Lakes basin (Neff, 2005).

The Maumee basin also has the lowest average permeability rate (2.03 cm/hr) and minimum watershed slope (0.42%) of the basins considered, and thus more water is available on the surface for ET, resulting in a larger reduction in flows as observed in Figure 5. In contrast, a larger increase in runoff is projected for the St. Louis basin than the neighboring Bad watershed, despite the higher mean watershed slope of Bad. This could be a result of the larger increase in precipitation projected for St. Louis, offsetting the influence of watershed slope. In addition, the larger average permeability (10.6 cm/hr) in the St. Louis basin may contribute to more sustained baseflow and less water available for evaporative losses compared to the Bad River basin. Similarly, the larger flows predicted in the Saginaw River watershed may be attributed to its high stream density and relatively high base flow (average permeability ~13.2 cm/hr). Cattaraugus has the largest net increase in runoff, and this could be a consequence of its high runoff velocity due to its steep topography, indicated by the largest mean watershed slope (6.85%) of all the watersheds.

Unlike other watersheds, projections for the Au Sable River watershed in MI indicated reduced ensemble mean runoff throughout the year, as shown in Figure 6. During the baseline period, the Au Sable had relatively consistent runoff throughout the year, possibly due to its dominant baseflow regime, with monthly discharges ranging from 23 to 36 millimeters. For comparison, the surface flow dominated Maumee River watershed--a watershed thrice as large--

had monthly discharges ranging from 10 to 48 millimeters. The average permeability in the Au Sable watershed (28.6 cm/hr) is the largest of all watersheds considered, and it has the smallest streamflow density (0.31 km/km²). Therefore, the watershed has the potential to hold moisture for a longer period before it finally drains to the streams. Also, the largest decrease in summer precipitation occurs in Au Sable, with especially large decreases in July and August (for details, see Gyawali, 2013), while the watershed is also projected to have one of the largest absolute increases in PET. Therefore, there is a larger infiltration potential for the precipitation that occurs in fall, resulting in reduced runoff response in this season. However, as shown in Figure 6, there is less flow reduction projected in winter as actual evapotranspiration (AET) is low in this season and the soils become more saturated.

Relative humidity also has an important influence on the ET of the watershed, as ET is directly related to the moisture deficit in the air. The moisture availability in all 14 watersheds in the Great Lakes is assessed based on the Budyko hypothesis (Budyko, 1974), which relates the ratio of ET to precipitation to climate through an aridity index, defined as the ratio of PET to precipitation. Figure 7 indicates the humid and arid climates in the Great Lakes basin, showing the Au Sable watershed to have the most arid climate; and hence, the most potential for evaporative losses in warmer climates. The PET/P estimates calculated herein are typically higher than those estimated by Milly and Dunne (2011), but this could be due to the different PET estimation methods used in these studies.

Based on the LBRM projections of the selected watersheds (Figure 5), three types of hydro-climate change regimes are identified in the Great Lakes basin: large summer flow reductions (e.g., Maumee, Sandusky); small reductions in summer flows and large increases in spring/winter flows (e.g., St. Louis, Bad); moderate reductions in summer and moderate

increases in spring/winter flows (e.g., Fox, Lower Grand). Overall, projected decreases in runoff are generally more pronounced in spring and summer seasons, as PET estimates are significantly higher during these seasons.

Snow water equivalent (SWE) projections

Snow water equivalent (SWE) projections representing the three identified flow regimes and climatic regions, warm (Maumee), moderate (Fox) and cold (St. Louis) as simulated by LBRM in the Great Lakes basin are shown in Figure 8. To track SWE, LBRM uses a temperature based melt index method (a degree-day approach) to estimate snowmelt. The temperature based melt index method is governed by the principle that snowmelt is allowed only during periods with above-zero air temperatures. Additional details are provided in Croley (2002). As the snowmelt method in LBRM does not consider evaporation and sublimation from the snowpack, both EA and TA methods use the same temperature feed from the GCMs to estimate SWE. Unlike detailed energy balance approaches (Tarboton et al., 1996; You et al., 2004), the temperature melt index approach ignores other factors affecting snowmelt, including watershed slope and aspect, heat exchange with the ground, heat input by rain, radiative heat fluxes, and evaporation and condensation to the snowpack.

Compared to the streamflow projections, there is larger variability in SWE projections across the selected watersheds. Projections show a net decrease in SWE in the future periods (Figure 8), despite a consistent increase in precipitation during the winter months. As SWE is more sensitive to changes in temperature and precipitation than runoff, more extreme changes in SWE are expected under future climates, including shorter snow seasons and earlier spring runoff. Although winters are projected to warm across the region, the St. Louis watershed continues to experience sub-zero monthly average temperatures in winter months (and also the

Fox watershed in January) under future climate projections (details shown in the supplementary material). However, the temperature index snowmelt model does not capture the effects of warmer yet below zero temperatures under future climate projections. With radiative fluxes readily available from GCM outputs, a more robust energy-balance snowmelt algorithm in hydrologic models would be an important advancement in hydro-climatic impact assessment in snow-affected regions such as the Great Lakes basin.

Conclusion

Results from this study show that in warmer climates, temperature proxy PET methods can predict large increases in ET, leading to reduced runoff in hydro-climatic projections. However, PET is not only a function of air temperature; and other outputs from GCMs, including radiative fluxes, may be used to better represent the dynamic land surface-atmosphere system. Because the temperature-adjustment (TA) method does not account for any feedback between variables within the GCMs, it is argued that TA is an inconsistent approach with respect to the energy budget. As an alternative to temperature-based PET methods, latent and sensible heat fluxes output directly from the GCMs are employed herein to estimate PET in a future climate. This energy-adjustment (EA) approach maintains a consistent energy budget between climate and hydrologic models and is therefore recommended for hydro-climate impact studies using GCMs.

Simulations of 14 Great Lakes watersheds using the TA method predict large decreases in runoff in all watersheds and all seasons, while using the EA method results in flow responses showing both regional and seasonal variability. The EA-based flow responses are characterized by three flow regimes: (1) large reductions in summer flows; (2) small reductions in summer flows and relatively large increases in spring/winter flows; and (3) moderate reductions in

summer flows and moderate increases in spring/winter flows. Differences in flow regimes are attributed to differences in watershed characteristics, aridity index, and future climate projections. For example, the agriculture-dominated southern watersheds (e.g. Maumee and Sandusky) have a relatively flashy response to precipitation (Croley, 2006; Gyawali and Watkins, 2013), increasing surface flows and evaporative losses compared to baseflow-dominated watersheds. Overall, it is seen that the hydrologic impacts of climate change become more severe in the far future period (2081-2100) compared to the near future period (2046-2065) period, although in some instances PET increases offset precipitation increases.

The EA-based simulations show that the watersheds are prone to changes in seasonal flow conditions depending on watershed characteristics and future climate projections. In some watersheds (e.g. Maumee, Sandusky, Fox, Clinton and Lower Grand), lower seasonal flows are projected in summer and fall seasons in the future periods relative to the historic period, while higher flows are projected in the winter and spring. With the exception of Au Sable, all of the watersheds considered show a consistent increase in spring streamflow in the future periods. Overall, this increased seasonal variability of runoff could potentially result in an increase in the range of Great Lakes water levels, although further research is necessary to investigate this outcome.

In addition to streamflow, snow water equivalent (SWE) of the selected watersheds is simulated. Compared to streamflow projections, larger variability is observed in SWE simulations due to increased sensitivity of snowmelt to temperature increases and more precipitation falling as rain rather than snow. As inputs to the surface energy budget are becoming more readily available from climate models, energy balance methods should be

developed for more accurately representing snowmelt in hydrologic models compared to current degree-day methods.

As there are many empirical PET estimation methods, a future direction of this work is to evaluate the sensitivity of evaporative responses using other common methods (e.g., Hamon, Jensen and Haise, Penman-Monteith and Priestley and Taylor). These PET equations include either temperature-proxy methods (e.g. Jensen and Haise) or hybrid temperature-energy methods (e.g. Priestly and Taylor, Penman-Monteith), as defined in Bae et al. (2011). It should be noted that the energy balance variables (e.g. short wave and long wave radiation, wind speed, atmospheric vapor pressure, and drought moisture indices) have also been expressed in terms of temperature-based relationships (Maurer et al., 2002; Dai et al., 2004). The validity of these approaches should be scrutinized when using GCM-derived variables to maintain an energy balance within the models.

For this analysis, the ratio of latent and sensible heat fluxes from coarse-grid GCMs was applied at the resolution corresponding to the hydrologic unit code 8 (HUC8) watershed scale. Regional factors such as the influence of the Great Lakes could impact the radiative budget at the watershed scale significantly, and thus an area of future research is to use regional climate models (RCMs) rather than GCMs to account for local and regional factors. The CMIP5 generation of models can allow analysis based on additional models and updated emissions scenarios and will further facilitate this research area.

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References

- Aeschbach-Hertig, W. and T. Gleeson (2012). "Regional strategies for the accelerating global problem of groundwater depletion." *Nature Geosciences* 5(12): 853-861.
- Angel, J. R., and Kunkel, K. E. (2010). "The response of Great Lakes water levels to future climate scenarios with an emphasis on Lake Michigan-Huron." *Journal of Great Lakes Research*, 36(Supp. 2), 51–58.
- Bae, D.-H., I.-W. Jung, et al. (2011). "Hydrologic uncertainties in climate change from IPCC AR4 GCM simulations of the Chungju Basin, Korea." *Journal of Hydrology* 401(1-2): 90-105.
- Barnett, T. P., J. C. Adam, et al. (2005). "Potential impacts of a warming climate on water availability in snow-dominated regions." *Nature* 438(7066): 303-309.
- Brekke, L.D. et al., (2009). "Climate change and water resources management – A federal perspective: U.S. Geological Survey Circular 1331, 65 p (Also available online at <http://pubs.usgs.gov/circ/1331/>.)
- Brutsaert, W. and M. Parlange (1998). "Hydrologic cycle explains the evaporation paradox." *Nature* 396: 30.
- Chao, P. (1999). "Great Lakes water resources: Climate change impact analysis with transient GCM scenarios." *Journal of the American Water Resources Association*, 35(6), 1499–1507
- Croley, T. E., II (2002). Large basin runoff model. *Mathematical models of large watershed hydrology*, V. Singh, D. Frevert, and S. Meyer, eds., Water Resources Publications, Highlands Ranch, CO, 717–770.
- Croley, T. E. and He, C. (2005). Distributed-Parameter Large Basin Runoff Model. I: Model Development. *Journal of Hydrologic Engineering* 10: 173-181. DOI: 10.1061/(asce)1084-0699(2005)10:3(173).
- DeMarchi, C., Xing, F., Croley, T. He, C., Wang, Y. (2010). Application of a Distributed Large Basin Runoff Model to Lake Erie: Model Calibration and Analysis of Parameter Spatial Variation. *Journal of Hydrologic Engineering* 16: 193-202. DOI: 10.1061/(asce)he.1943-5584.0000304.
- Dai, A., K. E. Trenberth, and T. Qian, (2004). "A global dataset of Palmer Drought Severity Index for 1870–2002: Relationship with soil moisture and effects of surface warming." *Journal of Hydrometeorology* (5) 1117–1130.

- Fry, L.M., Hunter, T.S., Phanikumar, M.S., Fortin, V., Gronewold, A.D. (2013). Identifying streamgage networks for maximizing the effectiveness of regional water balance modeling. *Water Resources Research* 49: 2689:2700. DOI: 10.1002/wrcr.20233
- Golubev, V. S. (2001). "Evaporation changes over the contiguous United States and the former USSR: a reassessment." *Geophysical Research Letters* 28(13): 2665-2668.
- Gyawali, R., A hydro-climatic modeling framework for adaptive water resources mangagement in the Great Lakes basin , Ph.D. Thesis, Michigan Technological University, August, 2013
- Gyawali, R., and D.W. Watkins (2013). "Continuous Hydrologic Modeling of Snow-Affected Watersheds in the Great Lakes Basin Using HEC-HMS." *Journal of Hydrologic Engineering* 18(1):29-39.
- Haddeland, I., Heinke, J., Voß, F., Eisner, S., Chen, C., Hagemann, S., & Ludwig, F. (2012). Effects of climate model radiation, humidity and wind estimates on hydrological simulations. *Hydrology and Earth System Sciences* 16(2), 305.
- Hamon, W. R. (1963). "Computation of direct runoff amounts from storm rainfall." *Int. Assoc. Sci. Hydrol. Publ.*, 63, 52–62.
- Hartmann, H. C. "Climate change impacts on Laurentian Great Lakes levels." *Climatic Change* 17(1990): 49-67
- Konikow, L. F. (2013). "Overestimated water storage." *Nature Geosci* 6(1): 3-3.
- LaBeau, M.B., Mayer, A.S., Griffis, V.J., Watkins, D. W., Gyawali, R., Robertson, D.M., (2013). "Climate Induced Changes on Phosphorus Export into the Great Lakes: Development of Linkages between Extreme Weather Events and Tributary Phosphorus Loading." *Journal of Hydrology* (submitted).
- Leavesley, G.H., Litchy, R.W., Troutman, M.M., and Saindon, L.G., (1983), Precipitation-runoff modeling system--User's manual: U.S. Geological Survey Water-Resources Investigations Report 83-4238, 207 pp.
- Lofgren, B. M., T. S. Hunter, et al. (2011). "Effects of using air temperature as a proxy for potential evapotranspiration in climate change scenarios of Great Lakes basin hydrology." *Journal of Great Lakes Research* 37(4): 744-752.
- Lofgren, B.M., A.D. Gronewold, A. Acciaoli, J. Cherry, A. Steiner, and D. Watkins. "Methodological Approaches to Projecting the Hydrologic Impacts of Climate Change," *Earth Interactions*, accepted, 2013.
- Maidment, D. R. *Handbook of Hydrology* (1993), McGraw –Hill, New York

- Maurer, E. P., A. W. Wood, et al. (2002). "A Long-Term Hydrologically Based Dataset of Land Surface Fluxes and States for the Conterminous United States*." *Journal of Climate* 15(22): 3237-3251.
- Milly, P. C. D. and K. A. Dunne (2011). "On the Hydrologic Adjustment of Climate-Model Projections: The Potential Pitfall of Potential Evapotranspiration." *Earth Interactions* 15(1): 1-14.
- Neff, B. P., and J. R. Nicholas, (2005), Uncertainty in the Great Lakes Water Balance, Date Posted: November 23, 2005: U.S. Geological Survey Scientific Investigations Report 2004-5100, 42 p. [<http://pubs.water.usgs.gov/sir2004-5100>]
- Meehl, G., C. Covey, et al. (2007). "The WCRP CMIP3 Multimodel Dataset: A new era in climate change research." *Bulletin of the American Meteorological Society* 88(9): 1383-1394
- Penman, H. L. (1948). "Natural Evaporation from Open Water, Bare Soil and Grass." *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences* 193(1032): 120-145.
- Peterson, T. C., V. S. Golubev, et al. (1995). "Evaporation losing its strength." *Nature* 377: 687-688.
- Pokhrel, Y. N., N. Hanasaki, et al. (2012). "Model estimates of sea-level change due to anthropogenic impacts on terrestrial water storage." *Nature Geosci.* advance online publication < doi:10.1038/ngeo1476 >.
- Priestley, C. H. B., & Taylor, R. J. (1972). On the assessment of surface heat flux and evaporation using large-scale parameters. *Monthly Weather Review*, 100, 81–92.
- Ramanathan, V., et al., (2001). Aerosols, climate, and the hydrological cycle, *Science*, 294, 2119–2124
- Rasmussen, J. et al., (2012) "Climate change effects on irrigation demands and minimum stream discharge: impact of bias-correction method." *Hydrol. Earth Syst. Sci.* 16(12): 4675-4691.
- Sanford, W. E. and D. L. Selnick (2013). "Estimation of Evapotranspiration Across the Conterminous United States Using a Regression With Climate and Land-Cover Data1." *Journal of the American Water Resources Association* 49(1): 217-230.
- Shaw, S. B. and S. J. Riha (2011). "Assessing temperature-based PET equations under a changing climate in temperate, deciduous forests." *Hydrological Processes* 25(9): 1466-1478

- Stanhill, G., & Cohen, S. (2001). Global dimming: a review of the evidence for a widespread and significant reduction in global radiation with discussion of its probable causes and possible agricultural consequences. *Agricultural and Forest Meteorology*, 107(4), 255-278
- Sumner, D. M. and Jacobs, J. M. (2005). Utility of Penman-Monteith, Priestley-Taylor, reference evapotranspiration, and Pan evaporation methods to estimate pasture evapotranspiration, *Journal of Hydrology* 308, 81-104.
- Tarboton, D. G. and C. H. Luce (1996). Utah energy balance snow accumulation and melt model (UEB), Utah Water Research Laboratory.
- Thornthwaite, C. W. (1948). "An Approach toward a Rational Classification of Climate." *Geographical Review* 38(1): 55-94.
- Wada, Y. et al. (2010). "Global depletion of groundwater resources." *Geophys. Res. Lett.* 37, L20402
- Wild, M. and B. Liepert (2010). "The Earth radiation balance as driver of the global hydrological cycle." *Environmental Research Letters* 5(2): 025203.
- You, J., Tarboton, D.G., Luce, C.H. (2004). Modeling the snow surface temperature in an energy balance snowmelt model. Lincoln, Nebraska, 68583

Table Captions

Table 1 Selected GCMs runs, corresponding grid size, emission scenario and representative future climate used as inputs to LBRM

Table 2 Range of projected changes in runoff in the study watersheds across nine climate change scenarios

Table 3 Selected watershed characteristics from the GAGESII dataset (Falcone et al., 2012) and baseflow coefficients from the LBRM.

Figure Captions

Figure 1 Selected watersheds in the Great Lakes basin.

Figure 2 Future climate scenarios in the Great Lakes basin represented by ΔP , the percentage change in precipitation, and ΔT , absolute change (degree Celsius) in temperature, between the historic and the near future period 2046-2065 from 53 BCCA CMIP3 projections; selected climate scenarios representative of characteristic future climates are highlighted.

Figure 3 Comparison of temperature adjust (TA) and energy adjust (EA) method estimated of potential evapotranspiration (PET) of the baseline (1980-1999) and the mean and standard deviation of the ensemble of the nine scenarios for the future periods (2046-2065) and (2081-2100) for Maumee River watershed.

Figure 4 Annual changes in runoff, precipitation and PET of the selected watersheds between the baseline period (1980-1999) and the ensemble mean of the near-future period (2046-2065) based on EA simulations.

Figure 5 Energy adjust (EA) projections of a) Maumee, b) Fox and c) St. Louis River watersheds as simulated by LBRM. Standard deviations are shown about ensemble means of near future (2046-2065) and far future (2081-2100) periods. The units are the equivalent depth of runoff uniformly distributed over the watershed area.

Figure 6 Energy adjust (EA) projections of Au Sable River watershed as simulated by LBRM. Standard deviations are shown about ensemble means of near future (2046-2065) and far future (2081-2100) periods. The units are the equivalent depth of runoff uniformly distributed over the watershed area.

Figure 7 Characterization of the humidity regime of the selected watersheds in the Great Lakes basin based on the ratio of actual ET to precipitation as a function of ratio of PET to precipitation. Values are based on LBRM simulations, calibrated to observations (1961-1999).

Figure 8 Snow water equivalent (SWE) projections of Maumee, Fox and St. Louis River watershed as simulated by Large Basin Runoff Model (LBRM). Standard deviations

are shown about ensemble means of near future (2046-2065) and far future (2081-2100) periods.

Table 1. Selected GCMs runs, corresponding grid size, emission scenario and representative future climate used as inputs to LBRM. S.N. is scenario number.

S.N	GCM runs	Emission Scenario	Grid size	Representative future climate
S10	cnrm_cm3.1.	a1b	2.81° X 2.79°	wet cool extreme
S11	cnrm_cm3.1.	a2	2.81° X 2.79°	wet warm average
S20	ipsl_cm4.1.	a2	3.75° X 2.54°	dry warm average
S25	miroc3_2_medres.2.	a2	2.81° X 2.79°	dry warm extreme
S27	miroc3_2_medres.2.	b1	2.81° X 2.79°	dry cool extreme
S33	miub_echo_g.3.	a2	3.75° X 3.71°	wet warm extreme
S39	mri_cgcm2_3_2a.1.	a1b	2.81° X 2.79°	wet cool average
S41	mri_cgcm2_3_2a.3.	a1b	2.81° X 2.79°	dry cool average
S51	mri_cgcm2_3_2a.3.	b1	2.81° X 2.79°	wet cool extreme

Table 2. Range of projected changes in runoff in the study watersheds across nine climate change scenarios.

Watershed	Range of % change in projected runoff between (1980-1999) and (2046-2065)	Range of % change in projected runoff between (1980-1999) and (2081-2100)
Sandusky	-6.52 to -12.45	-4.22 to -19.04
Maumee	-11.67 to -18.06	-10.07 to -23.30
Cuyahoga	0.27 to -5.54	-0.68 to -13.52
St. Joseph	1.03 to -8.75	3.1 to -16.05
Cattaraugus	7.33 to 14.29	5.43 to 16.08
Clinton	-2.45 to 6.23	-4.44 to 4.86
Lower Grand	-2.89 to -5.94	4.73 to -10.50
Milwaukee	1.88 to -0.08	3.87 to -1.35
Saginaw	4.22 to 10.14	4.22 to 8.79
Black	-2.59 to 3.13	-4.92 to 10.416
Au Sable	-6.44 to -15.43	-8.24 to -15.17
Lower Fox	10.22 to 2.34	12.12 to -0.98
Bad	7.01 to -2.09	10.02 to 3.59
St. Louis	8.44 to 0.54	6.02 to 14.83

Table 3 Selected watershed characteristics from the GAGESII dataset (Falcone et al., 2012) and baseflow coefficients from the LBRM.

Watershed	Average permeability (cm/hr)	Mean watershed slope (%)	Stream density (km/km ²)	log (Percolation coefficients)	log (Interflow plus deep percolation coefficients)
Sandusky	2.51	0.52	0.87	-1.1	-2.2
Maumee	2.03	0.42	0.85	-1.2	-4.8
Cuyahoga	4.65	0.52	0.82	0.8	-0.5
St. Joseph	20.2	0.97	0.54	1.1	-0.2
Cattaraugus	5.90	6.85	0.71	0.3	-0.2
Clinton	2.82	0.99	0.70	1.1	-0.3
Lower Grand	9.24	1.22	0.63	-0.8	-1.6
Milwaukee	10.5	1.98	0.56	0.6	-1.2
Saginaw	13.2	0.74	0.79	-0.8	-1.6
Black	13.5	5.54	0.84	-6.0	-4.6
Au Sable	28.6	1.91	0.31	1.0	-1.7
Lower Fox	12.0	1.55	0.61	2.2	-1.9
Bad	5.05	3.45	0.76	0.4	-1.1
St. Louis	10.6	1.03	0.54	-0.5	-2.2

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6

Figure 7

Figure 8