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Research article

Developing a stochastic hydrological model for informing lake water level drawdown management

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ABSTRACT

Winter drawdown (WD) is a common lake management tool for multiple purposes such as flood control, aquatic vegetation reduction, and lake infrastructure maintenance. To minimize adverse impacts to a lake's ecosystem, regulatory agencies may provide managers with general guidelines for drawdown and refill timing, drawdown magnitude, and outflow limitations. However, there is significant uncertainty associated with the potential to meet management targets due to variability in lake characteristics and hydrometeorology of each lake's basin, making the use of modeling tools a necessity. In this context, we developed a hydrological modeling framework for lake water level drawdown management (HMF-Lake) and evaluated it at 15 Massachusetts lakes where WDs have been applied over multiple years for vegetation control. HMF-Lake is based on the daily lake water balance, with inflows simulated by a lumped rainfall-runoff model (Cemaneige-GR4J) and outflow rate calculated by a modified Target Storage and Release Based Method (TSRB). The model showed a satisfactory performance of simulating historical water levels ($0.53 \leq NSE \leq 0.86$), however, uncertainties from meteorological inputs and TSRB determined lake outflow rate affected the result accuracy. To account for these uncertainties, the model was executed stochastically to assess the ability of study lakes to follow the Massachusetts' general WD guidelines: drawdown by Dec 1 and fully refilled by Apr 1. By using the stochastic HMF-Lake, the probabilities of each lake to reach the drawdown level by Dec 1 were calculated for different drawdown magnitudes (1–6 *ft*). The probability results suggest it was generally less possible for most of study lakes to achieve a drawdown of 3 *ft* or more by Dec 1. Moreover, we employed the stochastic model to derive the annual latest refill starting dates that ensure a 95 % probability of reaching the normal water level by Apr 1. We found starting a refill in March for drawdowns up to 6 *ft* was feasible for most of study lakes. These results provide lake managers with a quantitative understanding of the lake's ability to follow the state guidelines. The model may be used to systematically evaluate current WD management strategies at state or regional scales and support adaptive WD management under changing climates.

1. Introduction

Fluctuations in lake water levels are controlled not only by natural processes such as precipitation and evaporation, but also by management practices that aim to provide human (e.g. recreation, water supply, flood protection) and ecosystem (e.g. minimum downstream flows) services (Gronewold and Rood, 2019). Winter drawdown (WD) is one of these management strategies, employed in temperate and boreal regions, that involves lowering water levels during the winter and refilling in the spring (Carmignani et al., 2021). The application of WDs can have multiple purposes for different years and even for different lakes, such as hydroelectric power generation (Mjelde et al., 2013), flood control (Schenk and Bragg, 2021), infrastructure maintenance (Madsen et al., 2017), and aquatic vegetation reduction (Carmignani and Roy, 2017). Compared with other aquatic vegetation reduction approaches such as using chemical herbicide, because WDs are simpler to implement and have lower costs, it has become a popular management strategy in many lakes (Helfrich et al., 2009).

Despite the benefits of WDs, there are potential negative effects on lake ecosystems. Within the lake, WDs can alter the physical habitat and macrophyte assemblages (Carmignani and Roy, 2021), affecting lake biota including macroinvertebrates, freshwater mussels, and fishes (Carmignani, 2020). Decrease in water storage might cause the

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potential loss of habitats during winter, affecting fish species interactions (Sammons and Bettoli, 2000; Yamanaka, 2013). Moreover, potential spring refill delays can disturb spawning activities of fish because of insufficient lake storage (Carmignani and Roy, 2017; McDowell, 2012). Finally, downstream flow regimes are altered by increasing flows during winter drawdown and reducing flows during spring refill, adversely impacting downstream ecosystems (Hamilton et al., 2022; Schenk and Bragg, 2021).

There are several guidelines for WD management that aim to minimize ecological impacts (New Hampshire Department of Environmental Services, 2022; Muskingum Watershed Conservancy District, 2022). For example, Massachusetts Division of Fisheries and Wildlife (MassWildlife) provides a set of guidelines related to the drawdown magnitude (<3 ft; if deeper, a permit is needed), timing (drawdown must be initiated after November 1st and completed before December 1, and refill must be achieved before April 1) and outflow restrictions (<4 cfsm, cubic feet per square mile of its contributing area, during recession and >0.5 cfsm during refilling) or water level recession rates (<3 inch/day) (Mattson and Wagner, 2004). In cases in several states, such as in Massachusetts (MA), New Hampshire (NH) (New Hampshire Department of Environmental Services, 2022), Ohio (OH) (Muskingum Watershed Conservancy District, 2022), Wisconsin (WI) (Minong Flowage Association, 2021), the latest refill completion date guidance aims to minimize damages to spring spawning activities. Nonetheless, the optimal refill start date given a completion date constraint (e.g., April 1 for MA) can be highly site- and year-specific depending on the watershed yield and lake capacity, and affected by uncertainty in climatic factors (rainfall, ice formation, etc.). Therefore, it can become difficult for lake managers to develop drawdown schedules or evaluate "what-if" scenarios (e.g., related to climate change) (Carmignani et al., 2021).

A hydrological model that can simulate the lake water balance and management operations could address this knowledge gap and potentially aid resource managers (Carmignani et al., 2021; Magee et al., 2019). Many existing hydrological models represent reservoir/lake processes and can support customization of operation rules for water resource management, such as Soil and Water Assessment Tool plus (SWAT+) (Wu et al., 2020), Variable Infiltration Capacity (VIC) (Dang et al., 2020), Distributed Hydrology Soil Vegetation Model (DHSVM) (Zhao et al., 2016). Yassin et al. (2019) summarized current reservoir operation models, which can be divided into three categories: inflow-and-demand based methods, neural network-based methods and target storage-and-release-based methods. The inflow-and-demand based methods use empirical equations to determine reservoir release from inflows and downstream demands (irrigation, water supply, hydroelectric, etc.) (Allawi et al., 2019; Biemans et al., 2011). Neural network-based methods are powerful tools that have mostly been used to forecast reservoir water levels by using inflows and weather variables as input to infer operation rules (Yang et al., 2019; Zhang et al., 2018). One of the major limitations of neural networks for assessing different WD schedules is their "black box" nature (Oyebode and Stretch, 2019) that makes it difficult to map actual management strategies to network parameters. Target storage-and-release-based methods (TSRB) are designed to simulate dam operations by dynamically altering the outflow in order to drawdown/refill the lake to the target storage within a given period. For example, SWAT+ calculates the release rate in every model time step from the difference between current storage and target storage, and a user-specified adjustment coefficient (Arnold et al., 1998). TSRB methods appear to be the most promising approach to model WDs, because the WD storage could be considered as the target storage during the winter. However, most studies that use this method target multi-purpose reservoirs over larger scales (Dang et al., 2020; Yassin et al., 2019; Zhao et al., 2016), whereas lakes that implement WDs tend to be smaller in size and single-purpose. Although these types of models can be modified to assess WDs, their formulations are generic and can be overtly complicated as they need to account for multi-purpose reservoirs. More importantly though, current models attempt to replicate management strategies by calibrating a set of parameters to observations. However, WD strategies vary in time and are often influenced by factors (e.g., political) that are not captured in current models.

Our study aims to address the issues of complexity and uncertainty in WD lake management by developing a hydrological modeling framework for lake water level drawdown management (HMF-Lake). To demonstrate the application of HMF-Lake, we selected 15 gauged WD lakes in MA, USA to build, calibrate, and validate our model against *in-situ* observations. In addition, we employed the HMF-Lake model to assess the feasibility of these lakes to conduct WDs based on the MA general WD guidelines. Specifically, we assessed (1) the probability of completing drawdown by December 1 given a November 1 start and different drawdown magnitudes, and (2) the timing of refill start to achieve full pool levels by April 1 with different drawdown magnitudes. As such, we demonstrated how a modeling framework such as HMF-Lake can provide actionable information to lake managers. Finally, we discuss other possible applications of this modeling framework along with potential improvements that could lead to better WD management in practice.

2. Methods

2.1. Data acquisition and pre-processing

We developed and evaluated a hydrological model using in-situ measurements (2014 to 2018) of water levels at 15 recreational lakes in Massachusetts (Fig. 1 and Table 1) that conduct WDs (Carmignani et al., 2021). Although data from 18 lakes were available from Carmignani et al. (2021), three WD lakes (Lake Wyman, Silver and Cranberry Meadow) were eliminated because of missing data that would mislead the identification of the WD period (See Fig S1). As our modeling framework operates at a daily time step and requires daily water level observations, we resampled the raw bi-hourly water levels to daily by calculating the mean value. In addition to water levels, lake bathymetry measurements conducted during full pool conditions during the summer available.

Weather data were obtained from the Daymet dataset, which comprises of daily minimum temperature, maximum temperature, precipitation, shortwave radiation, vapor pressure, snow water equivalent on a 1 km grid (Thornton et al., 2020). The raw data from Daymet are gridded, therefore the area-weighted spatial averages were calculated over the watershed of each WD lake from 1 January 2010 to 31 December 2020 using the `daymetpy` Python package (https://github.com/bluegreen-labs/daymetpy). Since the model developed in Section 2.3 requires potential evapotranspiration as input, we applied a temperature-based method to estimate it for each basin (Oudin et al., 2005). The calculated basin mean average annual evaporation of study lakes are presented in Table 1.

In order to simulate lake inflows, the model also requires the drainage basin characteristics (drainage area, land cover, etc.) of each WD lake. In this study, we used Streamstats (Ries III et al., 2008), a web-GIS application developed by the U.S. Geological Survey (USGS) for streamflow analysis, to delineate the drainage watershed at the outlets of the WD lakes and acquire the statistics of the basin characteristics (See Table 1). In addition to watershed delineation, we extracted drainage area, average annual precipitation, mean basin elevation, percent of basin that is sand and gravel deposits, percent of basin that is wetlands, percent of basin that is open water, and average maximum monthly temperature for each WD lake drainage basin to aid model calibration via regionalization (described in more detail in Section 2.3.1). The data used in this study including data source and processing methods are summarized in Table S1.

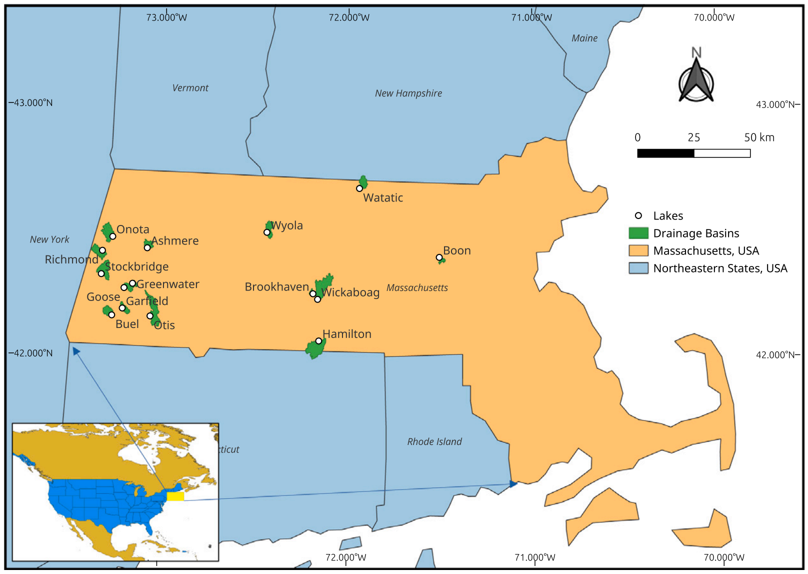

Fig. 1. Location of the 15 study lakes and associated drainage basins in Massachusetts, USA. (See Table 1 for details about each lake).

Table 1
Lake morphometric features and the basin characteristics for 15 study lakes in Massachusetts, USA. AREA = Lake Area (km^2), VOL = Full lake volume (10^6 m^3, measured from bathymetry), DRNAREA = Drainage area (km^2), RATIO = drainage area/lake area, BLSDEM10M = Mean basin slope computed from 10 m DEM (Percent), PRECPRIS00 = Basin average mean annual precipitation for 1971 to 2000 from the PRISM dataset (mm), ETDAYMET = Basin average mean annual evaporation for 2010 to 2020 from Daymet dataset calculated by the method from Oudin et al. (2005) (mm), HSIMGAUGE = the USGS gauge number where the drainage basin is hydrological similar to the lake watershed. (See Fig. 1 for lakes included in the table).

Lake Unit	AREA km^2	VOL 10^6 m^3	DRNAREA km^2	BSLDEM10M %	PRECPRIS00 mm	ETDAYMET mm	RATIO	HSIMGAUGE
Buel	0.83	5.10	14.19	12.25	1198.88	619.04	17.1	01175670
Brookhaven	0.14	0.20	3.60	9.58	1226.82	618.61	25.70	01181000
Boon	0.73	2.17	5.11	4.27	1198.88	617.94	7.00	01111500
Watatic	0.56	1.65	15.68	9.96	1239.52	616.69	28.00	01097300
Greenwater	0.38	2.91	3.91	17.72	1330.96	618.46	10.30	01174565
Wickaboag	1.30	2.79	44.85	8.51	1226.82	618.71	34.50	01198000
Richmond	0.95	3.81	20.43	12.01	1231.90	617.88	21.50	01082000
Wyola	0.50	1.84	17.60	8.13	1270.00	617.50	35.20	01174565
Hamilton	1.68	6.17	46.54	10.97	1272.54	619.46	27.70	01095220
Ashmere	1.14	3.32	11.51	8.13	1318.26	617.81	10.10	01174565
Stockbridge	1.60	14.19	29.76	12.12	1203.96	618.30	18.60	01174565
Onota	2.66	19.18	27.40	13.69	1214.12	617.62	10.30	01198000
Goose	1.30	9.06	11.05	12.35	1280.16	618.54	8.50	01181000
Garfield	1.11	4.35	10.32	11.44	1224.28	618.91	9.30	01175670
Otis	4.21	27.96	41.68	6.26	1399.54	619.05	9.90	01176000

2.2. Massachusetts winter drawdown guidelines

As winter drawdowns are frequently applied in Massachusetts reservoirs, lakes, and ponds for aquatic vegetation control, MassWildlife provides general guidelines for lake managers. In these guidelines, a proposed WD must achieve the following performance standards: (1) For lakes with a proposed WD of more than 3 ft, a site-specific review by the Division of Fisheries and Wildlife must be conducted before the WD. (2) Drawdowns must be initiated after Nov 1 as the water level reduction in warm Fall seasons might result in potential fish kills due to the increasing oxygen depletion particularly in shallow and heavily vegetated lakes. (3) Water levels must reach the target WD value before Dec 1 in order to provide sufficient time for aquatic animals to relocate habitats before the lake is fully iced. (4) The maximum outflow during recession must not exceed 4 cfsm (cubic feet per second per squire mile of drainage area). Unexpected high release might cause downstream flooding and pose dangers to the stream ecosystem (Ligon et al., 1995). (5) Refills must be completed before April 1, as late spring refill would be harmful to the fish recruitment due to the habitat loss in littoral zones (Carmignani and Roy, 2017). (6) Outflow must be maintained to at least 0.5 cfsm while the lake is refilling to provide sufficient in-stream flow.

Our objective here is to evaluate the ability of the study lakes to follow these guidelines. Specifically, we define that ability in terms of the probability of achieving the end date requirements (3) and (5) while the rest of the performance standards (1), (2), (4) and (6) are met (The numbers refer to the 6 performance standards in Massachusetts WD guidelines which are explained in the paragraph above). The refill starting date and the drawdown magnitude (the distance between the normal level and the designed drawdown level) are not specified in the guidelines. As the primary purpose of WDs in the study lakes was aquatic vegetation control, the larger area of exposure (larger drawdown magnitude) and longer winter drawdown duration (later refill starting dates) would be preferable in terms of vegetation removal efficiency (Siver et al., 1986). However, selecting a larger drawdown magnitude and later refill starting date might preclude the lake of achieving requirements (3) and (5). Therefore, a numerical tool could help optimize the possible largest drawdown magnitude and the latest refill date of a WD lake within the constraints of the MA guideline requirements.

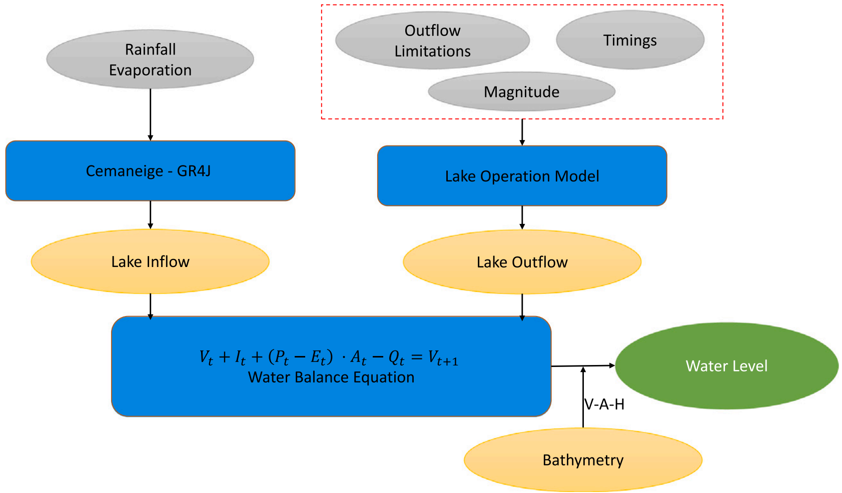

Fig. 2. Flow diagram of the hydrological modeling framework for drawdown lake management (HMF-Lake). V_t is the storage at the current time step t. I_t is the lake inflow, which is simulated by the Cemaneige-GR4J with inputs of rainfall (P_t) and evaporation (E_t). Q_t os tje lake outflow, which is determined by the lake operation model. V–A–H is the statistical relationship between the lake storage, area (A) and water level (H).

2.3. Hydrological modeling framework development

We started building the hydrological modeling framework for lake water level management (HMF-Lake) from a simple water balance equation (Eq. (1)):

$$\frac{V_{t+1} - V_t}{\Delta t} = I_t - Q_t + A_t(P_t - E_t) \tag{1}$$

where V_t (m^3), A_t (m^2) are the storage, water surface area on day t; P_t (mm/d) and E_t (mm/d) are the direct precipitation and evapotranspiration, obtained from the Daymet; I_t (m^3/d) is the lake inflow; Q_t (m^3/d) is the lake outflow. V_t, A_t, H_t (water level at day t) can be calculated from each other by using the V–A–H relationship derived from the measured lake bathymetry. In particular, the V–A and A–H relationships were obtained by fitting the polynomial functions $V = aA^b$ and $A = cH^d$ (Khazaei et al., 2022) to the volume, area and height data from bathymetric measurements. In order for HMF-Lake to simulate lake drawdown, we needed to estimate inflows I_t as a function of weather conditions and mathematically represent drawdown operations. For the latter we adapted a general TSRB method (Section 2.3.2) while a rainfall-runoff model was employed to simulate the former (Section 2.3.1) (see Fig. 2).

2.3.1. Lake inflow generation: Rainfall-runoff model

A daily lumped rainfall-runoff hydrological model, Cemaneige-GR4J (Valéry, 2010), was used to estimate lake inflows within the developed framework. The Cemaneige-GR4J has daily precipitation, potential evapotranspiration data as inputs and six parameters that describe basin characteristics to simulate runoff at the basin outlet. Although lumped hydrological models such as the Cemaneige-GR4J were designed to simulate streamflow at the basin outlet, they can also be applied to model lake inflow by assuming the inflow location as the outlet of its drainage basin (Huang et al., 2018; Gaborit et al., 2017; Ogilvie et al., 2018).

Building a rainfall-runoff model for lake inflows requires historical *in-situ* observations, which are mostly unavailable since most lakes are gauged for measurements of water levels and outflows (Hamilton et al., 2022; Schenk and Bragg, 2021). In order to overcome the limitation of lacking *in-situ* inflow observations, we used a scheme for transferring calibrated model parameters from other basins based on hydrological similarity (Wagener et al., 2007). Hydrological similarity is derived from physiographic characteristics between basins, such as land cover or soil properties, and ideally result in a similar rainfall-runoff relationship. This parameter transfer strategy has been extensively used in streamflow prediction in ungauged basins (Cantoni et al., 2022; Arsenault et al., 2019). Du et al. (2020) reported that regionalization method in streamflow simulation can reach 80% performance of the local calibration. Furthermore, the National Water Model (NWA) developed by the National Center for Atmospheric Research (NCAR) which aims to simulate and forecast real time water components such as streamflow discharge across the entire US also adopted such hydrologically similarity strategy to regionalize parameters (Heldmyer et al., 2022). Numerous methods have been proposed to identify hydrologically similar watersheds, such as the nearest neighbor (Patil and Stieglitz, 2015), k-means clustering (Kratzert et al., 2019), or neural network based parameter learning (Feng et al., 2022).

In this study, we applied the Massachusetts Sustainable-Yield Estimator (MA-SYE) (Granato and Levin, 2018), a software developed by the USGS for assessment of sustainable water use at ungauged sites in Massachusetts, US, to find hydrologically similar watersheds for each of our study lake basins. The MA-SYE returns a gauge number from the National Water Information System (NWIS) network based on a number of features including drainage area, average annual precipitation, mean basin elevation, percent of basin that is sand and gravel deposits, percent of basin that is wetlands, percent of basin that is open water, average maximum monthly temperature. The hydrologically similar basins' gauge numbers for the 15 WD lakes were obtained by using the MA-SYE and are presented in Table 1. We used the Python package `RRMPG` https://github.com/kratzert/RRMPG to set up and calibrate the Cemaneige-GR4J model against streamflow measurements from these gauges in the hydrologically similar watersheds. The calibrated model parameters were then transferred to the Cemaneige-GR4J model in the corresponding WD lake basin to simulate lake inflows.

2.3.2. Lake outflow simulation

Each type of lake outflow structure has its own governing equation to calculate releases, parameterized based on its hydraulic characteristics. For example, the outflow at an overtop spillway dam can be calculated by: $Q_t = CLH^{1.5}$, where C is the discharge coefficient, L is the spillway gate length, and H is the hydraulic head above the spillway. This equation has been commonly applied and incorporated in many existing hydrological models (Klipsch and Evans, 2006; Hughes et al., 2021). Nevertheless, applying this method to a large number of lakes is impractical as dam information is generally unavailable. Consequently, a general TSRB which can emulate WD release without specific dam information is needed. We started by adapting a simple TSRB equation from SWAT model (Wu et al., 2020):

$$Q_t = \begin{cases} \frac{(V_t - V_{\text{target}})}{a\Delta t}, V_t > V_{\text{target}} \\ 0, V_t \le V_{\text{target}} \end{cases} \tag{2}$$

where Q_t is the outflow, V_t is storage, V_{target} is the target storage, Δt is the time step (In this study, $\Delta t = 1$ day), a is the number of required time steps (days) for the lake to reach target storage. This equation simulates drawdowns/refills by setting the target storage as the winter drawdown storage and the normal pool storage, respectively. The outflow rate during spring refills could be arbitrarily set to zero but that is inappropriate in practice due to downstream flow requirements. Moreover, Eq. (2) does not explicitly include the inflow term making it difficult to address requirements such as the one in the MA guidelines about lake outflow and inflow being equal when the target drawdown level has been achieved. In order to address these issues, we further modified Eq. (2) for winter drawdown lakes to:

$$Q_t = \begin{cases} \frac{(V_t - V_{\text{target}})}{a\Delta t} + I_t, Q_{min} < Q_t < Q_{max} \\ Q_{min}, Q_t \le Q_{min} \\ Q_{max}, Q_t \ge Q_{max} \end{cases} \tag{3}$$

where I_t is the inflow at time t, Q_{min} and Q_{max} are the minimum and maximum allowed outflows. This equation determines the daily outflow rate by reducing/increasing volume per day to inflow resulting in a positive (drawdown) or negative (refill) change in water storage. Minimum and maximum outflow, Q_{min} and Q_{max}, are embedded in Eq. (3) in order to satisfy dam capacity constraints or potential downstream flow requirements. We separate the entire WD to 4 phases according to Carmignani et al. (2021): Recession, Stable, Refill, Non-drawdown. The V_{target} of the Recession and Stable phases was set to the winter drawdown storage: V_{drawdown}, and the Refill and Non-drawdown seasons had the normal pool volume: V_{normal} as the V_{target}. In order to increase flexibility in the model, we assigned the coefficient a (number of days to reach target storage) as separate for each phase. Similar to Eq. (2), the V_{target} was considered as the lower bound, and the outflow rate was determined to maintain the storage above V_{target}. As the time to complete each phase is unknown a priori and there are outflow constraints, there is a possibility that the Recession or Stable phases will never complete (depending on how inflows compare to minimum required outflow). Therefore, we implemented a dynamic residual volume factor that ensures the completion of each drawdown phase and subsequent transition. This factor has the form $V_{\text{target}} = V_{\text{drawdown}} - f(V_{\text{normal}} - V_{\text{drawdown}})$ with f being a coefficient that is region-dependent but we found that for the study area lakes a value of 0.05 is a reasonable estimate.

The final equation for the outflow rate in all 4 phases is then

$$Q = \begin{cases} min\left(Q_{max}, max\left[Q_{min}, I_t + \frac{V_t - V_{\text{drawdown}} - 0.05(V_{\text{normal}} - V_{\text{drawdown}})}{\alpha\Delta t}\right]\right) & T_1 < t < T_2, \text{Recession} \\ min\left(Q_{max}, max\left[Q_{min}, I_t + \frac{V_t - V_{\text{drawdown}} - 0.05(V_{\text{normal}} - V_{\text{drawdown}})}{\beta\Delta t}\right]\right) & T_2 < t < T_3, \text{Stable} \\ min\left(Q_{max}, max\left[Q_{min}, I_t + \frac{V_t - V_{\text{normal}}}{\gamma\Delta t}\right]\right) & T_3 < t < T_4, \text{Refill} \\ min\left(Q_{max}, max\left[Q_{min}, I_t + \frac{V_t - V_{\text{normal}}}{\theta\Delta t}\right]\right) & T_4 < t < T_1, \text{Non-Drawdown} \end{cases}$$

where α, β, γ and θ were different form of the a in each phase. T_1 and T_3 are drawdown and refill initiation timings, which are given by users. T_2 and T_4 are the drawdown and refill completion timings, which are determined when $V_t \le V_{\text{drawdown}}$ and $V_t \ge V_{\text{normal}}$.

2.4. Historical winter drawdowns simulation

In order to demonstrate the applicability of HMF-Lake on simulating winter drawdowns, we assessed how well it could reproduce historical water levels. Since the dam/gate operation records were not available, the winter drawdown timing and magnitude were inferred from the hydrographs (see Carmignani et al. (2021) for details on the methodology). Other than timing and magnitude, other parameters that are required in HMF-Lake were unknown in the context of these historical simulations including Q_{min} and Q_{max}. Therefore, we calibrated HMF-Lake to obtain the optimal combinations of Q_{min}, Q_{max}, t_α, t_β, t_γ and t_θ using the historical *in-situ* water level observations. The range of plausible values for Q_{min}, Q_{max} were [1%, 50%] and (50%, 99%] of the inflows. For corresponding ranges for α and β were [1, Recession duration days], and [1, Refill duration days] for γ and θ. A differential evolution algorithm (Virtanen et al., 2020) was employed to optimize these model parameters. The KGE (Kling–Gupta efficiency) (Schaefli and Gupta, 2007) and NSE (Nash–Sutcliffe efficiency) (Nash and Sutcliffe, 1970) were selected as the metrics for evaluating the model's performance.

2.5. Evaluation of the ability to meet the MA winter drawdown guidelines

After the historical winter drawdowns simulation, HMF-Lake was applied to assess the ability of each lake to achieve the MA winter drawdown guidelines. The ability can be reflected by the probability of the lake to achieve requirements (3) and (5) while the rest of the performance standards (1), (2), (4) and (6) were met (The performance standards were explained in Section 2.2). We selected 10/01/2015–04/01/2018, which includes 3 years of winter drawdowns in the simulation time period of all study lakes. The drawdown starting date was set as November 1, which is the earliest drawdown date suggested in the guidelines. The maximum outflow in the recession phase was 4 cfsm, and the minimum outflow in the refill phase was 0.5 cfsm. The outflow limitations in other phases were set as the calibrated values in the historical drawdown simulation (Section 2.4). In this simulation, there are three major uncertainties which would affect the simulated results: (1) potential errors in weather inputs; (2) unknown refill starting date and drawdown magnitude; and (3) unknown daily release rates. In order to account for these uncertainties we executed the model stochastically.

For the meteorological uncertainty, we acquired 20 years (2000–2020) daily precipitation, maximum and minimum air temperature at regional weather stations where study lakes were closest to from the Global Historical Climatology Network daily (GHCND) dataset, and calculated the residual between the Daymet data at the same location. The closest GHCND stations study lakes were listed in Table S2. We then fit a Laplace probability distribution to the residual, ϵ, for each meteorological variable and assumed that the distribution is the same across the study lakes (Empirical and fitted distributions for each GHCND station were presented in Fig S3). In every time step of the HMF-Lake simulation, the ϵ will be sampled from the fitted Laplace PDF and added to the Daymet weather estimate. The uncertainty in refill timing and drawdown magnitude was accounted for by creating an ensemble of 540 WD plans that consisted of 6 different drawdown magnitudes (1–6 ft) and 90 refill starting dates (Jan 1 to Mar 30). In terms of the daily release rate, the coefficients α, β, γ and θ in Section 2.3.2 are generally not fixed for each phase. As the release rate also depends on the inflow, the time to phase completion is not known a priori. For example, the guidelines require the lake to reach drawdown levels in 30 days (November 1 to December 1) but drawdown might be complete on any date between November 1 to December 1 ($1 \le \alpha \le 30$). Thus, on each time step t during [Nov 1, Dec 1], the release rate is determined to reach the drawdown level on any date by December 1, which means $\alpha_t = U[1, Dec1 - t]$ (we assumed it is uniformly distributed). Similarly, γ_t on each time step in the Refill phase can also be any value from 1 to $Apr1 - t$, which means $\gamma_t = U[1, Apr1 - t]$. To account for the uncertainty in the release rate we further enhanced the 540 WD plans in a Monte Carlo experiment performing a simulation for each plan for 1000 sets of coefficient values. Consequently, there were 540 × 1000 water level time series for each lake and their ability to achieve the Dec 1 drawdown was calculated by $P = \frac{N}{1000}$, where N is the number of simulations whereby the target drawdown level was reached by Dec 1. The ability for a lake to comply with the refill requirement was quantified by the latest refill starting date for which the lake has over 95% probability to achieve full refill by April 1.

3. Results

3.1. Lake inflows

Since the *in-situ* lake inflow observations were not available for study lakes, the lake inflow model (Cemaneige-GR4J) was parameterized by calibrating against the streamflow observations of hydrologically similar watershed. According to the simulated flow at gauge 01181000 showed in Fig S4, the locally calibrated model, which directly calibrated against the streamflow observations at 01181000, had a NSE of 0.657 and a KGE of 0.746. Meanwhile, the KGE and NSE of the parameter transferred model, which is calibrated by using the records at 01198000 (the hydrological similar station of 01181000), were 0.539 and 0.497, the performance of which was slightly lower than the locally calibrated model but still remained satisfactory. This further demonstrated that transferring parameters from a hydrologically similar watershed is applicable for streamflow simulation in ungauged basins. Nine USGS gauges were identified to be hydrologically similar to the study lakes by the MA-SYE (See Table S3). Among these gauges, the Cemaneige-GR4J showed a satisfactory performance of streamflow simulation, where 0.63 ≤ KGE ≤ 0.86 and 0.30 ≤ NSE ≤ 0.80 during validation period (See Table S3).

The calibrated model parameters from these gauges were used to simulate daily inflows to the study lakes between 2000 and 2020. The simulated inflows were summarized with boxplots (see Fig. 3). Lake Otis had the highest high flow (75 percentile = 46.41 cfs), whereas Lake Hamilton had the largest overall inflow magnitude among the study lakes (median = 27.15 cfs). Lake Brookhaven had the lowest inflow among the study lakes, with the lowest values for extreme flow (75th percentile = 3.01 cfs), median flow (1.88 cfs), and low flow (25th percentile = 0.83 cfs). Regarding inflow variability, Lake Otis had the highest standard deviation of 63.82 cfs, which indicates that it had the most variable inflow among the study lakes. In contrast, the standard deviation of the Lake Brookhaven inflow is the lowest: 2.7 cfs, which means the inflow to Lake Brookhaven is less variable comparing with other study lakes.

3.2. Historical winter drawdown simulations

The overall performance of simulated water levels comparing with *in-situ* observations was satisfactory, where the KGE ranged from 0.65 to 0.89 and the NSE varied between 0.53 and 0.86 (Fig. 4). The comparison of the simulated and observed water levels of study lakes is presented in Fig S2. From the plot, despite the high KGE and NSE values of the model simulation, there are still some water level fluctuations that were not captured and incorrect drawdown/refill completion timings simulated by the model. The missing water level fluctuations can be attributed to the potential errors from the weather input. For example, in Fig. 5A, the *in-situ* observations at Lake Wyola suggest that there was a 2 ft water level rise before the 2017 spring refill. However, the inflow rate that was simulated based on the Daymet rainfall and temperature did not show a corresponding increase during that period, resulting in the absence of such a rise in the water level simulations. The misaligned drawdown/refill completion timings (see Fig. 5B) may be due to limitations of the deterministic TSRB equation (Section 2.3.2) in accurately describing human operations, which are inherently stochastic. For instance, the 2016 spring refill in Lake Greenwater was paused at −0.8 ft for 28 days since Feb 25 that was not captured by the model, resulting in the simulated refill completion date was 1 month earlier than the actual date (See Fig. 5B). The model determined the outflow rate in order to reach the target water level, however, the actual release rate might be adjusted for other purposes such as increasing downstream demand that cannot be accounted by the deterministic model. To sum up, the deterministic HMF-Lake was able to re-create historical water levels but was still subject to the uncertainties from the meteorological inputs and the TSRB equations (Section 2.3.2). Therefore, it is important to account these uncertainties when applying the model to assess lakes' ability to meet the state WD guidelines.

3.3. Probability of completing drawndown by Dec 1

The probability to reach the target drawdown level by Dec 1 varied across lakes (See Fig. 6, the exact probability were listed in Table S4). Some lakes had relatively lower probability to meet the Dec 1 deadline, such as Lake Greenwater where there was less than 5% possibility to complete a 2 ft drawdown by Dec 1 for every simulated year. In contrast, Lake Wyola and Lake Richmond had over 99% probability for all designed drawdown levels (1 ft to 6 ft). In order to demonstrate these differences across lakes, Fig. 7 shows time series of water level and inflow/outflow for Lake Greenwater and Wyola during November 2015. In Fig. 7, the shaded area is the range of 5%–95% percentile. From the water level plots (A1 and A2 in Fig. 7), the deepest level the Lake Greenwater can reach by 12/01/2015 was around −2.1 ft (relative to the normal pool level), whereas Lake Wyola can achieve the December 1 deadline for all selected drawdown levels. The outflows in Lake Greenwater (shaded area in B1, Fig. 7) for >2ft drawdowns have almost zero spread as they were mostly capped to 4 cfsm, which is the maximum allowed release rate in the MA guidelines. In contrast, the outflows in Lake Wyola (shaded area in B2, Fig. 7) were under 4 cfsm allowing for reaching the target drawdown level. Lake Wyola also had lower inflow (relative to 4 cfsm) than Lake Greenwater, which enabled larger capacity to release extra storage.

In addition to the difference across study lakes, the ability to achieve the December 1 drawdown also varied in different years. For most of lakes, the probabilities to meet the December 1 drawdown in 2017 were generally lower than 2015 and 2016 (See Fig. 6). One of the typical examples is that Lake Hamilton had over 99% probability to meet the December 1 deadline for all designed drawdown levels in 2015–2016 and 2016–2017 but had <1% possibility to implement a >3 ft drawdown in 2017–2018. The simulated water levels of Lake Hamilton (A1–A3, Fig. 8) also showed that it was able to reach 1–6 ft drawdown levels by December 1 in the first two years, but the deepest drawdown that could be reached by Dec 1, 2017 was ~4.4 ft. By comparing the inflow between each year in Lake Hamilton (solid blue lines in B1–B3, Fig. 8), the inflow was averagely higher in 2017 (mean = 47.75 cfs) than 2015 (mean = 21.59 cfs) and 2016 (mean = 24.37 cfs). In order to reach the target levels by December 1, Lake Hamilton needed to release more water in 2017 than in other two years. The simulated outflows (shaded area in B1–B3 Fig. 8) show that for drawdowns greater than 4 ft, the simulated outflows had zero spread and were mostly capped to 4 cfsm through the entire November in 2017, but not in the other two years. Consequently, Lake Hamilton was able to reach >4 ft drawdowns by December 1 in 2015 and 2016, but not in 2017.

3.4. Latest refill starting dates for April 1 requirement

As later refill starting dates are beneficial in terms of vegetation reduction, we evaluated the ability of successful refills by the latest starting date that ensures full refill with a 95% probability. Our results

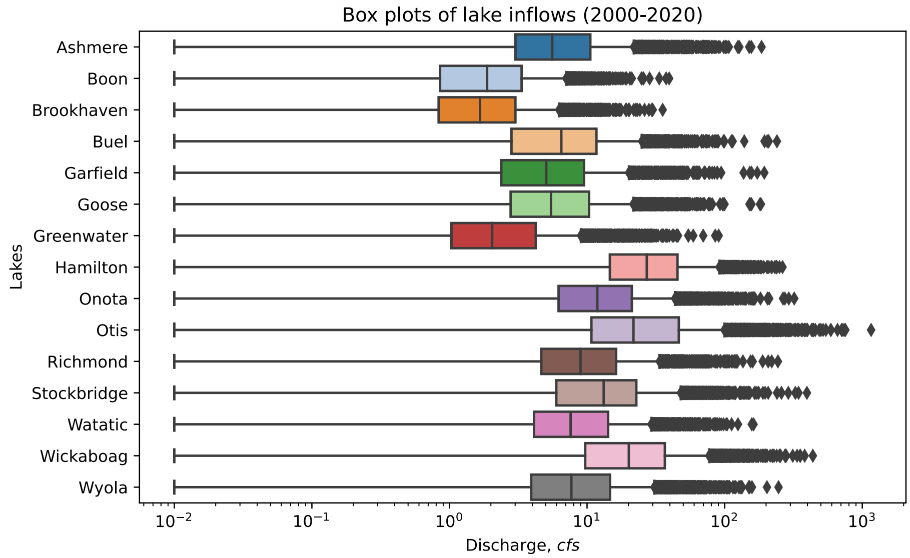

Fig. 3. Box plots of inflows to the study lakes from 2000 to 2020. $0.01cfs$ is added to zero inflows for better visualization.

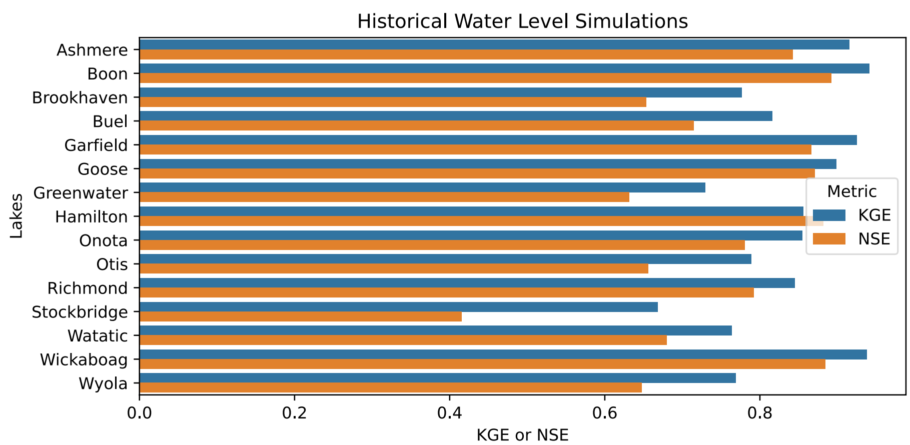

Fig. 4. Model performance of historical water level simulations. The time series of simulated water levels in study lakes are presented in Figure S2.

show a deeper drawdown required an earlier timing to start the spring refill, and the latest refill starting dates varied across different lakes and years.(See Fig. 9, the exact dates were listed in Table S5). For most of lakes, starting refills in March for all selected drawdown levels (up to 6 ft) was feasible. For example, during Spring 2016, Lake Onota and Wyola could begin refilling after Mar 7 at drawdowns of 6 ft and still meet the April 1 requirement. Nonetheless, there were a few exceptions either at higher drawdown levels (>5 ft) or for specific lakes. For instance, Lake Boon would require starting the refill procedure in January when drawdown was >3 ft. When examining different years, there are some cases of significant differences between refill starting dates for the same lake. Those can be attributed to the differences in inflows from year to year. For example, refill starting dates for Lakes Brookhaven, Buel and Hamilton in 2017 were later than those in 2016, 2018 coinciding with comparatively lower inflows (see Fig S8).

4. Discussion

4.1. Implications for WD management

Decisions for management of lake storage levels and outflow are influenced by a number of factors and therefore, a tool such as HMF-Lake can help managers assess the efficacy of these decisions both retrospectively and otherwise. This becomes important when considering contradicting constraints for lake water levels. By constraining the release rate to the guidelines in our model, we provide managers with a quantitative understanding of the lake's ability to follow the guidelines that can be used to guide management decisions. If the model consistently yields low probabilities of being fully refilled by April 1 when the lake starts refilling at March 1, the lake manager may consider either a shallower drawdown magnitude or starting refill earlier than March to ensure meeting the timing guidelines. Furthermore, given that managers may want to keep drawdowns as long as possible to increase the efficiency on invasive vegetation reduction (Carmignani et al., 2021; Siver et al., 1986; Dugdale et al., 2012), the model can also provide the latest refill starting dates that ensure (95% probability) achieving the goal of refilling by April 1. Due to the interannual weather variability, the latest refill start timing will vary across years. Our model can be potentially used for long term simulation to provide information about interannual variability in drawdown and refill timing with different drawdown magnitudes which helps individual lake managers make climate-informed decisions toward optimizing their management objectives (e.g., maximizing time the lake is drawn down) while ensuring they meet regulatory guidelines.

In addition to assessing individual lakes, the model can also be employed for statewide feasibility assessments. For example, based on

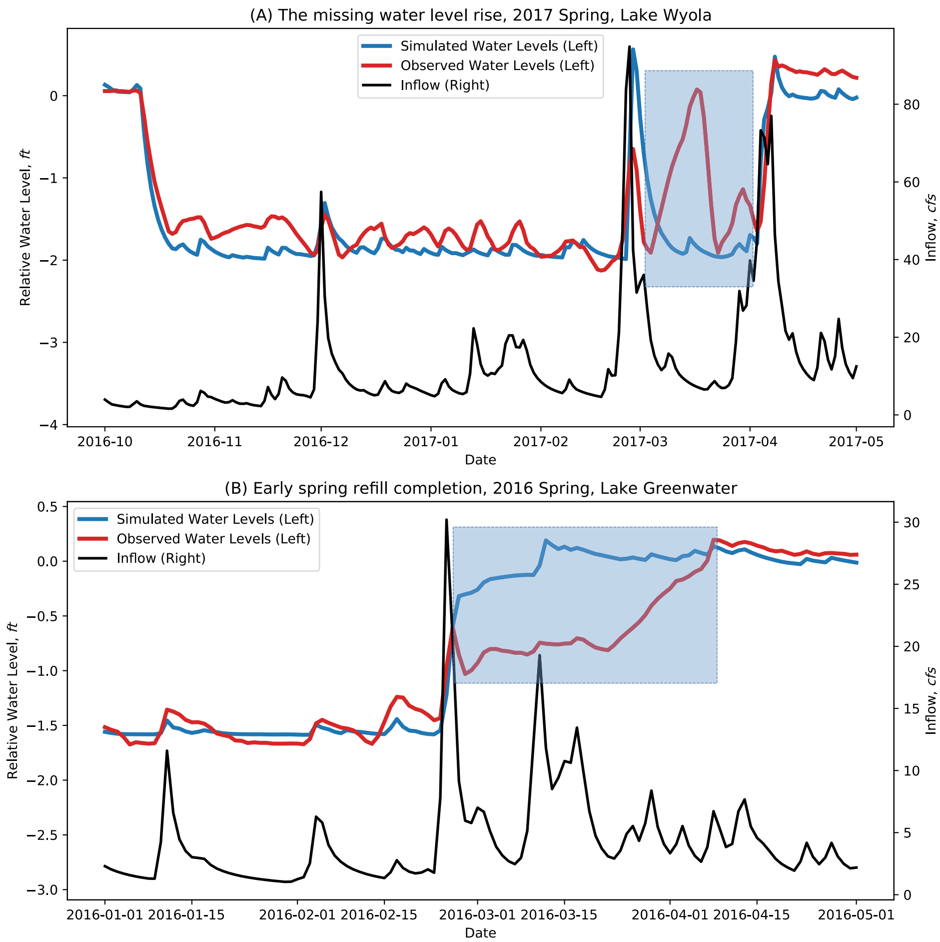

Fig. 5. Example figures for showing the uncertainties of the historical water level simulations. The water levels are relativized to the normal pool level. Both measured (red) and simulated (blue) water levels correspond to the left *y*-axis. Lake inflows (black) values correspond to the right *y*-axis. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

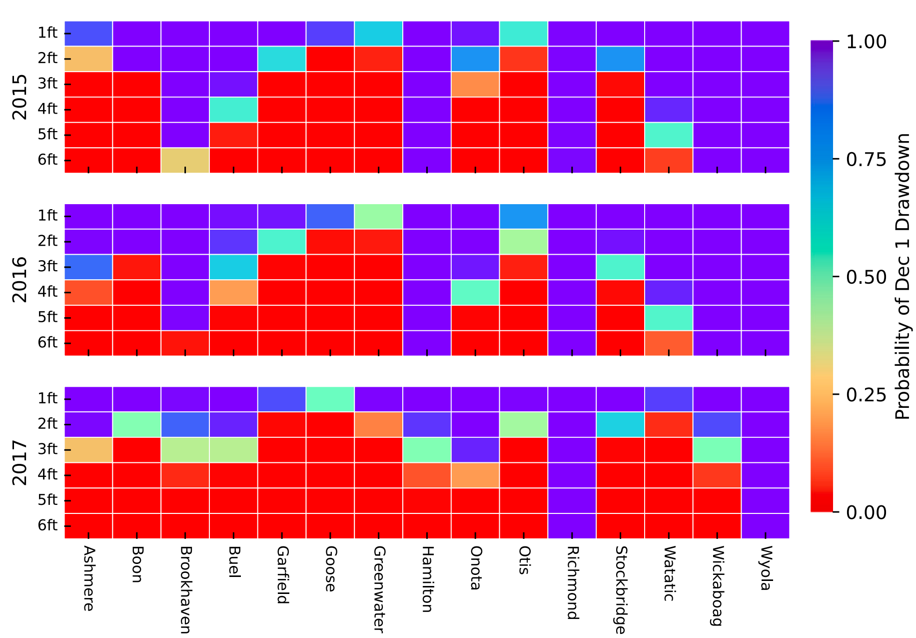

Fig. 6. Heat maps of the probabilities for study lakes achieve drawdown guidelines in 2015, 2016, 2017. The *x* axis represents the lake names, and *y* axis represents different drawdown magnitudes (1-6ft). The probabilities are colored with different colors and scaled from red (0.00) to blue (1.00). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

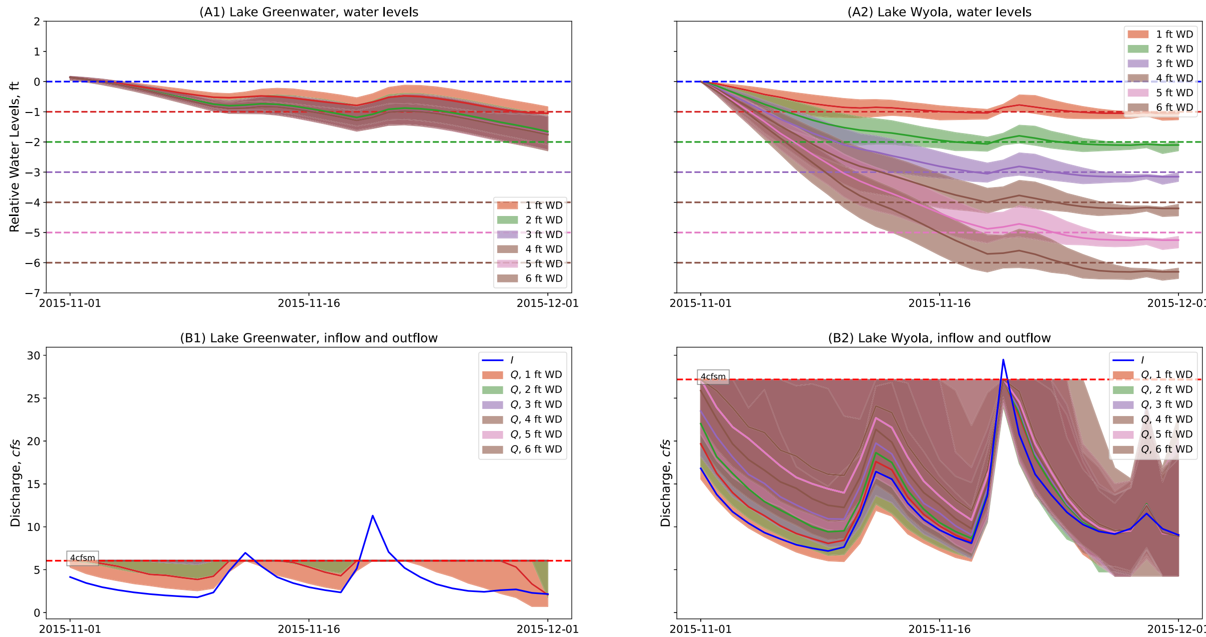

Fig. 7. Simulated water levels (A1 and A2) and inflow/outflow (B1 and B2) of Lake Greenwater and Lake Wyola in November, 2015 with the Massachusetts general winter drawdown guidelines as operation rules. The water level simulations of other study lakes were documented in (Fig S5, S6 and S7). The shaded area represents the range between 5% and 95% percentile of the ensemble water levels or outflows. The area color indicates different designed drawdown levels. The blue solid lines in B1 and B2 represent median values of the lake inflows. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

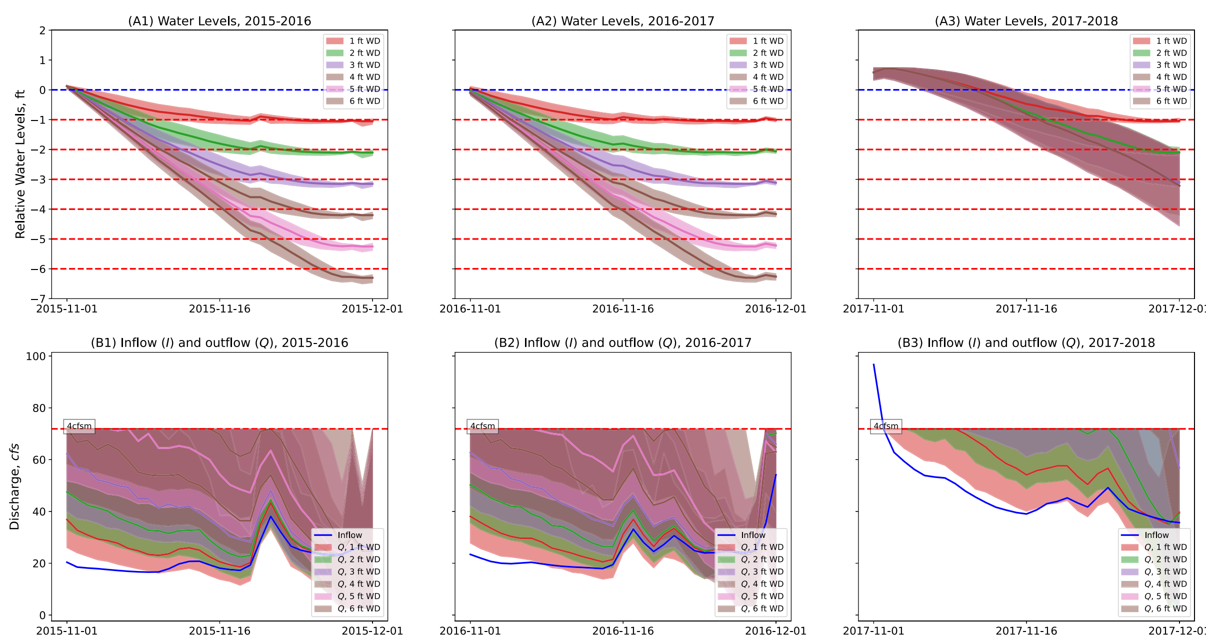

Fig. 8. Simulated water levels (A1, A2, A3) and inflow/outflow (B1, B2, B3) of the Lake Hamilton in each simulation year. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

many years of lake drawdown experience in Massachusetts, Wagner (2020) found the maximum outflow limit (4 cfsm) does not allow many lakes to achieve the target drawdown level (3 ft from the guidelines) before Dec 1, especially for lakes with small drainage ratio (drainage basin area : lake area < 10:1). As Fig. 6 shows, none of the lakes with small drainage ratios (<10:1): Lake Boon, Goose, Garfield and Otis achieved 3 ft drawdown. In contrast, the lakes that successfully achieved a drawdown of 3 ft in one or more years, such as Lake Brookhaven, Hamilton, Richmond, Wickboag, and Wyola, have significantly higher drainage ratios (>20:1) compared to the other lakes (See Table 1). The state drawdown management agencies may want to further validate the empirical knowledge for all drawdown lakes statewide and consider adjusting the outflow limitation by taking the drainage ratio into consideration. The model does not require any *in-situ* water level or flow observations, but operates on inputs of drainage basin characteristics, daily weather data, and bathymetry which can

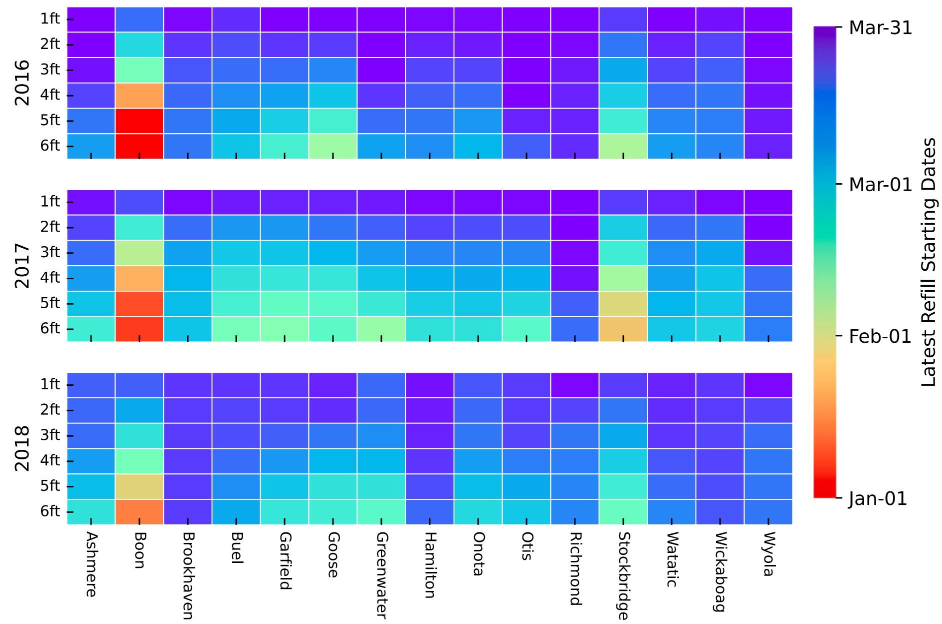

Fig. 9. Heat maps of the latest refill starting dates for study lakes in 2016, 2017, 2018. The *x* axis represents the lake names, and *y* axis represents different drawdown magnitudes (1-6ft). The latest refill starting dates are colored with different colors and scaled from red (Jan 1) to blue (Mar 31). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

be acquired even in data-poor regions. Drainage basin characteristics can be obtained from the global datasets of DEM (e.g., SRTM Van Zyl, 2001), land cover (e.g., MODIS Land Cover Friedl et al., 2002), and soil types (e.g., Harmonized World Soil Database Fischer et al., 2008). Regarding the daily weather data, there are numerous remotely sensed weather data products, e.g., from the Geostationary Operational Environmental Satellites (GOES)-R Series (Hu et al., 2020), that can be utilized to obtain daily rainfall and temperature data for regions outside the US. For bathymetry, GLOBathy estimated the bathymetry for over 1.4 million lakes in the world based on a GIS framework, although different countries and states may have more accurate bathymetry data (e.g., MA has bathymetry for over 300 ponds and lakes Division of Fisheries and Wildlife, 2022). Nevertheless, the model was designed based on small drainage lakes in a temperate zone and therefore, it would need to be adjusted for different regions (further discussed in Section 4.2).

Winter drawdown management strategies may need to be adapted given the challenges from climate change (Palmer et al., 2008). For instance, recent climate change studies have reported an increase in temperature, an increase in rainfall in winters, and a timing shift of spring rainfall events in the northeastern U.S. (Hayhoe et al., 2008; Demaria et al., 2016). These changes may potentially result in an increased difficulty to complete drawdowns and refills on time, particularly if in the presence of warmer temperatures managers favor longer drawdown times waiting for freezing temperatures. In this context, another application of HMF-Lake would be the assessment of the impact of management decisions under different climate conditions. Daily weather projections can be obtained from various General Circulation Model (GCM) products, such as Coupled Model Intercomparison Project (CMIP6) (O'Neill et al., 2016), Community Earth System Model (CESM) (Danabasoglu et al., 2020) and the Commonwealth Scientific and Industrial Research Organization (CSIRO) (Gordon et al., 2002). Alternatively, climate stress tests could be used to assess the applicability of any guidelines to changing climate. For example, by rescaling historical rainfall intensity, the comparison between the probabilities of April 1 refill under potential drier future climates, and past climate conditions can elucidate how current guidelines are affected by rainfall changes.

4.2. Model uncertainty and potential improvements

The current model shows a satisfactory performance in this study ($0.53 < NSE < 0.86$). Hughes et al. (2021) also used a similar lake hydrological model: SHETRAN-reservoir to simulate water levels in human operated reservoirs and the NSEs ranged from 0.53 to 0.82 which had similar performance with our current model. To improve the model performance, there are some uncertainties needed to address. In this study, we used Daymet as the meteorological input to simulate inflows and water levels. However, for gridded weather product such as Daymet, the interpolation process of generating such spatial continuous may cause underestimation of peak precipitation rate which further result in low simulated peak streamflow (Bárdossy and Anwar, 2023). In addition to the uncertainty of the meteorological input, the lumped configuration of the Cemaneige-GR4J model that simulates inflows is limited in terms of capturing the spatial variability of hydrological processes. When that variability is large, spatially distributed models and semi-distributed models such as DHSVM (Zhao et al., 2016), SWAT+ (Wu and Chen, 2012) and SHETRAN (Hughes et al., 2021) could be better options. Nonetheless, distributed models usually require additional inputs and longer computation times compared to lumped models, with the latter time differences exacerbated when stochastic simulations are required. Moreover, using distributed hydrological models cannot guarantee a higher accuracy than lumped models due to the more complex parameter space, especially when data availability is limited and the basin is relatively homogeneous (Darbandsari and Coulibaly, 2020; Carpenter and Georgakakos, 2006).

The Cemaneige-GR4J model also assumes no human regulation (reservoirs, irrigation etc.) upstream of the modeled watershed, potentially affecting the simulated lake inflow. Although some hydrological models such as SWAT+ can include upstream human operations such as irrigation, obtaining full operation records of the upstream watershed is challenging due to limited access to such information (Cui et al., 2018; Pathiraja et al., 2018). Data-driven models, including machine and deep learning algorithms, might be a potential alternative because they can infer rainfall-runoff relationships directly from observations rather than prescribed model structures (Schmidt et al., 2020). Therefore, if the training dataset is large enough, data-driven models could learn the impact of upstream human regulation and provide more accurate inflow estimations compared to process-based models (Swain and Patra, 2017; Feng et al., 2022; Shortridge et al., 2016; Wi and Steinschneider, 2022).

5. Conclusion

The stochastic HMF-Lake can account the spatial heterogeneity of the watershed characteristics and also annual variability of the precipitation & temperature, which allow us to calculate the site- and year-specific probability of December 1 drawdown and latest refill starting date, which ensure over 95% probability to achieve Apr 1 refill. These results can provide quantitative references of the ability of study lakes to follow the guidelines. Since the model does not require any *in-situ* real time observations such as streamflow or water levels, it could be potentially applied for any winter drawdown lake in the world. For state or regional winter drawdown managers (e.g., Massachusetts), the model could be applied in all managed lakes in the state to evaluate the applicability of the general guidelines. Furthermore, given the challenges from potential future climate changes, such as more frequent spring droughts, our model could be employed to evaluate how these climate changes could impact drawdown management and provide guidance for future winter drawdown management adaptations.

CRediT authorship contribution statement

Xinchen He: Writing – original draft, Methodology, Software, Visualization. **Konstantinos Andreadis:** Methodology, Software, Supervision, Data curation, Writing – review & editing. **Allison H. Roy:** Project administration, Resources, Funding acquisition, Writing – review & editing. **Abhishek Kumar:** Writing – review & editing, Data curation. **Caitlyn S. Butler:** Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Xinchen He reports financial support was provided by U.S. Geological Survey Northeast Climate Adaptation Science Center.

Data availability

We have included data and code repository in the acknowledgment in the manuscript.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.118744.

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