The Global Lake Area, Climate, and Population Dataset: A New Tool for Addressing Critical Limnological Questions

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Abstract

Given climatic uncertainty and human population growth, tracking the world’s freshwater availability is essential. Fortunately, data necessary to identify surface water patterns are abundant. Wrangling these data into an analytically friendly format, however, can be difficult for researchers not experienced in data manipulation and high-performance computing. To increase data accessibility, we developed the Global Lake area, Climate, and Population (GLCP) dataset. The GLCP offers annually aggregated surface area, temperature, precipitation, and human population estimates for over 1.42 million lakes globally between 1995 and 2015. Our dataset is peer-reviewed and publicly available in a tabular format, enabling researchers with a range of skill levels to effectively work with the data. All aggregation procedures were performed within Google Earth Engine and R, empowering future users to replicate and modify scripts. Three case studies are presented to highlight concrete applications of the GLCP with emphasis on natural resource management at local, regional, and national scales.

Introduction

Climatic uncertainty and growing human population heighten the need to understand global availability of drinking water, a resource most readily accessed in surface waters of the world. This key societal need calls for holistic, local-to-global analyses of the world’s freshwater, which in turn demands a suite of scientific specialties and techniques. At the global scale, data synthesis approaches have proven useful not only in highlighting widespread environmental patterns but also spurring new research directions (Hampton et al. 2013; LaDeau et al. 2017). At the regional to local scale, increasing openness of in situ data and broader availability of modeled data products facilitates both research and management (Soranno et al. 2015, 2019; Pollard et al. 2018; Thackeray and Hampton 2020; Wagner et al. 2020). With the greater availability of environmental data, freshwater researchers from ecological, natural resources, hydrological, and engineering backgrounds alike are embracing the challenge of unifying often complex data formats for tackling novel basic and applied research questions.

Among the potential data sources available to tackle new limnological questions, remote sensing offers a rich and ever-expanding repository of data across multiple spatial and temporal scales. At the global scale, Lehner and Döll (2004) were among the first to create a global dataset of lakes larger than 10 ha. Similarly, Verpoorter et al. (2014) created the Global Water Bodies (GLOWABO) dataset of ~117 million lakes from LANDSAT’s GeoCover database. For groundwater, Richey et al. (2015) used GRACE satellite data to understand recharge potential of the world’s largest aquifers. Pekel et al. (2016) employed LANDSAT data to calculate permanent and seasonal global surface water area. Together, spatially and temporally extensive freshwater datasets are powerful assets to researchers working at local, regional, and global scales by offering estimates of water quantity that may otherwise be unattainable by conventional field measurements.

This rich and open catalog of the world’s waterbodies is foundational for understanding global water availability, yet these data can remain just out of reach for many researchers. These data largely exist in formats that may be unfamiliar to aquatic researchers or require large computing infrastructures. To increase accessibility to these data resources, the Global Lake area, Climate, and Population (GLCP) dataset combines disparate global datasets of interest to many scientists and natural resource managers with data stored in a more familiar format (Labou et al. 2020; Meyer et al. 2020).

Comprising over 1.42 million lakes, the GLCP offers environmental researchers and natural resource managers a powerful tool by
providing lake surface area measurements from 1995 to 2015 (Table 1; Fig. 1). The GLCP merges disparate data sources, such that researchers can efficiently integrate data pertaining to lake and basin water quantity without a need for advanced computing skills or hardware. This tool is especially timely in light of several studies suggesting lake water quantity as a driving factor for a suite of limnological phenomena, including transitions in lake color (Leech et al. 2018), terrestrial dissolved organic matter (tDOM) concentration (Solomon et al. 2015), as well as water clarity (Lisi and Hein 2019). By providing surface area as a proxy for lake water quantity, the GLCP offers researchers the capacity to capitalize on measurements for disentangling relationships between abiotic and biotic processes within and between lakes. Additionally, the GLCP serves as a synthesis tool to explain abiotic and biotic variability as a function of lake water abundance across large spatial and temporal scales. To aid future researchers, the GLCP is constructed with a “tidy” format (Wickham 2014)—a consistent and familiar data format in which each variable is a column, each observation is a row, and each type of observational unit is a table—such that users with a range of computational skill sets are better able to work with the GLCP and integrate additional data. As a net result, the GLCP supports researchers in addressing basic and applied questions at and across a range of spatial and temporal scales.

**Brief methods**

As a derived data product, the GLCP is an aggregation and harmonization of several remote sensing and global climate modeling (reanalysis) datasets. The GLCP connects data from the Joint Research Centre (JRC) Global Surface Water dataset (Pekel et al. 2016), the HydroLAKES (Messager et al. 2016) and HydroBASINS (Lehner and Grill 2013) datasets, as well as NASA’s MERRA-2 (Gelaro et al. 2017) and Gridded Population of the World (GPW) (Doxsey-Whitfield et al. 2015) data. Within the final GLCP, the HydroLAKES and HydroBASINS identifier columns (“Hy Lak_id” and “HYBAS_ID”) have been retained to improve interoperability with additional datasets.

To develop the GLCP, we employed a heterogeneous computational framework to spatially and temporally merge disparate data sources. First, we estimated yearly lake surface area by pairing global surface water with lake shapefiles and summing water pixel areas. Stemming from the data structure of the JRC dataset, surface area was calculated for annual permanent and seasonal water. Permanent water is defined as water present for all 12 months, whereas seasonal water is defined as water present for at least 1 month but not for the entire year. Second, lakes were matched with an accompanying basin as provided in HydroBASINS. Third, basin mean monthly precipitation, annually accumulated precipitation, average monthly temperature, and human population count were calculated for each basin using the MERRA-2 and GPW datasets. Finally, the basin level climate and population data were merged with the lake surface area data. The resulting peer-reviewed dataset contains annual aggregations of climate, population, and surface water area for each lake and year combination between 1995 through 2015. A complete, detailed explanation of the methods involved to produce the GLCP are provided in Meyer et al. (2020).

Where possible open source software was used in the development of the GLCP. All global lake area and climate calculations were performed in Google Earth Engine (Gorelick et al. 2017) and all data manipulations were performed using the R Statistical Environment (R Core Team 2019). As a result, the entire workflow and directory architecture can be downloaded without restrictions from the Environmental Data Initiative (EDI) as a “.tar.gz” file (Labou et al. 2020). If desired, users can recreate the GLCP de novo or incorporate their own variables of interest (e.g., wind speed, land-use cover) with little alteration to the original GLCP production code provided they have access to sufficient computational resources.

**Commitment to the spirit of FAIR principles**

From its inception, the GLCP was created with FAIR principles in mind—Findable, Accessible, Interoperable, and Reproducible (Wilkinson et al. 2016). First, the GLCP data are findable through the Environmental Data Initiative (EDI). Second, through EDI, the data are accessible without restrictions, such as paywalls and account registrations. Third, the GLCP is highly interoperable, as it retains the original unique identifiers Hy Lak_id and HYBAS_ID relational keys from HydroLAKES and HydroBASINS.

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**TABLE 1.** Average and median total lake area records and median monthly precipitation, temperature, and population by lake size class for the GLCP dataset. All data span the period from 1995 through 2015, with annual records per lake.

| Size class (ha) | Count | Average area (ha) | Median area (ha) | Median monthly precip (mm) | Median annual temp (°C) | Median population (people) |
|----------------|-------|------------------|-----------------|---------------------------|------------------------|---------------------------|
| 0–10           | 5,700,040 | 5.1              | 6.7             | 56                        | −2.7                   | 8.5                       |
| 10–100         | 20,786,622 | 29.9             | 22.3            | 49.2                      | −5.7                   | 0                         |
| 100–1000       | 3,075,149  | 252.4            | 180.6           | 52                        | −3.7                   | 3.2                       |
| 1000–10,000    | 278,627   | 2546.2           | 1791.8          | 55.4                      | −0.1                   | 120.7                     |
| 10,000–100,000 | 28,604    | 25,857.6         | 18,850          | 56.2                      | 2.1                    | 9119.7                    |
| 100,000–1,000,000 | 3094  | 253,120.4        | 186,006.9       | 56.5                      | 4.3                    | 454,089.1                 |
| 1,000,000–10,000,000 | 324 | 3,509,822        | 2,903,250       | 63                        | 7                      | 6,832,507.7               |
| 10,000,000–100,000,000 | 19   | 33,960,972       | 34,787,191      | 38.3                      | 7.3                    | 115,772,535.2             |
Global Lake Area, Climate, & Population Dataset

![Infographic summary of the GLCP dataset](labouetal2020; meyeretal2020).

**As a result, the GLCP can be merged efficiently with each of its parent datasets.** Fourth, the GLCP was produced with a commitment to reproducibility. All input data, derived products, as well as Google Earth Engine and R scripts are publicly hosted on EDI in a compressed format.

**Potential uses for the GLCP**

To highlight the GLCP’s utility in an applied context, we present three case studies using the GLCP at local, regional, and national scales for researchers within academic as well as natural resource management positions. For each case study, we have provided R scripts in a public GitHub repository (https://github.com/mbrousil/glcp_lo), so that others can reproduce our examples; if users are less familiar with the R statistical environment (R Core Team 2019), these scripts can serve as templates with which to tailor analyses to a specific research question.

**Using lake area to understand fish carrying capacity in Buffalo Lake (Washington, U.S.A.)**

As a case study of local applications of the GLCP, we explore Buffalo Lake (Hyak.id = 104312). Buffalo Lake is an oligotrophic lake located on the Confederated Tribes of the Colville Indian Reservation in north-central Washington State, U.S.A. (centr_lat = 48.08134, centr_lon = −54.311). The lake is characterized by steep littoral drop-offs and is unusual in that it has limited ephemeral surface inputs and no outlets. Its water, as well as allochthonous nutrient sources, mainly enters through subsurface connectivity. Currently, Buffalo Lake is managed for recreational fishing opportunities and actively monitored by Tribal natural resources managers (Artzrnurn 2003). The lake supports a mixed stock warm-coldwater fishery of kokanee, hatchery-maintained Rainbow Trout, Largemouth Bass, Pumpkinseed Sunfish, and Black Crappie, some of which utilize both littoral and pelagic habitats. Similar to many lakes with steep littoral zones, environmental conditions can alter littoral-pelagic food web dynamics (Lanouette 2020). For example, lake level rise can markedly increase available nearshore habitat, thereby coupling pelagic-littoral food webs (Lanouette 2020). Conversely, reduced water levels can further decouple pelagic and littoral food webs. Given the relation between food web linkages, available littoral habitat, and lake area, natural resource managers may wish to better manage their fishery by understanding how Buffalo Lake’s surface area (1) compares to other lakes in the region and (2) has changed over time.

First, recognizing that seasonal water may be most influential in creating littoral habitat, local managers could use the GLCP to compare Buffalo Lake’s water area to other lakes in Washington state (Fig. 2a). Leveraging the extensive number of lakes incorporated in the GLCP, local managers could compare Buffalo Lake’s mean surface area with other lakes at the county, state, or national scale to evaluate if food web relationships associated with water level may be occurring in similar lakes as well. Through this comparison, managers could better estimate available spawning and feeding habitat and therefore assess the lake’s food web interactions influencing production. At a state level, Buffalo Lake seems to be representative of larger lakes in Washington; managers, therefore, could be cognizant of which lakes are appropriate comparisons with Buffalo Lake, especially as it pertains to population stock estimates.

Second, local managers may also wish to evaluate how temporal shifts in lake surface area, climate, and human population data from the GLCP are associated with in situ water quality or biological data (Fig. 2b). For example, changing human population, temperature, precipitation, and water area over the GLCP’s 21-yr time series may be associated with increasing nutrient loading, changes in food web structure, or fisheries management practices. Because the GLCP integrates lake and basin data, the GLCP is able to easily pair with in situ data. Additionally, all Google Earth Engine and R scripts are provided, empowering others to aggregate additional variables of interest, such as wind speed, ice cover, or normalized difference vegetation index (NDVI). In the event local managers wish to include additional variables for contextualizing their system, they can efficiently pair data collected from disparate sources, such as remote sensing or process-based models, with their own in situ data.

Lake surface water area in response to forest fires (Pacific Northwest, U.S.A.)

Beyond providing context for individual systems, the GLCP can be used to better understand regional patterns and processes that may influence lake water availability. For example, projected increases in forest fire frequency and size in the United States’ Pacific Northwest require the attention of the region’s forest managers (Halofsky et al. 2020). Paired terrestrial and aquatic responses to fire are one area needing further study. Recent research has demonstrated that forest fires can increase river flows (Bart and Hope 2010; Gould et al. 2016; Hallema et al. 2018), yet the capacity for forest fires to influence lake water quantity is less explicit (Tague et al. 2009; McCullough et al. 2019). Closing this knowledge gap is particularly important, as fluctuations in lake water quantity can dilute or concentrate solutes that may be contributed by forest fires.
For example, forest fires can mobilize terrestrial nitrogen and phosphorus (Spencer and Hauer 1991), increase total suspended solids (Sheridan et al. 2007) that can affect turbidity (Oliver et al. 2012), as well as increase dissolved organic matter that can react with disinfectants upon treatment (Hohner et al. 2016). While concerns have been raised about the potential for increasing nutrients from forest fires to lead to localized eutrophication, increasing solute concentrations in tandem with increasing water quantity likewise has the potential to dilute contributed solutes. The magnitude of response may be system-dependent, complicating the question of how lake water quantity and quality may be responding to forest fires.

In an effort to synthesize and contextualize changes in lakes near forest fires, researchers can assess regional trends in fire and lake responses by combining the GLCP with forest fire databases. As an example, the GLCP can be paired with data from the Monitoring Trends in Burn Severity (MTBS; Eidenshink et al. 2007) database (Fig. 3). MTBS contains the most extensive forest fire data for the United States. In addition to location and severity, MTBS also provides a diverse range of fire data, such as acres burned, as well as coordinates for the fire’s centroid and origin. In the case of the Pacific Northwest, many of the fires between 1995 and 2015 occurred within and across basins contained within the GLCP (Fig. 3). Because the GLCP uses HydroBASINS as a source for basin locational and morphological data, the Pfafstetter basin taxonomy is retained, and all basins are hierarchical. All basins are categorized as level 01 through 12, where level 01 is near-continental scale and level 12 is more localized (median basin area: 2.46 km²). Managers can assess how fires may be correlated to within- and cross-scale processes. For example, a fire spanning across two or more level 06 basins may influence lake water area across the surrounding level 05 basin. Such data are important, as decreased vegetation following the fire may lead to losses in evapotranspiration, which in turn may cause water to either accumulate within or flow through aquatic systems more quickly. If interested in water quantity for conservation purposes or human demand following a fire, resource managers working at regional scales may find that combining the GLCP with other regional datasets is an efficient way to make prudent, data-driven decisions.

Assessing drinking water availability in India

Aside from contextualizing changes within systems, the GLCP contains data that may...
be used to inform policy at the regional and national scale. Cities around the world are rapidly growing and these densely populated areas tend to concentrate water demands, leaving municipalities to develop water delivery and security strategies for residents. Despite cities also representing an agglomeration of economic and political capital that should increase water security (Bettencourt et al. 2007), a municipality’s physical distance from water sources, financial limitations, and infrastructure can all influence a city’s risk of water stress (McDonald et al. 2014). As institutional challenges are compounded with changing climate and hydrologic regimes (e.g., Sharma and Mujumdar 2017), recent years have seen an increase in municipalities simply not having access to clean drinking water. For example, Cape Town, South Africa (Cassim 2018), and Chennai, India (Murphy and Mezzirofiore 2019) have made international headlines for their strict water rationing programs that were set in place during extreme droughts. Regardless of the reason for the restricted drinking water availability, water agencies may require resources to create data-driven plans for drinking water shortages.

To help water agencies assess trends in water availability, the GLCP can be used to identify decadal and regional variation in lake and reservoir water availability. India presents as an excellent case study, where highly heterogeneous trends in lake area may be a product of both human consumption and climatic forcings (Fig. 4). In particular, cities located within regions where lakes tend to be decreasing may need to plan for future water stresses. In 2019, drought forced the town of Chennai to implement strict water rationing guidelines (Murphy and Mezziofiore 2019). While a suite of climate and human related factors may explain why the extreme drought occurred (Singh et al. 2014; Singh 2016), long-term trends within the GLCP suggest that western India’s lakes have been decreasing in area for the past two decades, whereas lakes in eastern India generally tend to be increasing. By providing decades of lake surface area for over 11,100 lakes in India, the GLCP could help managers understand historical trends in lake surface water quantity across the subcontinent, which in turn could inform whether cities should identify alternative drinking water sources. Similarly, when possible, local managers could contextualize local or regional lake area trends with additional data to either analyze or course-correct lake area decline, so as to prevent future reductions in water availability (Fig. 4).

In addition to assessing trends in drinking water availability in India, water agencies could use lake surface area data from the GLCP in tandem with other data sources both to contextualize lake area change and to better inform regional management policies and priorities. For example, while cities and local agencies may focus analyses on a handful of lakes within the GLCP, regional and national water agencies may wish to classify lakes and basins into broad categories that inform future policies. Water agencies could group basins by physiographic and socioeconomic attributes such as potential evapotranspiration, soil composition, and gross domestic product. To do so, managers could pair the GLCP with the HydroATLAS database (Linke et al. 2019). With an architecture similar to HydroLAKES and HydroBASINS, HydroATLAS is a global database with 56 hydrological, physiographic, climatic, soil and geological, and anthropogenic variables. As HydroATLAS is built off the HydroBASINS dataset, it is completely interoperable with HydroBASINS and, by extension, the GLCP. By combining the GLCP with HydroATLAS, managers could classify lakes in India based on basin physiographic or socioeconomic characteristics, enabling agencies to generalize policies for more similar settings.

Conclusions

The scope, format, and utility of the GLCP make it a powerful resource for addressing a diversity of basic and applied questions. Consisting of lake surface area with colocated precipitation, temperature, and human population data for over 1.42 million lakes globally between 1995 and 2015, the GLCP can be used from local to global scales. In addition, the GLCP’s tidy format makes it analytically friendly for researchers of many skill levels and without need for access to specialized computing resources. As a net result, the GLCP offers not only a

FIG 4. Slopes from regressions of z-scored total water surface areas in India from 1995 to 2015. Patterns in lake surface area demonstrate south-western India as having decreasing total lake surface area, whereas eastern and southern lakes tend to have increasing total lake surface area. Given increasing demand for water in many Indian cities, these data from the GLCP may inform planning for water resources infrastructure. This figure can be reproduced using scripts “03_subset_hydrolakes.R” and “06_make_india_map_figure_3.R” in the GitHub repository (https://github.com/mbrousil/glcp_lo).
data product but also a robust workflow to accelerate research and enhance understanding of water availability worldwide.

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