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Optimization of lake regulation: The case study of Ceresio

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Abstract: Lake level management, and more broadly, water basin regulation, has become increasingly challenging in recent decades, due to climate change and the rapid population growth. Climate change leads to more frequent extreme weather events, like floods and drought, while rising urbanization drives higher water demand for different purposes. In this context, effective water management is crucial to ensuring both flood and drought prevention while maintaining a reliable water supply for all uses. This research focuses on optimizing the water level regulation of Ceresio Lake (shared between Italy and Switzerland), a pre-Alpine glacial lake characterized by complex regulatory operations. The study analyses lake level variations and optimal water releases using a Discrete Dynamic Programming (DDP), which optimizes release policies by balancing multiple, sometimes conflicting, objectives. Historical hydrological and meteorological data from monitoring stations in Italy and Switzerland are first analysed, followed by the application of the DDP model to evaluate different scenarios and identify optimized regulation strategies. The outcomes offer decision-makers crucial insights to enhance the efficiency of reservoir operations. By providing a deeper understanding of the complexities involved in lake level regulation, this research supports the development of more resilient and forward-thinking management approaches, ensuring long-term water resource sustainability while addressing the needs of both ecosystems and local communities.

Key words: Lake regulation; reservoir optimization models; release policy optimization; discrete dynamic programming; climatic data analysis.

1. INTRODUCTION

In recent decades, the combined effects of climate change and population growth have heightened the need for effective lake water level management and environmental planning (Flörke et al., 2018; Mooij et al., 2005; Jeppesen et al., 2014; Hartmann, 1990). A site-specific and optimized regulation is essential not only to ensure territorial safety but also to meet the needs of multiple sectors, including navigation, tourism, and hydroelectric production (Cordell et al., 1993).

Lakes are complex ecosystems, strongly influenced by their drainage basin and interactions with the atmosphere. Climate plays a crucial role in lake regulation, affecting both inflows and outflows within the catchment (Shiau, 2003; Woolway et al., 2020; Havens & Jeppesen, 2018). Given the numerous factors involved, analysing lake regulation from a single disciplinary perspective can lead to misleading conclusions about its state and functioning.

Achieving effective management requires an interdisciplinary approach that incorporates reliable data and considers the entire lake system, including hydrological, chemical, and biological interactions with the surrounding environment (Xu et al., 2018). Due to their complexity, lake systems must be thoroughly analysed to ensure their optimal management. A comprehensive understanding can only be achieved by integrating insights from multiple scientific disciplines. This interdisciplinary approach is crucial for sustainable development, as it enables human use of lakes while ensuring their preservation for future generations (Wu & Tan, 2012).

Moreover, lakes play a key role in global water resources, representing the most accessible reserves of freshwater. Although Earth contains an estimated 1.4 to 1.7 billion km^3 of water, the vast majority is salty ocean water, unsuitable for terrestrial life. Freshwater lakes account for only 0.009% of the total water available, while rivers represent just 0.0001% (Bertoni R, 2006). Despite their limited volume, lakes are essential sources of freshwater for agriculture, industry, and municipalities, while also providing habitats for diverse plant and animal species (e.g., Ahmadaali et al., 2018; Panagopoulos & Dimitriou, 2020).

As the human population grows, the demand for lake and reservoir services will increase, while water levels will tend to decline. Additionally, more people will engage in recreational activities in these environments, altering shorelines, changing land use, and increasing the influx of sediments and nutrients into the water (Loucks & Van Beek, 2017).

Sustainable water resource management is one of the greatest engineering and environmental challenges of the 21st century (Duan et al., 2020; Ho & Goethals, 2019). Rising demand from domestic, industrial, and agricultural sectors, coupled with climate change impacts, necessitates advanced tools for decision-making in water resource planning and regulation (Viglione et al., 2014). In this context, planning, design, and management rely heavily on predictive modelling. Models help anticipate the effects of different infrastructure designs, management policies, and operational strategies (Celeste & Billib, 2009). However, they are inherently simplified representations of real-world systems, and their reliability depends on various factors, including available resources, model structure, input data quality, underlying assumptions, and, most importantly, the modeller's expertise in understanding both the system and the decision-making process (Li et al., 2014).

Today, computer-based modelling plays a crucial role in enhancing decision-making by providing structured, data-driven insights (Hemati et al., 2016). Mathematical simulation and optimization models, often integrated into interactive computer programs, allow planners and managers to assess the performance of proposed system designs and policies before implementation (Nicklow et al., 2010). Furthermore, effective modelling requires an understanding of the social and political context in which decisions are made (Shanono, 2020). When properly applied, well-structured models enhance comprehension, facilitate stakeholder discussions, and contribute to the development of robust and sustainable water management strategies (Jenkins, 2016).

To address the challenges involved, planners and managers must consider legal regulations, past decision-making history, the preferences of key stakeholders, and the possible reactions of those affected by any intervention. At the same time, they must balance the relative importance of the issues at stake while integrating technical knowledge from science, engineering, and economics (Loucks & Van Beek, 2017). Only by considering these elements together is it possible to develop effective and sustainable water management strategies (Hajkowicz & Collins, 2007).

The present work examines the regulation of Ceresio Lake (also known as Lugano Lake), a transboundary water body with a surface area of 48.9 km^2 (27.5 km^2 northern basin; 20.3 km^2 southern basin; 1.1 km^2 Ponte Tresa basin) of which, approximately, 63 % is situated in Switzerland, while 37% lies within Italy. As a result, its management falls under the jurisdiction of both countries, each of which operates distinct monitoring stations. Regulating its water levels presents significant challenges, particularly due to climatic variability and the need to balance competing targets, such as flood control and ensuring water availability during droughts (Barbieri & Polli, 1992; Mariotta, 2004).

Lake Lugano has a limited retention capacity, with only a small difference between its minimum and maximum water levels. This constraint makes optimizing its regulation increasingly critical, especially in the face of climate change. The primary objective of this study is to enhance the management of the lake's water levels through a comprehensive understanding of the factors driving hydrometric variations and the development of an optimized release strategy.

To achieve this, the study employs a Discrete Dynamic Programming (DDP) to model the lake's hydrological behaviour. By integrating the mass-balance equation with a discretized representation of lake volume, the method captures seasonal fluctuations, water losses, and competing management priorities to determine optimal release policies. The DDP approach establishes operational release policies, known as rule curves, by defining specific storage and discharge targets, each weighted according to its relative importance over time. The optimal policy is identified by minimizing deviations from these targets, creating a decision-making framework that enhances predictive capabilities and improves adaptability to changing hydrological conditions

(Sniedovich, 1978).

Data collected from existing monitoring stations were used to calibrate the DDP model, which was then applied to different seasonal scenarios to evaluate release strategies that effectively balance flood mitigation and water availability throughout the year.

The structure of the paper is as follows: Section 2 outlines the methodology and available data, Section 3 describes the study area and its key characteristics, Section 4 presents and discusses the main findings, and Section 6 summarizes the conclusions.

2. MATERIAL AND METHODS

Reservoir operation plays a crucial role in water resource management by balancing multiple objectives, including water supply, flood control, and hydropower generation. The storage capacity of a reservoir is typically divided into flood storage, active storage, and dead storage, with allocations varying seasonally based on hydrological conditions. Reservoir management relies on rule curves, which prescribe release decisions based on storage levels to optimize water allocation while minimizing flood risks and ensuring ecological sustainability. This study aims to define an optimal release policy for Lugano Lake using Discrete Dynamic Programming (DDP) to minimize deviations from target storage and release levels. The optimization approach integrates hydrological constraints and operational objectives to develop rule curves that guide decision-making across varying inflow scenarios.

2.1 Application of Discrete Dynamic Programming (DDP) to lakes

Lakes and reservoirs modelling is governed by a mass-balance equation (Equation 1), which considers storage volumes, inflows, and losses due to evaporation and seepage to compute the possible releases at each time step or stage t:

$$S_t + Q_t - R_t - L_t(S_t, S_{t+1}) = S_{t+1} \tag{1}$$

where:

S_t: initial storage volume

S_{t+1}: final storage volume

$L_t(S_t, S_{t+1})$: evaporation and seepage losses

R_t: release

Q_t: mean inflow rate.

Reservoir operation must account for downstream water demand, recreational activities, navigation requirements, and flood protection objectives. However, achieving all storage and release targets simultaneously at every stage (e.g., season or month) and for each mean inflow rate is not always feasible. Therefore, the optimal operation strategy is determined by minimizing the weighted sum of squared deviations from the predefined target values over the entire period (Equation 2).

$$TSD_t = ws_t^R \cdot [(TS_t^R - S_t)^2 - (TS_t^R - S_{t+1})^2] + ws_t^F \cdot [(ES_t)^2 + (ES_{t+1})^2] + wr_t \cdot [DR_t^2] \tag{2}$$

TSD_t: weighted sum of squared deviations

ws_t^R: weight associated to the recreation component

TS_t^R: recreation storage target volume

ws_t^F: weight associated with storage volumes (S_t) higher than flood control target volume

ES_t: storage volume exceeding the flood storage target volume

wr_t: weight squared deficit deviations from a release target

DR_t: difference between the target release and the actual release.

ES_t is defined by Equation (3):

$$ES_t = \begin{cases} S_t - TS_t^F, \ S_t \geq TS_t^F \\ 0, \ S_t < TS_t^F \end{cases} \tag{3}$$

TS_t^F: flood storage target volume

DR_t is defined by Equation 4:

$$DR_t = \begin{cases} TR_t - R_t, TR_t \geq R_t \\ 0, TR_t < R_t \end{cases} \tag{4}$$

R_t: actual release
TR_t: target release.

The first term on the right-hand side of Equation (2) represents the weighted squared deviations from the recreation storage target, TS_t^R. The second term accounts for flood control, defining the weighted squared deviations associated with storage volumes exceeding the flood control target volume, TS_t^F. Finally, the last term represents the weighted squared deficit deviations from the release target, TR_t. The weights reflect the relative importance of meeting each target in each period t.

At each node, representing a discrete storage volume S_t and an inflow Q_t, the objective is to determine the optimal release R_t that minimizes the cumulative sum of weighted squared deviations over all remaining seasons (or any chosen analysis period). The minimum sum of weighted squared deviations for all n remaining stages t is the optimal function, $F_t^n(S_t, Q_t)$, expressed as Equation (5):

$$F_t^n(S_t, Q_t) = min[TSD_t(S_t, R_t, S_{t+1}) + F_{t+1}^{n-1}(S_{t+1}, Q_{t+1})] \tag{5}$$

where n is the number of remaining periods t.

Initially, it is assumed that water regulation operations will conclude at a distant future time, and at the end of the last period. During this last period is suppose that:

$$F_0(S_t, Q_t) = 0 \tag{6}$$

Thus, when reaching the final regulation solution, the number of remaining seasons is $n = 0$.

The optimal release R_t for each successive season can be determined using a backward-moving solution method, commonly applied in reservoir analysis (Loucks & Van Beek, 2017). This approach starts from the final stage (e.g., $t = 4$, representing the last season) and moves backward, optimizing decisions at each preceding stage, one time step at a time, until reaching the present.

The iterative procedure continues until the annual policy stabilizes, meaning it repeats consistently across years for all S_t, Q_t and t, with the number of remaining seasons increasing over time. Stabilization occurs when, for example, in the case of a seasonal study:

$$F_t^{n+4}(S_t, Q_t) - F_t^n(S_t, Q_t) = constant \tag{7}$$

It is important to ensure that the following constraint is met to satisfy the optimization:

$$0 \leq S_t + Q_t - R_t - L_t(S_t, S_{t+1}) \leq W \quad or \quad 0 \leq S_{t+1} \leq W \tag{8}$$

where W represents the reservoir capacity.

2.2 Study area

The Discrete Dynamic Programming (DDP) approach described in Section 2.1 was applied to Lake Ceresio (Lugano Lake), a glacial subalpine lake located in the Insubrian Prealps, straddling the Po Valley and the Central Alps, as well as the Italy-Switzerland border.

Lugano Lake, the fifth largest subalpine lake, has a surface area of 48.9 km² and can be divided into three sub-basins: the northern basin (27.5 km²), the southern basin (20.3 km²), and the Ponte Tresa basin (1.1 km²), which is located further west. Approximately 63% of the lake lies in Switzerland, while the remaining 37% is in Italy. It has a perimeter of 94 km, a maximum depth of 288 m, an average depth of 130 m, and a total volume of 5,860 million m³.

Several monitoring stations are installed around the lake, including flow meters, hydrometers, and rain gauges. Figure 1 illustrates the lake's division into the three sub-basins, distinguished by different colours, along with the locations of the monitoring stations. The figure also highlights the main inflows and outflows of the lake. The northern and southern basins are separated by a bridge-dam, which comprises a road, railway section, and pedestrian walkway. The structure, an arch bridge made of reinforced concrete and steel, facilitates water flow through a series of openings. Instead, the Ponte Tresa basin is connected to the southern basin by a narrow passage.

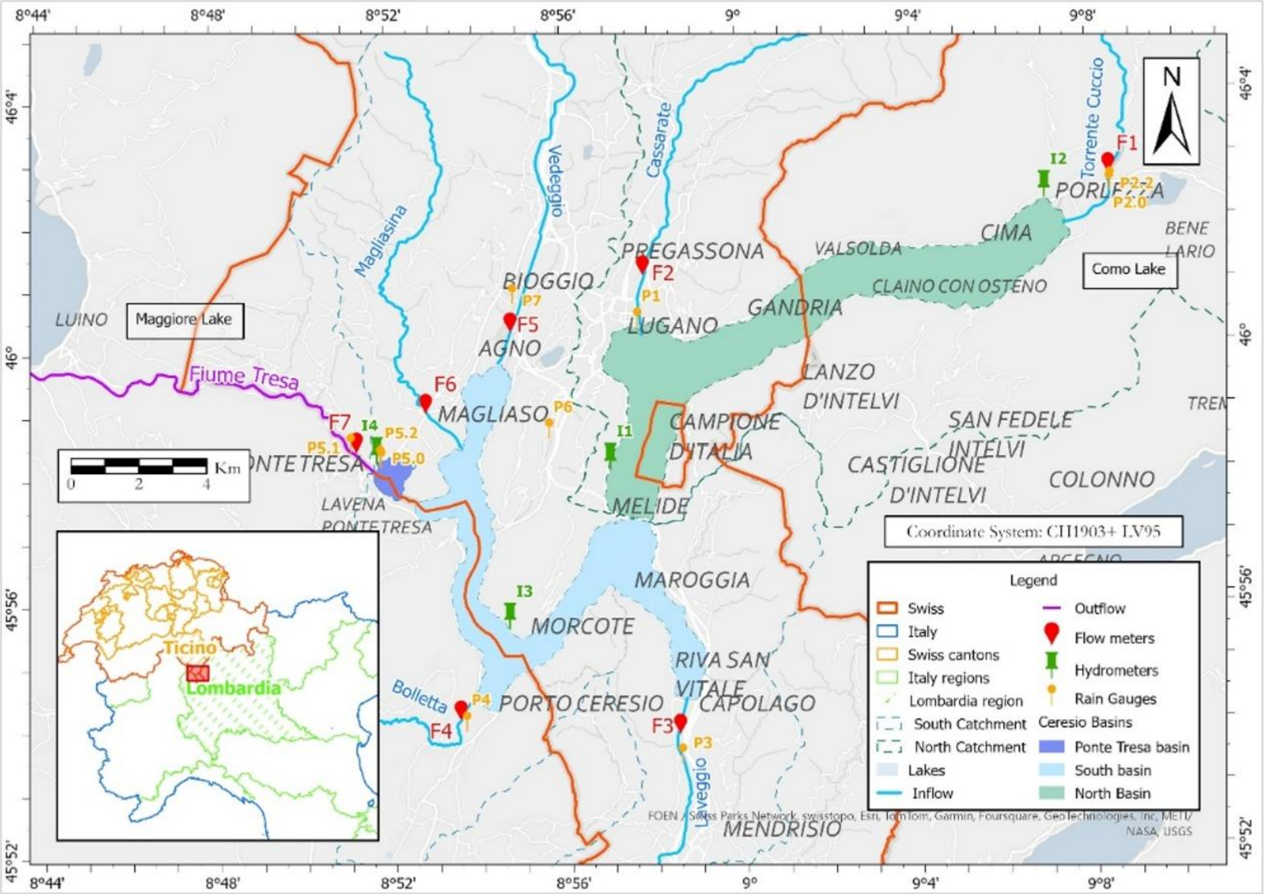

Figure 1. Lake subdivision and main monitoring stations close to Lake Lugano basin.

The analysis of hydrological and meteorological data is essential for understanding the dynamics of Lake Lugano and developing effective management models. This phase involves a thorough investigation of the monitoring stations located near the lake. Accurate and reliable data analysis is crucial for understanding hydrological processes and optimizing water management strategies.

To analyse hydrometric level trends, a sufficiently long historical dataset is necessary for reliable computations. Only two hydrometric stations meet this criterion: Melide "I1" in the northern basin and Ponte Tresa "I4" in the corresponding smaller basin. In Figure 2, the mean daily water level variations at Melide (I1) are compared with those at Ponte Tresa (I4). Due to the extensive dataset available for both stations (from 1965 to 2024), only data from 2000 to 2024 (00-24) is presented for clarity.

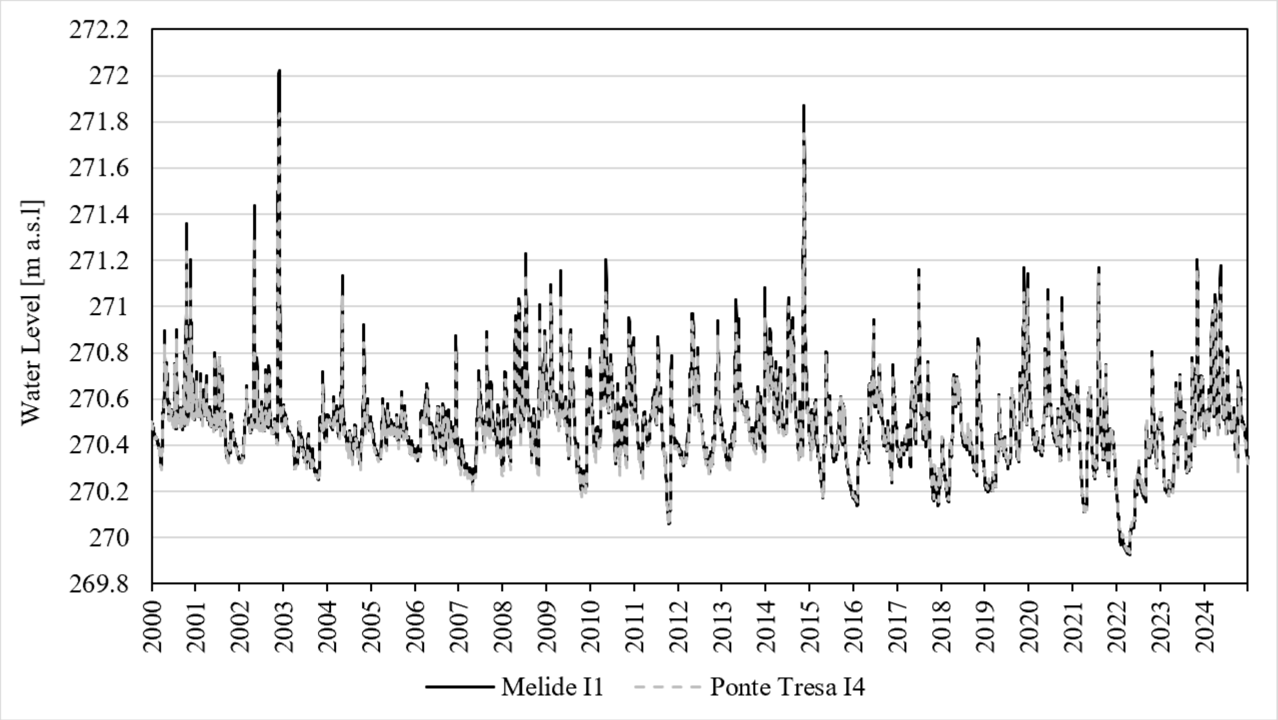

Figure 2. Mean daily water level measured: I1 vs I4 in the period 2000-2024.

As shown in Figure 2, both water level fluctuations following a similar pattern. Variations and peaks correspond to flood or drought events, such as those observed in 2002, 2014, 2015, and 2022. This indicates a strong correlation between the sub-basins of Ceresio Lake, despite the presence of the Melide bridge-dam, which impedes the natural water flow between the northern and southern basins (Table 1). Therefore, for subsequent analyses, the hydrometric levels recorded at Melide (I1) in the northern basin will primarily be considered.

Table 1. Statistics of the two measures stations.

	Statistics [m a.s.l.]	
Station	**I1 (Melide)**	**I4 (Ponte Tresa)**
Mean	270.48	270.47
Max	272.02	271.83
Min	269.92	269.93
dev. Std.	0.19	0.18
MAE	0.02	
RMSE	0.02	
Pearson [-]	1.00	

The application of Discrete Dynamic Programming (DDP) for optimizing regulation policy is tested exclusively on the northern basin of Lake Lugano. Despite the presence of the Melide bridge-dam, which restricts natural water flow between the basins, their water level trends remain similar. While this obstruction becomes significant during flood events, causing level differences of over 20 cm, it is generally negligible.

To ensure a realistic yet manageable model, the following assumptions are made:

- The lakebed is approximated as having vertical shores, given that urban structures directly face the water.
- Daily mean flow rates are used, assuming uniformity throughout the day.

- Dynamic lamination is neglected, treating water levels as uniform despite the lake's length.
- Although the international regulation focuses on outflows, lake levels are used for DDP since a strong correlation exists between Tresa River outflows and lake levels (see Figure A0 in the Appendix Section).
- A uniform minimum navigation level of 269.8 m a.s.l. is applied, despite variations.
- The hazard level definitions provided by the Federal Office for the Environment of Switzerland (UFAM) for Lugano Lake have been used as the primary guideline for defining storage volume targets (see Table A0).
- The minimum active storage level is set at 269.9 m a.s.l., maintaining a 10 cm safety margin above the navigation limit.
- Maximum active storage levels are defined as 270.9 m a.s.l. and 271.9 m a.s.l. (near historical max).
- Losses included in the water balance depend solely on lake surface evaporation, while infiltration losses are neglected.

3. RESULTS AND DISCUSSION

The first step in applying Discrete Dynamic Programming involves evaluating the water losses due to lake surface evaporation, which is incorporated into the mass balance equation (1). Evaporation data, expressed as daily sums, are recorded by the MeteoSwiss meteorological station in Lugano and refer to the FAO reference evaporation (as defined by the United Nations Food and Agriculture Organization). Since these values typically represent evapotranspiration, i.e., water losses from both water surfaces and vegetation, additional analyses have been conducted to account for these differences. To estimate lake surface evaporation more accurately, empirical formulas have been used to compare measured data with calculated values. Specifically, the Visentini, Dragoni, and Lugeon formulas have been employed (see Appendix Section). The Visentini formula is an empirical method for estimating mean monthly evaporation from open water surfaces, such as lakes and reservoirs, based solely on the air temperature. It is widely used due to its simplicity. In contrast, the Dragoni and Lugeon formulas are more complex, as they consider additional factors, though neither accounts for the effects of wind or solar radiation. Figure A1 illustrates the behaviour of all three formulas compared to measured values. The evaporation data provided by MeteoSwiss have been selected as the reference values for subsequent calculations in the DDP method. The differences between the measured values and those obtained from empirical formulas are minimal, except for the Visintini formula, indicating that this approach provides a reasonably accurate estimation.

The first analysis, as the following ones, focuses on the northern basin of the lake, considering a seasonal subdivision of the problem. Water level data and losses, measured close to the northern basin, are used to reconstruct four distinct loss matrices, one for each season, where:

$t = 1$: Winter
$t = 2$: Spring
$t = 3$: Summer
$t = 4$: Autumn.

As previously said, evaporation is the only type of loss considered in this case study, and, according to equation (1), it varies based on the actual storage level S_t and the subsequent storage level S_{t+1}. Discrete storage levels, i.e. the levels used in the DPP method, are determined by considering the possible water levels of Ceresio Lake. For this first analysis water levels are discretized by a storage interval of 0.5 metres (see Table A1). Table A2 shows the matrices, one for each season, obtained starting from measured evaporation data. Values fluctuate seasonally, with higher evaporation rates occurring in spring and summer, while lower rates are observed in autumn and winter.

Mean daily inflows for each season are calculated using data series from the Cuccio and Cassarate rivers (2000–2024), as they represent the only available and reliable discharge data for the northern basin. The total inflow, given by the sum of these two contributions (Table A3), is used in the DDP balance equation.

Storage target values for flood (TSf) and recreation (TSr) and the target release (TR) for the first analysis are reported in Table A4. During winter, lake levels are lowered to mitigate spring flood risks caused by heavy precipitation and snowmelt. A flood control target storage level of 271.4 m a.s.l. is set for this period. In spring and summer, the target storage level is raised to 271.9 m a.s.l. to support recreational activities. No specific target is defined for autumn, as inflows are lower due to the absence of snowmelt, and tourist activity declines.

Flood control and recreation storage targets apply throughout each season, from initial to final storage. Hazard levels defined by the Swiss Federal Office for the Environment (UFAM) are not considered in this analysis but will be incorporated later. Weights assigned to flood storage, recreation storage, and target release are all initially set to one, assuming equal importance. Figure 3 presents the optimal release policy (represented by the black line) obtained by following the procedure of the Discrete Dynamic Programming approach described in Section 2.1, outlining a preliminary reservoir release rule curve for further refinement through simulation.

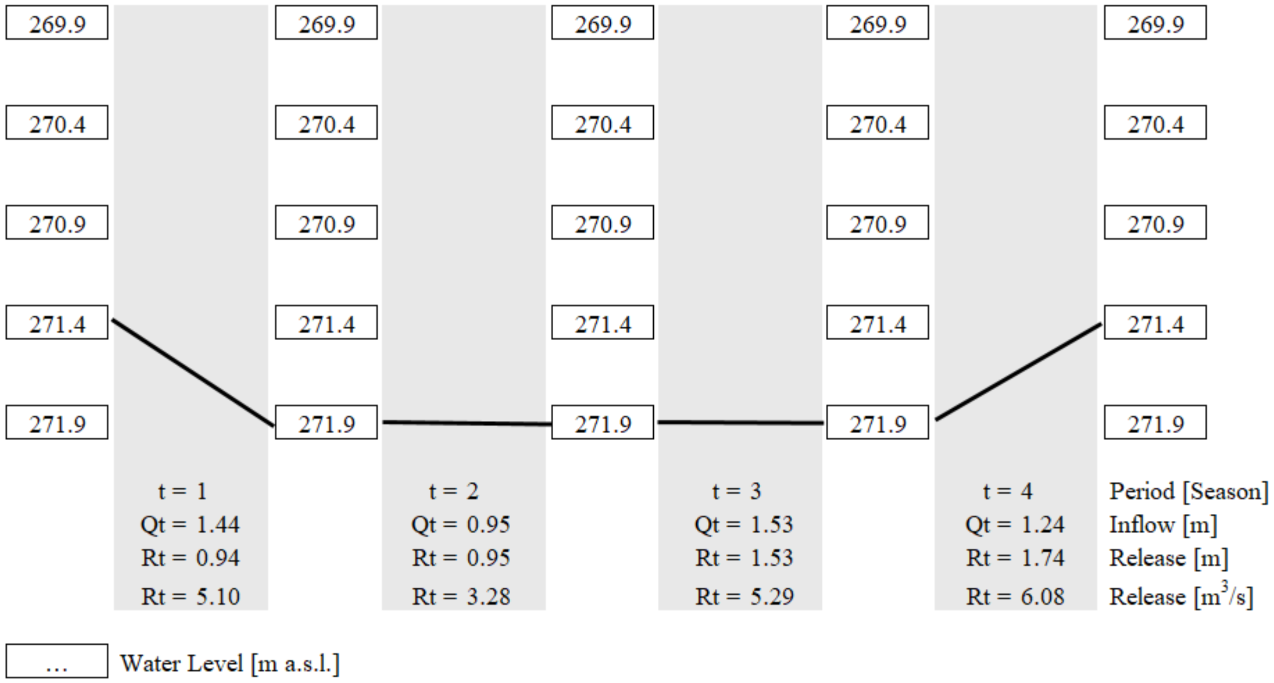

Figure 3. Optimal release policy (or rule curve) in the first analysis.

The results from the first analysis do not accurately reflect realistic lake conditions. The assigned targets, when compared to the UFAM hazard levels, correspond to excessively high hazard classifications. In particular, the flood target set for the winter period at 271.4 m a.s.l. falls between hazard levels 3 and 4 (marked and strong hazard, respectively). Similarly, the recreation target levels correspond to hazard level 5 (very strong hazard).

To address this issue, it is essential to integrate the UFAM-defined hazard levels into the determination of target storage levels. A second analysis was conducted to better represent realistic lake conditions by adjusting storage target levels, incorporating mean monthly inflows, and modifying target releases by considering the trend of the mean monthly inflows. Evaporation losses values, mean daily inflow Q_t and the discretization step of 0.5 metres remain unchanged. The revised scenarios, which aim to provide a more realistic representation of lake conditions, are summarized in Table A5. Figure 4 shows the results obtained from the second analysis.

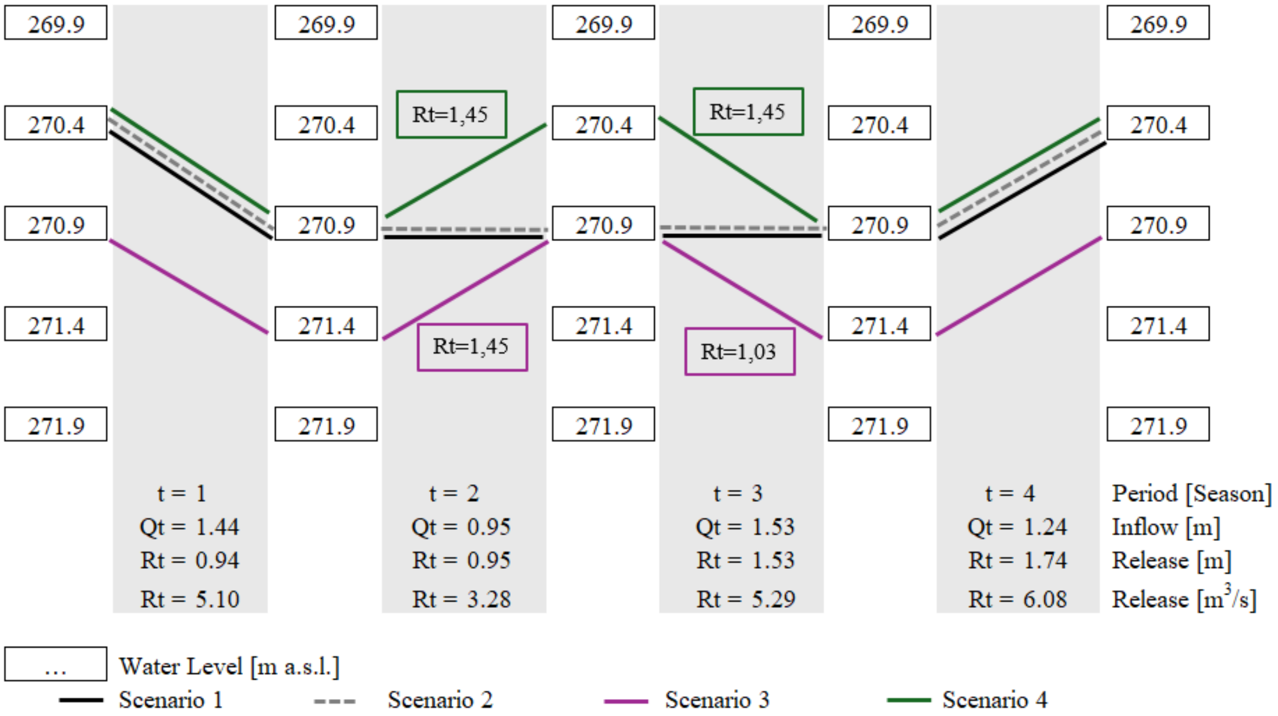

Figure 4. Optimal release policy (or rule curve) for the second analysis.

The second analysis yields different results from the first due to the consideration of alternative input values that better represent realistic lake conditions. As a result, the solution does not reach the lake's highest levels, which fall within the danger zones identified by the UFAM. The model, while maintaining a low computational cost, enables the development of an optimal lake regulation policy based on the most suitable input data. By starting from the characteristic parameters of the case and incorporating specific needs that vary depending on the context, it is possible to define different storage targets for flood control and recreational purposes (or other uses, if required), along with corresponding release targets, to achieve an optimal solution. The model's accuracy depends not only on the reliability of the input data but also on the chosen level of discretization. In this case, a discretization step of 0.5 meters was adopted; however, in other scenarios, finer discretization could be used to further improve accuracy. For instance, if hydrometric data indicate that lake level variations are minimal, occurring only within a few centimetres, a smaller discretization step could be selected. This would allow for a more precise representation of the lake's behaviour and lead to a more reliable solution. This method can serve as a preliminary tool for water managers to assess potential optimal release policies based on specific objectives. It also allows for an evaluation of possible differences in results as these objectives change.

4. CONCLUSIONS

The application of Discrete Dynamic Programming (DDP) proved to be an effective tool for optimizing water release policies, balancing competing demands, reducing flood risks, and ensuring adequate water availability during dry periods.

One important aspect is the significance of incorporating advanced hydrological models alongside continuous monitoring systems. Enhancing predictive capabilities would allow decision-makers to anticipate inflow variations and implement proactive measures to mitigate extreme hydrological events, such as floods and droughts. The ability to dynamically adjust regulatory policies in response to changing climatic and hydrological conditions will be crucial, especially given the long-term uncertainties in water availability. Additionally, the transboundary nature of Lake Lugano highlights the need for stronger coordination among authorities, institutions, and stakeholders. A cooperative regulatory framework, based on shared decision-making, transparent communication, and an integrated management approach, would enhance the efficiency and resilience of lake level regulation, ensuring sustainable water resource management. Increasing temporal discretization by analysing water levels on a monthly rather than a seasonal basis would provide a more detailed understanding of short-term variations and improve regulatory strategies. Similarly, refining spatial discretization by further segmenting water volume levels could enhance model precision. Expanding the analysis to all sub-basins of Lake Lugano, incorporating their specific inflows and evaporation rates, would allow for a more comprehensive evaluation of the lake's water balance dynamics.

Future developments should focus on integrating real-time meteorological data and climate projections into decision-making processes. Exploring alternative modelling approaches, such as combining dynamic programming with other optimization or simulation techniques, could further strengthen water management strategies. Emerging technologies like machine learning and artificial intelligence offer promising opportunities to refine predictive models, optimize reservoir operations, and improve decision-making under uncertain future conditions.

Overall, this study contributes to a deeper understanding of lake behaviour and provides valuable insights into water management practices. While DDP has demonstrated its effectiveness in determining optimal water release policies, future research should explore additional constraints, such as ecological flow requirements and energy production considerations. By integrating scientific research, technological advancements, and collaborative governance, adaptive and data-driven management strategies can be developed to enhance the sustainability and resilience of lake regulation and water resource planning in the coming decades.

AUTHOR CONTRIBUTIONS

Noemi Maglia: Writing-Original Draft, Writing-Review & Editing, Methodology, Validation, Investigation, Visualization. *Carlo Rava:* Conceptualization, Formal analysis, Data curation, Methodology, Validation, Investigation, Resources. *Anita Raimondi:* Supervision, Project administration, Funding acquisition, Writing-Review & Editing, Methodology.

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DECLARATION AND COMPETING INTEREST

The Authors declare that they have no conflict of interest. All authors involved in this study provided informed consent to participate.

DATA AVAILABILITY

Data will be made available on request.

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APPENDIX

Visentini, Dragoni, and Lugeon formulas:

Visentini formula:

$$E_v = b \cdot T_m^{1.15}$$

E_v: mean monthly evaporation [mm/month]
b: empirical coefficient, equal to 2 for big lakes
T_m: mean monthly air temperature [°C].

Dragoni formula:

$$E_d = 0.9 \cdot b \cdot \ i_m^{a1} \cdot \ t_i^{a2}$$

E_d is the mean monthly evaporation [mm/month]
b= 19.007; a_1=3.063; a_2=0.489
t_i: monthly mean temperature [°C]
i_m: Thornthwaite insolation monthly indexes [-]; For Lugano Lake, whose latitude is about 46° N, they are equal to the following values:

Month	**m**	**i_m**
Jan	1	0.79
Feb	2	0.81
Mar	3	1.02
Apr	4	1.13
May	5	1.29
Jun	6	1.31
Jul	7	1.32
Aug	8	1.22
Sep	9	1.04
Oct	10	0.94
Nov	11	0.79
Dec	12	0.74

Lugeon formula:

$$E_l = 0.398 \ \cdot n \cdot (P_{smax} - P) \cdot \frac{273 + t}{273} \cdot \frac{760}{B - P_{smax}}$$

E_l: mean monthly evaporation [mm/month]
n: number of days in the month
t: mean monthly of the maximum daily temperature [°C]
P_{smax}: saturation vapor pressure at temperature *t* [mm of Hg]
P: actual vapor pressure at temperature *t* [mm of Hg]:
B: mean monthly barometric pressure [mm of Hg]

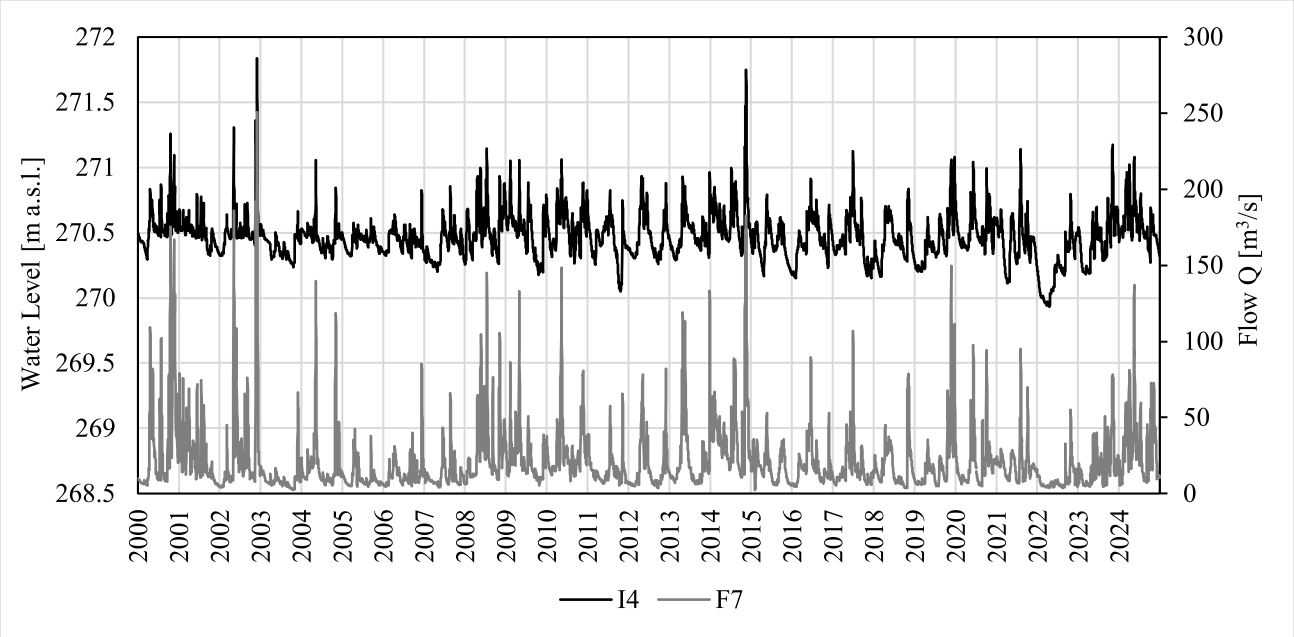

Figure A0. Correlation between water levels in Ponte Tresa basin (I4) and Tresa River outflows (F7) during the period 2000-2024.

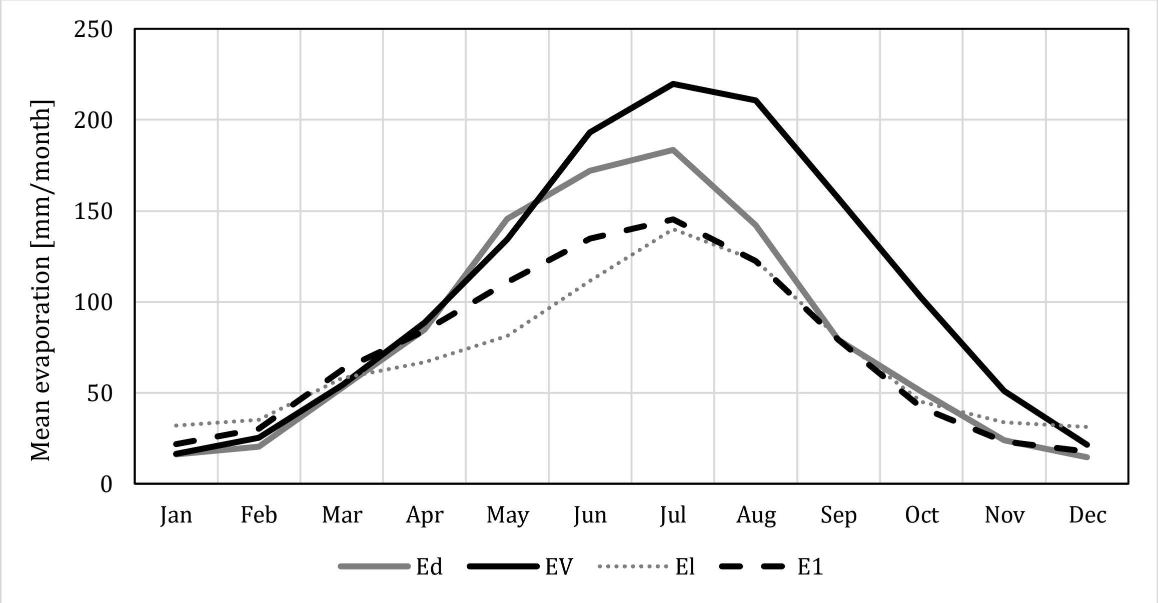

Figure A1. Evaporation behaviours, the three empirical formulae (Ev, Ed, El) vs measured data in Lugano (E1) during the period 2000-2024.

Table A0. Hazard level classification defined by UFAM for Lake Lugano the possible level limits for the DDP application.

Hydrometric Level [m a.s.l.]	Description	Hazard level by UFAM
272.08	Maximum level since 1963 (30.10.2002)	very strong hazard
271.90	**Max active level 2**	**very strong hazard**
271.25	Second flood damage (Lugano City)	marked hazard
271.10	First flood damage (Agno, campsites)	moderate hazard
271.00	Max navigation level	moderate hazard
270.90	**Max active level 1**	**null or low hazard**
270.49	Average annual water level (1965–2012)	null or low hazard
269.94	Minimum level since 1963 (February 1966)	null or low hazard
269.90	**Min active level**	**null or low hazard**
269.80	Min navigation level	null or low hazard

Table A1. Discrete storage levels used in the application of DDP (first analysis).

STATES - Storage Volume [m a.s.l.]					
S_t or S_{t+1}	269.9	270.4	270.9	271.4	271.9

Table A2. Evaporation losses matrixes in meters for all seasons.

	Evaporation Losses $L(S_t, S_{t+1})$ [m]					
	St, S_{t+1}	**269.9**	**270.4**	**270.9**	**271.4**	**271.9**
t=1	**269.9**	0.15	0.10	0.10	0.10	0.10
	270.4	0.10	0.10	0.09	0.09	0.09
	270.9	0.10	0.09	0.08	0.11	0.11
	271.4	0.10	0.09	0.11	0.00	0.00
	271.9	0.10	0.09	0.11	0.00	0.00

	Evaporation Losses $L(S_t, S_{t+1})$ [m]					
	St, S_{t+1}	**269.9**	**270.4**	**270.9**	**271.4**	**271.9**
t=2	**269.9**	0.00	0.33	0.31	0.31	0.31
	270.4	0.33	0.31	0.30	0.30	0.30
	270.9	0.31	0.30	0.30	0.31	0.31
	271.4	0.31	0.30	0.31	0.30	0.30
	271.9	0.31	0.30	0.31	0.30	0.27

	Evaporation Losses $L(S_t, S_{t+1})$ [m]					
	St, S_{t+1}	**269.9**	**270.4**	**270.9**	**271.4**	**271.9**
t=3	**269.9**	0.00	0.37	0.37	0.37	0.37
	270.4	0.37	0.36	0.37	0.37	0.37
	270.9	0.37	0.37	0.36	0.38	0.38
	271.4	0.37	0.37	0.38	0.36	0.00
	271.9	0.37	0.37	0.38	0.00	0.00

	Evaporation Losses $L(S_t, S_{t+1})$ [m]					
	St, S_{t+1}	**269.9**	**270.4**	**270.9**	**271.4**	**271.9**
t=4	**269.9**	0.00	0.11	0.10	0.10	0.10
	270.4	0.11	0.10	0.09	0.09	0.09
	270.9	0.10	0.09	0.07	0.06	0.06
	271.4	0.10	0.09	0.06	0.07	0.05
	271.9	0.10	0.09	0.06	0.05	0.06

Table A3. Mean daily discharge from Cuccio river (Q_{F1}) and Cassarate river (Q_{F2}) and the sum of them (Q_t), for each period t.

	t	**Q_{F1} [m³/s]**	**Q_{F2} [m³/s]**	**Q_t [m³/s]**	**Q_t [m]**
Winter	**1**	1.48	1.80	3.28	1.44
Spring	**2**	2.57	2.72	5.29	0.95
Summer	**3**	2.30	2.03	4.33	1.53
Autumn	**4**	2.49	2.60	5.10	1.24

Table A4. Target Storage and Target Release of first analysis.

	t	**Target storage level TS [m a.s.l.]**		**Target release level TR [m] >=**
		Recreation TS_r	Flood TS_f	
Winter	**1**		269.9+1.5=271.4	1.0
Spring	**2**	269.9+2=271.9		1.5
Summer	**3**	269.9+2=271.9		2.0
Autumn	**4**			1.5

Table A5. Storage targets and target releases for the second analysis.

Scenario	**TSf [m a.s.l.]**	**TSr [m a.s.l.]**	**TR**
1	270.4	271.4	TR1
2	270.4	270.9	TR1
3	270.4	271.4	TR2
4	270.4	270.9	TR2

	Target releases [m]		
	t	**TR1 >=**	**TR2 >=**
Winter	1	1	1
Spring	2	2	2
Summer	3	2	1.5
Autumn	4	1.5	1.5

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