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Simulating 2368 temperate lakes reveals weak coherence in stratification phenology

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ABSTRACT

Changes in water temperatures resulting from climate warming can alter the structure and function of aquatic ecosystems. Lake-specific physical characteristics may play a role in mediating individual lake responses to climate. Past mechanistic studies of lake–climate interactions have simulated generic lake classes at large spatial scales or performed detailed analyses of small numbers of real lakes. Understanding the diversity of lake responses to climate change across landscapes requires a hybrid approach that couples site-specific lake characteristics with broad-scale environmental drivers. This study provides a substantial advancement in lake ecosystem modeling by combining open-source tools with freely available continental-scale data to mechanistically model daily temperatures for 2368 Wisconsin lakes over three decades (1979–2011). The model accurately predicted observed surface layer temperatures (RMSE: 1.74 °C) and the presence/absence of stratification (81.1% agreement). Among-lake coherence was strong for surface temperatures and weak for the timing of stratification, suggesting individual lake characteristics mediate some – but not all – ecologically relevant lake responses to climate.

1. Introduction

Lakes are diverse ecosystems that respond in complex ways to the stressors of climate change (Blenckner et al., 2007; Carpenter et al., 1992; Roach et al., 2013). While lakes have shown regional-scale coherence in temperature (see Livingstone, 2008), biological features and dynamics often are unrelated in neighboring lakes (e.g., Soranno et al., 1999), confounding our understanding of how lakes respond to climate drivers. Interpreting dissimilar responses of lakes to current and future climate is one of the grand challenges of modern limnology.

Lake-specific properties (such as morphometry and surrounding land cover) are recognized controls on the structure and function of aquatic ecosystems, but there is disagreement as to the role they play as mediators of climate variability. Despite large diversity in lake properties, analyses of lake surface temperatures have established strong evidence for among-lake coherence to large-scale climate (Benson et al., 2000; Livingstone and Dokulil, 2001; Palmer et al., 2014). Conversely, coherence weakens or disappears below the lake surface (Kratz et al., 1998; Palmer et al., 2014), suggesting there is value in quantifying and explaining among-lake differences in responses to climate. At present, the diversity in lake responses to climate is not quantified; we lack the capacity to observe millions of lakes, and modeling approaches have not filled these information gaps.

Because temperature is a master factor for many aquatic ecosystem processes (Cardoso et al., 2014; Hanson et al., 2011; Magnuson et al., 1979; Paerl and Huisman, 2008), understanding thermal responses to climate is critical for predicting future biotic change (Sharma et al., 2007). Lake temperatures, stratification, and ice-cover durations are changing for many of the world's lakes (Livingstone, 2003; Magnuson et al., 2000; Schindler et al., 1990; Schneider and Hook, 2010), and these changes impact the timing and function of lake ecosystem processes (O'Reilly et al., 2003; Smol et al., 2005; Weyhenmeyer et al., 1999).

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Recent advances in observational capabilities have allowed limnologists to address research questions at larger spatial scales (Heffernan et al., 2014; Soranno et al., 2010). Federal and state sensor networks, citizen science monitoring programs, and satellite/airborne observations have expanded considerably, contributing “Big Data” to aquatic ecology (Hampton et al., 2013; Keller et al., 2008). Satellite observations have documented lake warming (Schneider and Hook, 2010) and estimated water quality (Torbick et al., 2013). Gridded time-series data capture retrospective meteorological drivers (Mesinger et al., 2006; Mitchell et al., 2004) or predictions for future climate (Hostetler et al., 2011; Wilby et al., 2000) for large numbers of lakes. There are tremendous opportunities to leverage these environmental Big Data for a better understanding of the local context of lakes (e.g., Soranno et al., 2010), and broad-scale hydroclimatic interactions (e.g., Kucharik et al., 2000; Leonard and Duffy, 2013). Coupling mechanistic modeling with big data may provide means to assess among-lake diversity of lake responses to climate.

At present, two dominant process-based approaches exist for evaluating lake temperature responses at temporal scales appropriate for climate: simulations of generic lakes at broad spatial extents (Fang and Stefan, 2009; e.g., Hostetler and Small, 1999; Stefan et al., 2001), and detailed modeling of small numbers of real lakes (Cahill et al., 2005; Fang et al., 2012; Hadley et al., 2013). In order to quantify climatically driven regional dynamics and among-lake variability for large numbers of real lakes, a new approach that leverages the advantages of both simulation types is necessary.

Here, we examine the diversity of lake responses to climate by introducing a new methodology that uses freely available, large-scale datasets to run unique hydrodynamic simulations for thousands of lakes. Methods and tools were created explicitly to support future analyses of lakes and their design was informed by the research needs of the limnological community. In order to maximize community use and acceptance, all data, methods, and tools are freely accessible and openly shared. This study leveraged these elements to simulate an unprecedented 2368 lakes for 33 years and contrast individual and population-level lake responses to climate variability.

2. Materials and methods

2.1. Hydrodynamic model

Because our primary objective was to estimate temporal dynamics in water temperature profiles, a one-dimensional (1D) dynamical model was used to simulate each of the study lakes. The General Lake Model version 1.2.0 (GLM; Hipsey et al., 2013) was chosen for this study. GLM combines fluxes of mass and energy with a Lagrangian layer structure that adapts to changes in vertical gradients, and is freely available to all users. Many energy budget algorithms and mixing schemes in GLM are modern implementations of methods applied in other widely used 1D models (Hamilton and Schladow, 1997; Mooij et al., 2010).

Heat flux is the primary driver of lake temperature (Wetzel and Likens, 2000), and components of this flux were formatted as time-series input to GLM for the variables of wind speed, air temperature, relative humidity, precipitation, and downwelling long- and shortwave radiation (Fig. 1). At each time step, GLM accounts for energy fluxes into (e.g., downwelling radiation) and out of (e.g., evaporation) the lake, and propagates the resultant temperature changes to various layers according to heat transfer and vertical mixing algorithms. Detailed formulations of these numerical routines can be found in Hamilton and Schladow (1997) or Hipsey et al. (2013), which also includes a full parameter list for GLM with recommended default values that are based on field and laboratory studies. Simulations did not include the influence of surface or groundwater flows, as coupling with hydrologic model output was beyond the scope of this study, but the impact of this omission on water temperature simulations was evaluated.

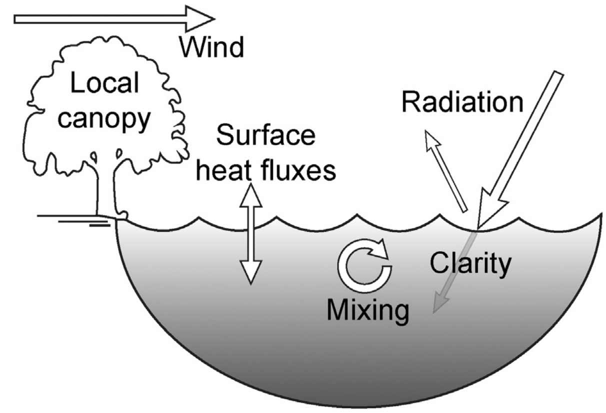

Fig. 1. A schematic of drivers and controls on lake temperature and stratification for a one-dimensional hydrodynamic model.

2.2. Model parameterization

Lake-specific data were used for static model inputs of hypsography, water clarity, and local wind sheltering (see below for details on how these were calculated or measured). The effects of these parameters on the hydrodynamic model are as follows: (1) hypsography influences size and depth dependent processes in the model, including the number of vertical layers used by the model, (2) water clarity controls the rate at which the visible wavelengths of solar radiation are attenuated in the water column, and (3) wind sheltering reduces the amount of energy from wind that is available for vertical mixing. Since a generic model parameterization that could be extended to other regions and lake types was desired, the remaining physical coefficients for GLM that parameterize equations of energy and momentum fluxes were set to default values.

The effect of water clarity on water temperature is parameterized in GLM according to the extinction coefficient for shortwave radiation (named ‘K_w’ in GLM, but we use the more common notation of ‘K_d’). The K_d parameter characterizes the exponential decay of light in the water column on a per meter (m^{-1}) basis. The parameter is used to define available light as $E(z) = E_0 \exp(-K_d z)$, where E_0 is the light energy at the surface and $E(z)$ is the remaining energy at depth z. As light is absorbed in the water column, it is converted into thermal energy and warms the waters. Thus, the general thermal effects of a smaller value of K_d (indicative of clearer waters) is to increase the amount of warming of deeper waters and decrease the warming of near-surface waters (Read and Rose, 2013).

Special attention was paid to the parameterization of mixing energy derived from wind speed because canopy and topographic features near the lake edge have a strong influence on physical dynamics in small and medium sized lakes (Markfort et al., 2010). The parameter in GLM that controls the flux of wind-driven mixing energy is the bulk aerodynamic momentum transfer coefficient, or C_M. The C_M parameter for each lake was scaled according to a cubic relationship with the wind sheltering coefficient (W_s; Hondzo and Stefan, 1993; Markfort et al., 2010), calculated as $C_M = 0.0013\, W_s^{1/3}$. Local canopy, topography, and lake size were included in the formulation of wind-sheltering coefficients for each lake, which were then converted to C_M values (see Van Den Hoek et al., *in review*). Contrary to many other multi-lake modeling efforts that specifically