Stochastic System Dynamics Modelling for climate change water scarcity assessment on a reservoir in the Italian Alps

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Abstract

Water management in mountain regions is facing multiple pressures due to climate change and anthropogenic activities. This is particularly relevant for mountain areas where water abundance in the past allowed for many anthropogenic activities, exposing them to future water scarcity. ~~To better understand the processes involved in water scarcity impact,~~Here an~~n~~ innovative stochastic System Dynamics Modelling (SDM) was implemented to explore~~s~~ water ~~stored~~ scarcity conditions affecting ~~and turbined in~~ the stored water and turbined outflows in the S.Giustina reservoir (Province of Trento, Italy). The analysis relies on a model chain integrating ~~integration of~~ outputs from climate change simulations ~~as well as~~ into ~~from~~ a hydrological model, which output was used for the creation of ~~and~~ statistical models into ~~the~~ a SDM. The study aims to simulate future conditions of ~~is a quick and effective tool to simulate past and future water availability and demand~~ turbined water and stored volume as well as implementing a set of metrics to analyse volume extreme conditions~~conditions~~.

Average results over the whole 30-years of simulations show that even under the RCP4.5 short-term scenario (2021-2050) future reductions for stored volume and turbined outflow are expected to be severe (-25.9% of turbined outflow and -19.9% of stored volume). The greatest reductions are expected for RCP8.5 long-term scenario (2041-2070; -26.3% of turbined outflow and -20.8% of stored volume). At monthly level, stored volume and turbined outflow are expected to increase for December (outflow only), January, February, March and April (volume only) depending on scenarios and up to +32.5% of stored volume in March for RCP8.5 2021-2050. Reductions are persistently occurring for the rest of the year (down to minima of -56.3% for turbined outflow and -44.1% for stored volume). Metrics of frequency, duration and severity of future stored volume values below the 10^{th}, 20^{th} and above the 80^{th} and 90^{th} percentiles suggest a general increase in terms of low volume

and decrease of high volume conditions. These results point at higher percentage increases in frequency and severity for values below the 10^{th} percentile, while volume values below the 20^{th} percentile are expected to last longer. Above the 90^{th} percentile, values are expected to be less frequent than baseline conditions, while showing smaller severity reductions compared to values above the 80^{th} percentile. ~~Short-term RCP4.5 simulations depict conditions of highest volume and outflow reductions starting in spring (-16.1% and -44.7% in May compared to the baseline). Long-term RCP8.5 simulations suggest conditions of volume and outflow reductions starting in summer and lasting until the end of the year. The number of events with stored water below the 30th and above the 80th quantiles suggest a general reduction both in terms of low and high volumes.~~ These results call for ~~the need to~~the adoption of adaptation strategies focusing on water demand reductions. Months of expected increases in water availability should be considered as periods for water accumulation while preparing for persistent reductions of stored water and turbined outflows. ~~adapt to acute short-term water availability reductions in spring and summer while preparing for hydroelectric production reductions due to the chronic long-term trends affecting autumn and mid-winter.~~ This study provides results and methodological insights that can be used for future ~~potential~~ SDM upscaling to integrate~~across~~ different strategic mountain socio-economic sectors (e.g., hydropower, agriculture and tourism)~~ to~~ _~~expand water scarcity assessments~~ and prepare for ~~p~~~~future~~ otential multi-risk conditions~~conditions and impacts~~.

Introduction

Mountains serve as "water towers" providing freshwater to a large portion of the global population (IPCC, 2014b, 2018; Rull, 2014; United Nations, 2012; Viviroli et al., 2007). Climate change~~-~~ affects mountain environments more rapidly than many other places, with impacts on glaciers, snow precipitation, water flows and on the overall supply of water (Viviroli et al., 2011; Barnett et al., 2005). These impacts call for the need to shift water management towards more sustainable and adaptive practices. Adaptation delays and unpreparedness to water availability changes can spread consequences across multiple systems, from natural ecosystems to anthropogenic activities relying on water (van den Heuvel et al., 2020; Mehran et al., 2017a; Fuhrer et al., 2014; Xu et al., 2009).

The European Alps are among those mountain regions where water abundance in the past allowed for the development of activities with intensive water use such as large hydropower plants and irrigated agriculture, making them susceptible to future impacts regarding reduced water availability (Majone et al., 2016; Beniston and Stoffel, 2014; Permanent Secretariat of the Alpine Convention, 2013). That is, in many Alpine regions the socio-ecological systems are unprepared for water scarcity and hence the impacts of water shortage can be more severe (Di Baldassarre et al., 2018).

Previous studies have assessed the hydrological processes involved in mountain environments, looking at the overall hydrological dynamics (Bellin et al., 2016) or specifically assessing topics such as glacier melt and runoff (Huss and Hock, 2018; Farinotti et al., 2012), and snowpack ~~runoff~~ (Etter et al., 2017; Wever et al., 2017). However, the interplay connecting natural processes and socio-economic activities, sometimes known as sociohydrology (Di Baldassarre et al., 2015; Sivapalan et al., 2012) calls for further research. There is a need to implement methodologies with the ability to unravel this complexity, ~~dynamically describing such interplays and system behaviours to~~and find which adaptation strategies ~~across economic sectors~~ can effectively tackle climate-related water issues.

System Dynamics Modelling (SDM) is a methodology used to improve the understanding of complex systems and their dynamic interactions. It makes use of four main modelling elements~~ connected to each other~~: (i) stocks (system state variables) – ‘accumulating’ material (e.g. water in a reservoir); (ii) flows (variable’s rate of change) –moving material into and out of stocks (e.g. river inflows and outflows), (iii) converters - parameters influencing the flow rates (e.g. temperature variable acting to alter evaporation ~~rates modulated~~from a water body~~ by temperature~~) and (iv) connectors – ~~-~~as arrows transferring information ~~causal connections and/or feedback loops~~within the model (e.g. linking the monthly effects on reservoir’ water discharges;~~ – (e.g. linking temperature variations to the evaporation rate)~~ (Sterman et al., 2000). The combination of these elements is applied to represent temporal changes in system elements accounting for endogenous and exogenous influences on system behaviour. This concept encourages a system thinking approach, splitting large systems into sub-systems and progressively increasing their interactions and complexity (Gohari et al., 2017; Mereu et al., 2016). SDMs can combine different metrics and indices, improving models by adding social, economic and environmental sectors (Terzi et al., 2019). Moreover, ~~it~~SDM can implement a graphical interface, supporting the visualization of interactions and feedback loops during participatory approaches.

While SDM was developed to improve industrial business processes (Forrester, 1971), it has been successfully applied to model human and natural resources interactions (Meadows et al., 2018). Moreover, SDM applications span a wide range of problems, from climate change risk assessments (Duran-Encalada et al., 2017; Gohari et al., 2017; Masia et al., 2018), water management issues (Davies and Simonovic, 2011; Gohari et al., 2017), disasters studies (Menk et al., 2020; Simonovic, 2001, 2015), water-energy-food nexus studies (Sušnik et al., 2018; Davies and Simonovic, 2008) and applications fostering participatory modelling (Malard et al., 2017; Stave, 2010). ~~It~~SDM has ~~is~~ therefore been proved to be a useful ~~the ideal~~ tool to study complex interactions and dynamic behaviour in a wide variety of complex systems (Ford, 2010).

However, SDM also shows some limitations, such as (i) the limited spatial representation since it works with lumped regions, although recent research has coupled SDM to GIS to account for spatially explicit system dynamics (Neuwirth et al., 2015; Xu et al., 2016); (ii) the ease of creating very complex what-if scenarios that can be difficult to validate, but which are useful to explore systems behaviour under potential futures, giving general ideas of likely system trajectories~~the reduced accuracy in comparison with dedicated physically based models~~; (iii) the fact that applications usually account for deterministic expert-based assumptions ~~approaches~~on existence and type of variable’s interactions (Mereu et al., 2016; Sahin and Mohamed, 2014; Sušnik et al., 2013), although statistical analysis of trends and interactions are crucial under uncertain climate change and risk assessments and recent~~ly, stochastic~~ analyse~~i~~s have been used for probabilistic SDM output (Sušnik et al., 2018)~~;~~. ~~(iv) the ease of creating very complex what-if scenarios that can be difficult to validate, but which are useful to explore systems behaviour under potential futures, giving general ideas of likely system trajectories.~~

~~Previous applications of SDM often rely on deterministic assumptions (Mereu et al., 2016; Sahin and Mohamed, 2014; Sušnik et al., 2013), while statistical analysis of trends and interactions are crucial under uncertain climate change and risk assessments (Terzi et al., 2019).~~ These ~~conditions~~ limitations call for methodological improvements.~~probabilistic system dynamics assessments to better understand the dependencies between anthropogenic and environmental processes, which can lead to multiple cascading and interrelated impacts, water disputes and crises.~~ The combination of ~~S~~statistical methods ~~combined~~ with SDM represent a~~n~~ valuable ~~innovative and powerful opportunity~~integration to overcome the current limitations involved in deterministic expert-based ~~assessments~~assumptions of variables interactions and dependencies. This improvement allows to test them under future uncertain of water availability conditions and explore potential impacts, water disputes and crises.

This study explores the S.Giustina reservoir in the Noce catchment, Province of Trento, Italy, considering current conditions and future climate change effects leading to critical levels of ~~states of~~ low and high stored volume ~~of water stored~~ and turbined outflows for hydropower production. Indices for frequency, duration and severity of the reservoir's critical states and its reduced water availability are explored and discussed. By doing so, the aim is to develop and ~~test and~~ demonstrate a stochastic SDM as a quick and effective tool to assess climate change impact o~~n~~f water scarcity in one of the main reservoirs in the north-~~-~~east of the Italian Alps supporting its adaptation planning.

~~In section 1, the concepts behind SDM and the innovation of its applications are described.~~ Section 1~~2~~ focuses on the case study characteristics and the recently arisen water management challenges. Section 2~~3~~ describes the methodology, data and scenario used for the simulations. Section ~~4~~3 focuses on the results of SDM application for both the baseline and future projections. Section 4~~5~~ involves the discussion of the results and its limitations. Future developments and applications are described in section 5~~6~~.

~~1 System dynamics modelling~~

~~SDM is an approach used in the field of complex system behaviour. It makes use of four main modelling elements connected to each other: (i) stocks (system state variables) – 'accumulating' material (e.g. water in a reservoir); (ii) flows (variable's rate of change) –moving material into and out of stocks (e.g. river inflows and outflows), (iii) converters – parameters influencing the flow rates (e.g. evaporation rates modulated by temperature) and (iv) connectors – transferring causal connections and/or feedback loops – (e.g. linking temperature variations to the evaporation rate) (Sterman et al., 2000). The combination of these elements is applied to represent temporal changes in system elements accounting for endogenous and exogenous influences on system behaviour. This concept encourages a system thinking approach, splitting large systems into sub-systems and progressively increasing their interactions and complexity (Gohari et al., 2017; Mereu et al., 2016). SDMs can combine different metrics and indices, improving models by adding social, economic and environmental sectors (Terzi et al., 2019). Moreover, it can implement a graphical interface, supporting the visualization of interactions and feedback loops during participatory approaches.~~

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~~This study focuses on a novel refinement of SDM applications implementing a stochastic assessment of variable interactions for robust validation of uncertainties and trends, particularly useful in the field of risk assessment. Conceptual diagrams of system variable interactions were elaborated using the Stella software (https://www.iseesystems.com/) while statistical correlations and dependencies were analysed in R (Duggan, 2016; R Core Development Team, 2013). This innovative combination contributes to improving SDM analysis accounting for the uncertainty and variability associated with past and future water flow data.~~

1~~2~~ Case study

The Noce river (Province of Trento, Italy) in the south-eastern part of the Alps (Figure 1~~Figure 1~~) is a tributary of the ~~Adige river~~Adige River, the second longest river in Italy. The Noce river basin is a typical Alpine basin with an overall area of 1367 km^2 and an average discharge of 33.78 m^3/s at the basin closure. It is characterized by intensive anthropogenic activities including hydropower plants in the upper part of the catchment relying on glacier melting, to intensive apple orchards shaping the landscape of valley bottoms. It also hosts a significant number of~~, and~~ tourists~~m~~ with peaks ~~flows with high~~of water demands during winter and summer time for sport activities (i.e. skiing, hiking and kayaking). The hydropower sector is the main water user (77.81% of the licensed water withdrawals is allocated to small hydropower plants with a nominal capacity <3MW) followed by agriculture (16.39%), domestic uses (3.98%), fish-farming (0.9%), industry (0.49%), snowmaking (0.28%) and others (0.15%; Provincia Autonoma di Trento, 2018).

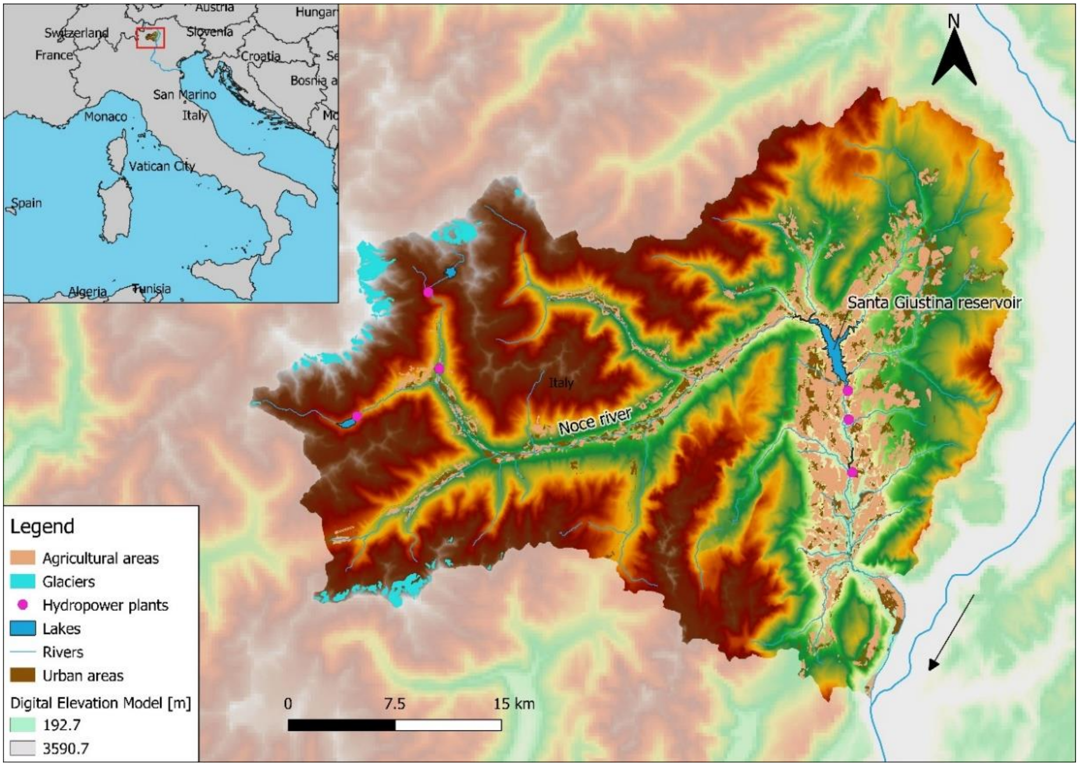

Figure 1 - Noce river basin and main characteristics. The black arrow specifies the Adige R~~r~~iver flow direction.

Water has always been considered abundant in most regions in the Alp~~ region,~~s and only recent events of water scarcity in 2015 and 2017 raised wider concerns about water quantity and quality (Stephan et al., 2021; Chiogna et al., 2018; Hanel et al., 2018; Laaha et al., 2017). Temperature increase, loss of glacier mass volume and decreased snow precipitation during winter are among the causes of reduced summer discharge and water availability both in mountain areas and downstream. At the same time, numerous activities have flourished such as increasing hydropower plants, agricultural production, urbanisation, industrial activities and more intense tourism all demanding large water amounts to satisfy their needs. Tensions for water allocation have recently arisen asking for a fair use of the resource among different actors, and at the same time (e.g. orchards irrigation coinciding with rising tourist water demand). In particular, associations and civil society groups (e.g. local association for the Noce river safeguard: https://nocecomitato.wordpress.com/) were established at provincial level showing their concerns about ecological impacts of further exploitation (i.e. hydropower plants). Within this context, climate change effects at regional level have already been recognized acting on the current water balance and triggering multiple impacts on a wide range of economic activities relying on water use (La Jeunesse et al., 2016; Zebisch et al., 2018).

In the Noce river basin, the S. Giustina reservoir provides a large buffer for water resources regulation. The reservoir has a storage capacity of 172 Mm^3 (equal to a maximum net available volume of 152.4 Mm^3), the largest reservoir volume within the Trentino-Alto Adige region. It was built in the 1940's and 1950's for hydropower purposes. Nowadays, the reservoir has a multipurpose function, producing a large amount of energy (i.e. installed power of 108 MW), and regulating water flow for downstream users and providing water for irrigation. Moreover, the local water use plan (Provincia Autonoma di Trento, 2006) established from 2009 onwards a ~~monthly~~ minimum ecological flow threshold ranging from 2.625 to 3.675 m^3/~~·~~s~~$^{-1}$~~ (the only water flow downstream the dam) according to each month of the year to continuously sustain fluvial ecosystems~~, raising concerns among the different stakeholders on the possible economic impacts of "unused" water releases~~.

Within this context, a better understanding of the complex interactions in the S.Giustina water management represents a crucial step to prepare to future impacts of climate change on freshwater resources~~ affecting different sectors~~. The representation of connections and interactions using SDM can help to depict the S.Giustina reservoir dynamics and its responses to future ~~pressures, including~~ climate change pressures~~ and anthropogenic factors~~. ~~-~~Such information could inform water operators, local and provincial authorities fostering a discussion on the implementation of climate change adaptation strategies in line with the Water Framework Directive (European Parliament & Council, 2000).

2~~3~~. M~~aterial and m~~ethods and exploited material

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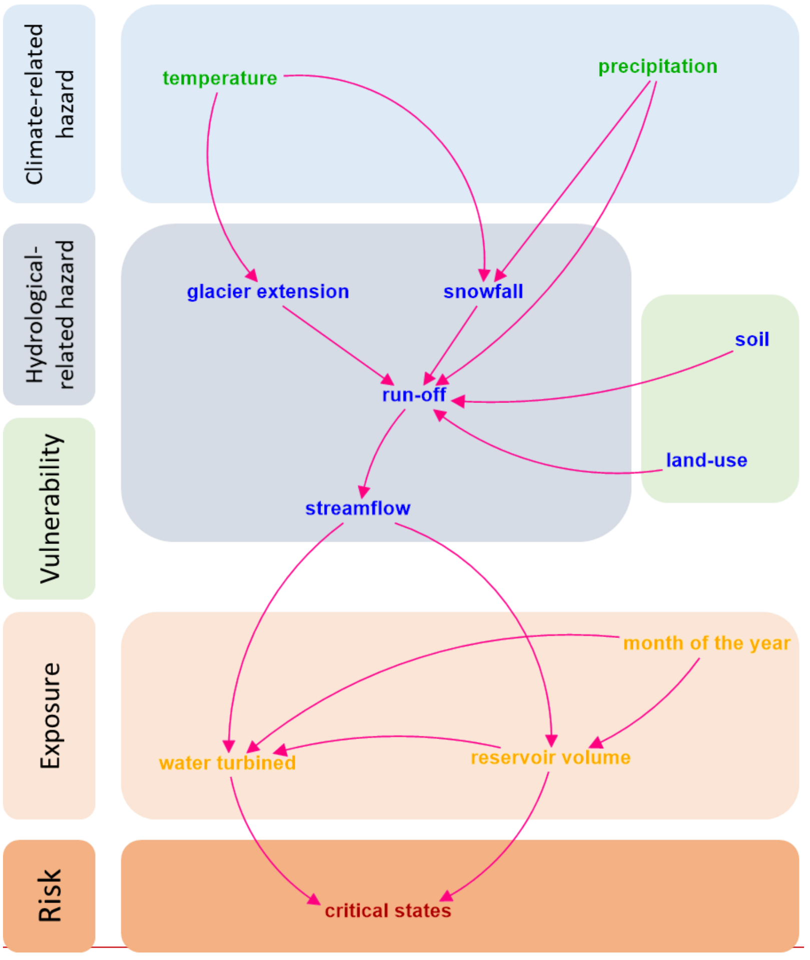
The methodological approach here presented is composed of 5 sequential phases, from (1) the SDM ~~development of a causal loop diagram, (2) the~~ set-up ~~of a System Dynamics Model (SDM)~~, (~~3~~2) the analysis of SDM variables' interactions, (~~4~~3) SDM model calibration and validation on historical observations ~~and finally~~ (~~5~~4) the integration of future projections in the SDM and test of statistical significance changes to the baseline and finally (5) the characterization of future low and high stored water critical conditions through a MonteCarlo sampling approach. Each of the stages is described in this section.

~~3.1 Causal loop diagram~~

~~A first system conceptualization aims to identify the variables and their interactions involved in S.Giustina dam management and climate effects on water availability. Following the terminology developed by IPCC (2014a) within the 5th Assessment Report, a causal loop diagram (CLD; Ford, 2010) was developed considering the S.Giustina water reservoir operations (Figure 2). The CLD was compared to the IPCC risk components to graphically represent the comprehension of variables and their interactions leading to critical states. Climate hazard was considered as future regime variations of temperature and precipitation with respect to the baseline. Vulnerability variables refer to physical-environmental definitions~~

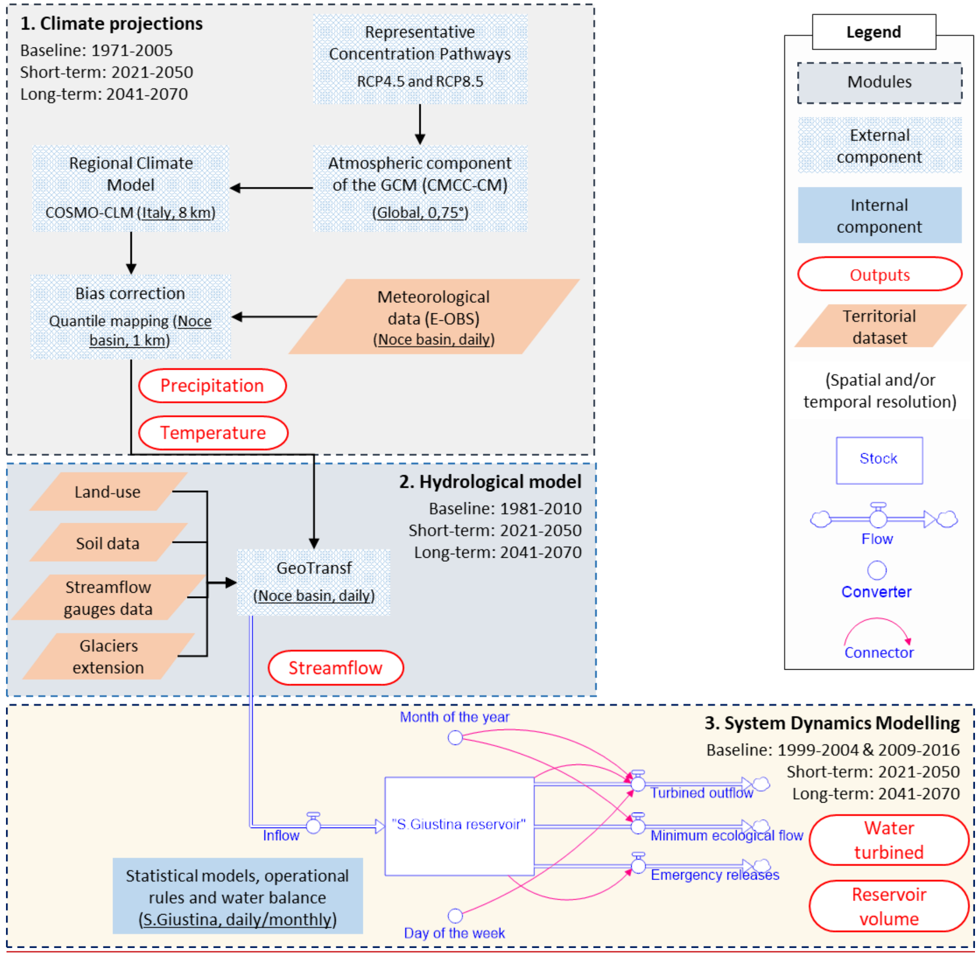
~~only, while exposed elements considered the S.Giustina dam reservoir and its operations potentially involved in risk conditions related to variations in the water turbined and the water volume stored in time.~~



~~Figure 2 - Causal loop diagram used to describe the risk variables and their interactions leading to critical states of S.Giustina reservoir operations. Climate variables are in green font, blue font for hydrological-related components, yellow font variables are~~

2~~3~~.1~~2~~ System dynamics modelling set-up and input data

~~Starting from the CLD conceptualization, an~~The SDM was set-up ~~developed~~ integrating multiple sources of data (e.g. observations, modelled values and climate projections) to replicate past and to simulate future ~~and connecting climate change effects with reservoir operations. By doing so, it was possible to explore impacts on~~ S.Giustina turbined water ~~stored and turbined~~ and stored reservoir volume. ~~in S.Giustina reservoir~~ The model chain considered for this objective consists of 3 main modules, namely climate projections in box 1, hydrological model in box 2 and the ~~from climate and water streamflow changes within the~~ SDM in box 3~~.~~ (Figure 2~~Figure 3) shows the different components which were used and incorporated in the SDM for the assessment of S.Giustina critical states~~.


1. Climate projections
Baseline: 1971-2005
Short-term: 2021-2050
Long-term: 2041-2070
Representative Concentration Pathways
RCP4.5 and RCP8.5
Regional Climate Model
COSMO-CLM (Italy, 8 km)
Atmospheric component of the GCM (CMCC-CM)
(Global, 0,75°)
Bias correction
Quantile mapping (Noce basin, 1 km)
Meteorological data (E-OBS)
(Noce basin, daily)
Precipitation
Temperature
2. Hydrological model
Baseline: 1981-2010
Short-term: 2021-2050
Long-term: 2041-2070
Land-use
Soil data
Streamflow gauges data
Glaciers extension
GeoTransf
(Noce basin, daily)
Streamflow
3. System Dynamics Modelling
Baseline: 1999-2004 & 2009-2016
Short-term: 2021-2050
Long-term: 2041-2070
Month of the year
Turbined outflow
Inflow
"S.Giustina reservoir"
Minimum ecological flow
Emergency releases
Day of the week
Statistical models, operational rules and water balance
(S.Giustina, daily/monthly)
Water turbined
Reservoir volume
Legend
Modules
External component
Internal component
Outputs
Territorial dataset
(Spatial and/or temporal resolution)
Stock
Flow
Converter
Connector

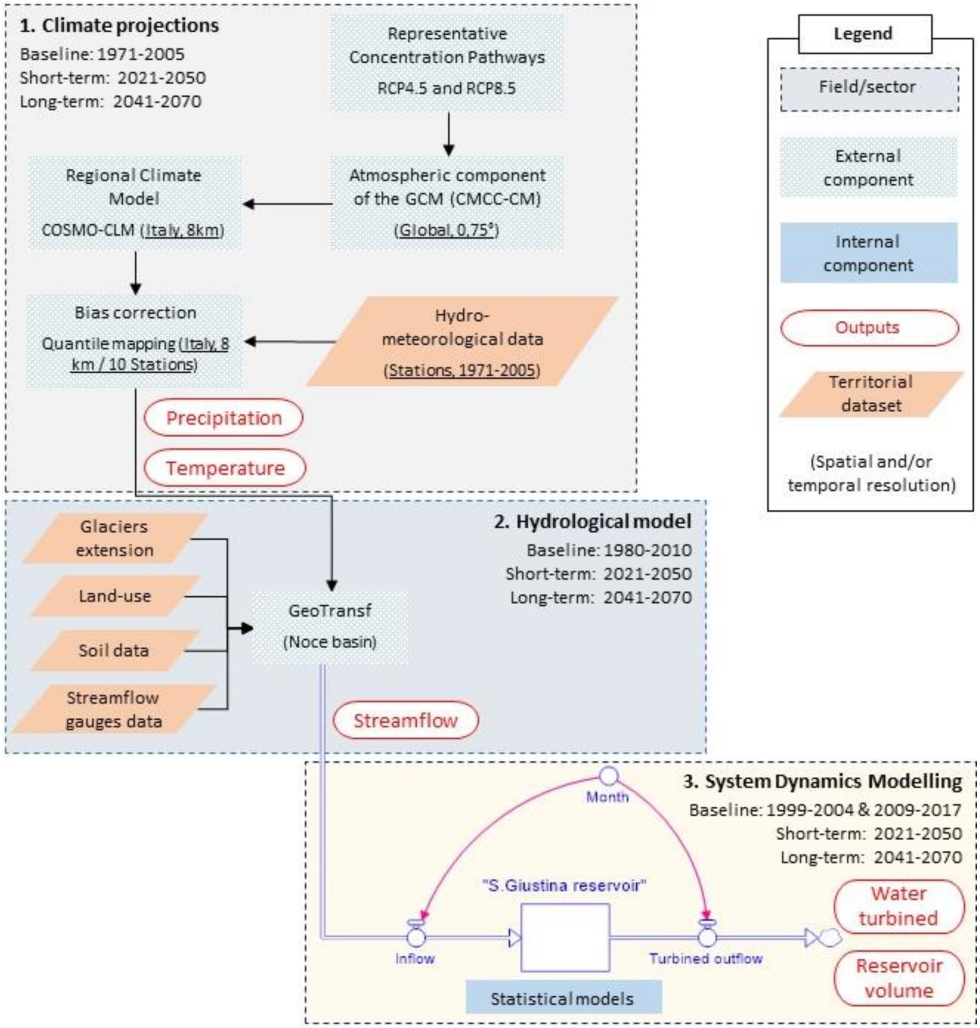


Figure 2~~3~~ - Models' chain considered in this study. Box 1 includes the climate modelling used as input for the hydrological model simulation of water streamflow in box 2. Box 3 contains the SDM components of stock (S.Giustina reservoir), flows (inflow and three outflows), converters (month of the year, day of the week) and connectors (red arrows) considered to simulate stored water in the reservoir and the turbined outflow for hydropower production. ~~Modelling approach to quantify the impacts of climate change (box 1) on water streamflow (box 2), water stored and turbined for hydropower production (box 3).~~ Sources: adapted from Pham et al., 2018; Ronco et al., 2017.

The climate projections ~~in box 1 (Figure 3)~~ provide information stemming from global climate models downscaled to regional level, and bias corrected through the quantile mapping method (Maraun, 2016; Teutschbein and Seibert, 2012) using the downscaled daily E-OBS dataset at 1 km resolution (Cornes et al., 2018) ~~with local weather stations~~ to better simulate climate local conditions. ~~In this study, t~~The regional climate model COSMO-CLM (Climate Limited-area Modelling) was selected for its spatial resolution of 0.0715° × 0.0715° (≈ 8km×8km) allowing local level climate impact assessment (Rockel and Geyer, 2008). Such model information was developed by the CLM community and provided by Euro-Mediterranean Centre on Climate Change (CMCC) as an external component for the application to the Noce catchment (Bucchignani et al., 2016). In the case of climate data from COSMO-CLM, precipitation and temperature baseline data were available from 1971 to 2005, they were also used to characterize the Noce catchment climatology and compare the baseline with future conditions of precipitation and temperature for the two Representative Concentration Pathways (RCPs).

Temperature and precipitation daily data were used as input to the physically-based model “GeoTransf” (external component, Bellin et al., 2016) together with topographical information to replicate streamflow conditions of the Noce river (box 2 in Figure 2~~Figure 3~~). These ~~blocks~~ two boxes were ~~provided~~ obtained from simulations developed ~~as an output~~ from the OrientGate project (http://m.orientgateproject.org/~~http://www.orientgateproject.org/~~) and used as an input to focus on the S.Giustina reservoir through the SDM (box 3 in Figure 2~~Figure 3~~). GeoTransf was calibrated and validated on past daily water flow data in the case study area considering a baseline time range from 1981~~0~~ to 2010 (Bellin et al., 2016; Majone et al., 2016). GeoTransf provides a description of the ~~hydrological~~ water flow ~~dynamics~~ within the Noce alpine river catchment relying on precipitation and temperature data (from box1), land use and soil type (http://pguap.provincia.tn.it/#), streamflow gauge data (https://www.floods.it/) and on glacier extension (https://webgis.provincia.tn.it/).~~, assessing variations in water contributions coming from climate change effects in terms of temperature, soil moisture, glaciers, snow and rainfall.~~ Moreover, GeoTransf was applied with COSMO-CLM precipitation and temperature scenarios from 2021 until 2070 over the Noce catchment to assess future conditions of river discharge at local level for the ~~Representative Concentration Pathways (~~RCPs~~)~~ 4.5 and 8.5 (Bucchignani et al., 2016).

The~~se applications of GeoTransf were used as input to the~~ stochastic SDM relied on the inflow values from GeoTransf applications as one input variable. Other input variables were initially considered and tested as additional input data in the SDM to replicate water turbined and stored volume (excluded to the modelling due to their low predictive performance, further information reported in the Supplementary material). ~~to focus on the S.Giustina reservoir operations and simulate future conditions accounting for climate change impacts and human management (box 3 in Figure 3).~~ The baseline simulation period was ~~bound~~ constrained by the reservoir volume ~~to available~~ data availability with a range 1999-2004 and 2009-2016. For this reason, measured values of inflows to S.Giustina were considered due to the missing temporal overlap of past GeoTransf values with observations of the S.Giustina stored volume ~~In the case of climate data from COSMO-CLM, precipitation and temperature data were available from 1975 to 2005. These data were used to consider the Noce catchment climatology and to compare the baseline with future conditions of precipitation and temperature for the two RCPs. For water inflows and outflows, and water volume stored in the reservoir, the baseline period ranges from 1999 to 2004 and from 2009 to 2017~~ (Table 1~~Table 1~~).

The SDM ~~in Figure 3~~ was run at a daily time resolution to replicate the different outflow’s regulations (e.g. minimum ecological flow and emergency outflows). Finally, simulations were aggregated to monthly values being a suitable time resolution for supporting reservoir volume management over long periods considering climate change effects (Solander et al., 2016)~~built from GeoTransf outputs aiming to integrate human dynamics in a probabilistic manner, assessing the management of the reservoir and its vulnerability to changing environmental conditions. The SDM covers two variables exposed to critical~~

~~conditions: one focusing on the water volume stored within the reservoir (Volume) and the other representing the water outflow diverted to the turbines for hydropower production (Outflow)~~.

Table 1~~1~~ - Selected variables within the ~~statistical~~ SDM ~~(in~~ box 3 in Figure 2) for the S.Giustina reservoir.

Data type	Variable name	Time range	Source
~~Simulated i~~Inflows to S.Giustina [m^3/s]	~~Geotransf_i~~Inflows	1981-2016~~0~~	Province of Trento – Agency for water resource and energy~~GeoTransf hydrological model~~ ~~Province of Trento – Agency for water resource and energy~~
S.Giustina outflows for hydropower use [m^3/s]	Outflow	1981-201~~7~~6	
S.Giustina volume [Mm^3]	Volume	1999-2004 2009-2016~~7~~	
Minimum ecological flow [m3/s]	MEF	1999-2016	
Emergency releases [m3/s]	Releases	1981-2016	

~~3~~2.2~~3~~ Variables' interaction analysis

This analysis aims to ~~quantitatively~~ statistically describe the existence and type of interactions among the systems variables. ~~Statistical regressions were carried out considering both different input variables (e.g. inflow, hydroelectric energy market price, temperature, precipitation and water outflows from an upstream dam reservoir) and statistical models, including linear regression and more flexible generalized additive models (Table 2).~~ For the simulations of ~~water stored and~~ turbined outflows different statistical models and variables interactions were tested and recursively implemented to simulate the stored water in S.Giustina applying the reservoir water balance equation.

2.2.1 Hydropower outflows

The simulation of turbined outflows from the S.Giustina reservoir for hydropower production considered regressions of different input variables (e.g. inflow, hydroelectric energy market price, temperature, precipitation and water outflows from an upstream dam reservoir) and statistical models, including linear regression and more flexible generalized additive models. After an initial screening, the variables hydroelectric energy market price, temperature, precipitation and water outflows from an upstream dam reservoir were rejected due to the low predictive performance and limited temporal overlap with the response variables affecting a robust simulation and validation of historical values of S. Giustina turbined outflows. Further information on input variables, their tested combinations for model selection and link to the open code is reported in the Supplementary material.

The best models for each model type are reported in Table 2. The "lme4" package in R (Bates et al., 2015) was applied for linear mixed effects models while the "mgcv" package in R (Wood, 2017; Wood and Scheipl, 2020) for the generalized additive models. Model #2 in Table 2 was selected as the best model for its performance of 0.42 adjusted-R^2 and 0.95 Mm^3 RMSE (daily resolution) increasing to the highest performance among the other models of 0.75 adjusted-R^2 and 16.57 Mm^3 RMSE at monthly resolution, its ability to account for weekday and monthly variations and its lower proneness to overfit calibration data compared to flexible non-linear models. The model simulated water diverted to the turbines (Q_{out}) as a function of water flowing into the reservoir (Q_{in}), the volume state in the previous day (V(t – 1), through the "lag" operator to shift the time series back by 1 time step), the day of the week and the month of the year. As fixed effect the water flowing into the reservoir and the volume in the previous day were here considered accounting for the linear relation with the water turbined. As a random effect to capture differences among different groups, day of the week and month of the year were selected to account for the recurrent water volume variations occurring according to the day of the week group and months group (distinguished by vertical bars in linear mixed effect models). By doing so, it was possible to describe the reservoir water volume combining the GeoTransf model outputs with statistical analysis aiming to explore the reservoir volume vulnerability to future changing conditions.

~~, a linear mixed effects model was selected (models #3 and #4, with adjusted R2 of 0.68 and 0.74 and RMSE of 12.12 Mm~~^{3} ~~and 12.35 Mm~~^{3}~~s~~$^{-1}$~~, Table 2) because of its ability to account for monthly variations and its lower proneness to overfit calibration data (i.e. compared to flexible non-linear models). A monthly time step was chosen to better describe the intra-seasonal dynamics of water availability, which can be useful for water demand assessments, and for long-term dynamics representation for climate impact assessment (e.g. seasonal changes). Further information on input variables, their tested combinations for model selection and link to the open code is reported in the Supplementary material.~~

Table 2~~2~~ - Best of each model type and their performance indicators calculated at daily resolution data and on monthly averaged data (R2 and the root mean square error, RMSE). The best selected model is reported in bold. The syntaxes follow that from the R packages "lme4" (for the linear mixed effects model), "mgcv" (for the generalized additive models) with the "bs" term set to "re" refer to the random-effect in the generalized additive mixed model; "s" is the function used in definition of smooth terms within the gam model formulae. Full list of tested models and their features is reported in the Supplementary material.

			Daily resolution		Monthly averaged	
Model types	**#**	**R syntax**	**Adjusted-R^2**	**RMSE ($\cdot 10^6$)**	**Adjusted-R^2**	**RMSE ($\cdot 10^6$)**
Multi-linear model	1.	lm(Outflow ~ Inflows + lag(Volume))	0.35	1.03	0.63	19,86
Linear mixed effect model	**2.**	**lmer(Outflow ~ Inflows + lag(Volume)+ (1|weekday) + (1|month))**	**0.42**	**0.95**	**0.75**	**16.57**
Generalized additive model	3.	gam(Outflow ~ s(Inflows) + s(lag(Volume))	0.50	1.07	0.61	20.31
Generalized additive mixed model	4.	gam(Outflow ~ s(Inflows) + s(lag(Volume)) + s(weekday, bs="re")+s(month, bs="re"))	0.54	1.02	0.65	19.27

~~**Tested model and their performance indicators (adjusted R^2 and the root mean square error (RMSE). The formula syntaxes follow that from the R packages "lme4" (for the linear mixed effects model) and "mgcv" (for the generalized additive model). Full list of tested models and their features is reported in the Supplementary material**~~

~~**Model types**~~	**#**	~~**Formulas**~~	~~**Adjusted R^2**~~	~~**RMSE**~~
~~Multi-linear model~~	~~1.~~	~~lm (Volume ~ lag(Geotransf_inflows) + lag(Outflow))~~	~~0.36~~	~~18.20~~
	~~2.~~	~~lm (Outflow ~ Geotransf_inflows + lag(Volume))~~	~~0.72~~	~~13.09~~
~~Linear mixed effect model~~	~~3.~~	~~lmer (Volume ~ Geotransf_inflows + (1|month))~~	~~0.68~~	~~12.12~~
	~~4.~~	~~lmer (Outflow ~ Geotransf_inflows + lag(Volume) + (1|month))~~	~~0.74~~	~~12.35~~
~~Generalized additive model~~	~~5.~~	~~gam(Volume ~ s(lag(Geotransf_inflows)) + s(lag(Outflow))~~	~~0.44~~	~~22.13~~
	~~6.~~	~~gam(Outflow ~ s(Geotransf_inflows) + s(lag(Volume) + s(mo))~~	~~0.72~~	~~16.86~~
~~Generalized additive mixed model~~	~~7.~~	~~gam(Volume ~ s(lag(Geotransf_inflows)) + s(lag(Outflow)) + s(mo, bs="re"))~~	~~0.50~~	~~20.88~~
	~~8.~~	~~gam(Outflow ~ s(Geotransf_inflows) + s(lag(Volume)) +s(mo, bs="re"))~~	~~0.72~~	~~16.86~~

2~~3~~.2~~3~~.~~1~~2 Reservoir volume

Simulated outflow values were used at each time step to replicate the volume stored through the water balance equation Eq. (1):

$$\frac{dV(t)}{dt} = Q_{in}(t) - Q_{out}(t) - Q_{mef}(t) - Q_{rels}(V) \qquad (1)$$

where Q_{in} is the water flowing into the reservoir, Q_{out} the water diverted to the turbines, Q_{mef} the minimum ecological flow released and Q_{rels} the water outflow for emergency flood releases. In particular, Q_{mef} was set to 2.1 m3/s in case of simulations before 2004 while equal to 2.63 m3/s for January-March and December, 3.68 m3/s for April-July, October and November, 3.15 m3/s for August and September from 2009-2016 (http://pguap.provincia.tn.it/#) as well as for future simulations. A simplified operational rule was implemented for emergency releases from flood gates considering the maximum daily emergency discharge value of 168.54 m3/s in case of daily stored volume greater than or equal to 159.30 Mm3.

~~The simulation of reservoir water volumes and outflows for hydropower production was developed combining Stella conceptualization with statistical analysis using R. The lme4 package in R (Bates et al., 2015) was applied to perform a linear mixed effect analysis of the relationship between water volumes stored in the reservoir (i.e. V) and the water flowing into the reservoir (i.e. Q_{in}) in Eq. (1):~~

~~$V(t) = f(Q_{in}(t), month)$ (1)~~

~~where, as the fixed effect the water flowing into the reservoir (i.e. Q_{in}) was considered, accounting for the linear relation with the water volume stored. As a random effect, the month of the year was selected (month) for its grouping effect on the recurrent water volume variations on a monthly scale. By doing so, it was possible to describe the reservoir water volume and future changes combining the physically-based model outputs with statistical analysis aiming to explore the reservoir volume vulnerability to changing conditions.~~

~~3.3.2 Hydropower outflows~~

~~A statistical analysis was carried out to simulate the turbined outflows from the S.Giustina reservoir for hydropower production. Similarly to equation 1, a linear mixed effect analysis was selected, simulating the water diverted to the turbines as a function of water flowing into the reservoir, the volume state in the previous month (V(t − 1)) and the month of the year in Eq. (2).~~

~~$Q_{out}(t) = f(Q_{in}(t) + V(t-1), month)$ (2)~~

2~~3~~.~~4~~3 Model calibration and validation

The statistical model~~s~~ for turbined water ~~were~~ was calibrated and validated over ~~168~~ 5061 days ~~months~~ of available data for the baseline period, representing a total of 14 years from 1999 to 2004 and from 2009 to 2016~~7~~. ~~Moreover, a~~A forward time-window approach was applied as a cross-validation technique to better estimate model fitting (i.e. based on training data) and predictive performance (i.e. based on temporally independent test data) using root mean square error (RMSE). The applied methodology is based on multiple separations of training and testing data sets. Within the first repetition, the predefined model setups (i.e. ~~dam reservoir volumes and~~ turbined outflows models) ~~are~~ is calibrated using a subset of the original data that relates to the first ~~110~~ 3650 ~~months~~ days of available data. The derived relationships are then tested using both training data (i.e. fitting performance) and the data set that relates to the remaining (not yet) considered ~~months~~ days (i.e. predictive performance). The following ~~58~~ 1410 repetitions are based on the same procedure, but on increasingly larger training data sets (i.e. consecutively adding 1 ~~month~~ day within the forward time-window approach). The mean value for RMSE was calculated considering all 1411 repetitions over the increasingly larger data set providing a more robust estimation of model performance and its variability using multiple temporally independent subsets of the original data (Hastie, 2009; Varma and Simon, 2006; Tashman, 2000; Kohavi, 1995). This methodology allows to overcome some limitations of common one-fold non-temporal validation methods (splitting of training and test data randomly; e.g. hold-out validation) associated with data temporal dependencies (i.e. autocorrelation) and an arbitrary choice of training and validation subsets. ~~Furthermore, the applied procedure allows a more robust estimation of model performance and its variability using multiple temporally independent subsets of the original data (Hastie, 2009; Varma and Simon, 2006; Tashman, 2000; Kohavi, 1995).~~ A major advantage of such multi-fold partitioning strategies is the possibility to exploit all the available data for the generation of the final prediction model.

~~3~~2.4~~5~~ Future projections and statistical testing

Future water inflow to the reservoir (coming from the GeoTransf application) were used to simulate future turbined outflow and volumes stored in the S.Giustina reservoir. GeoTransf simulations considered unchanged maximum water withdrawals in the Noce catchment in the future and although possible variations in the future may affect river water flows (e.g. from agricultural and touristic uses) this set-up provided a conservative assumption for future scenarios. Moreover, ~~and~~ integrated downscaled COSMO-CLM climate scenarios were considered (Bellin et al., 2016; Bucchignani et al., 2016). Such climate projections have been demonstrated to well represent climate forcing variables (i.e. precipitation and temperature) over Alpine regions (Montesarchio et al., 2013).

The RCP4.5 and 8.5 scenarios were selected according to the IPCC AR5 (IPCC, 2014a). Simulations stretched over two 30-year time horizons to represent short-term (2021-2050) and long-term (2041-2070) future climate conditions, affecting the Noce river flow, and the S.Giustina ~~dam~~ reservoir ~~and its~~ management.

Differences between the future and baseline simulated water turbined and volumes stored were statistically tested through the Wilcoxon Rank Sum test, a non-parametric test selected since it allows to deal with non-normally distributed, unpaired groups of data (Hollander and Wolfe, 1973). It was implemented to test whether future predicted values of stored volume were significantly different than the baseline and rejecting the null hypothesis (i.e. same tendencies among the tested groups) in case of a p-value ≤ 0.05.

2.5 Future critical conditions characterization

This study explored and analysed critical conditions of low and high future stored volume considering the 10^{th}, 20^{th} and 80^{th}, 90^{th} percentile thresholds calculated from water stored from the baseline (1999-2004, 2009-2016). Such thresholds provided a symmetrical reference of extreme conditions and were already identified in previous studies as significant levels to assess critical states in hydrological studies (Yilmaz et al., 2008). Considering these thresholds, a set of different metrics were calculated to characterize frequency, duration and severity of future critical volume conditions (Table 3) based on existing metrics used to describe extreme events (Vogt et al., 2018). In particular, frequency was considered both in absolute and relative terms. The absolute frequency of critical low- and high- volume conditions were estimated as the overall number of months over 14 years below or above the selected threshold used to define the level of volume critical conditions. The relative frequency was calculated as the ratio of absolute frequency over 14 years, hence describing yearly conditions of extreme events. Duration was described considering the maximum number of consecutive months below or above the selected thresholds. The severity metric describes the accumulated deficit/surplus of simulated volume values with respect to the total volume stored over the analysis window (relative severity). The final values provide information on the fraction of the total stored volume in deficit or surplus.

Table 3 - Metrics implemented to characterize extreme events of low and high volume stored in the S.Giustina reservoir for RCP4.5 and 8.5 future projections, adapted from Vogt et al., 2018.

#	**Metrics**	**Unit**	**Description**
1	Absolute frequency	Months	Number of months below or above the selected thresholds used to define the level of volume critical conditions
2	Relative frequency	Months/year	Number of months below or above the selected thresholds used to define the level of volume critical conditions over a 14-year period
3	Maximum duration	Months	Maximum number of consecutive months below or above the selected thresholds used to define the level of volume critical conditions
4	Relative severity	%	Computed as the sum of the differences, in absolute values, between simulated volume values and the selected thresholds over the total stored volume. $S_i = \frac{\sum \lvert V_i \rvert < \mathrm{Threshold}}{\sum V_i}$

Moreover, ~~Moreover, this study considered the number of times volume projections in the future exceed the 30th and 80th quantile thresholds corresponding to low and high levels of volume stored respectively. Such thresholds were calculated from the baseline data and were already identified in previous studies as significant levels to assess critical states in reservoirs (Majone et al., 2016; Yilmaz et al., 2008).~~

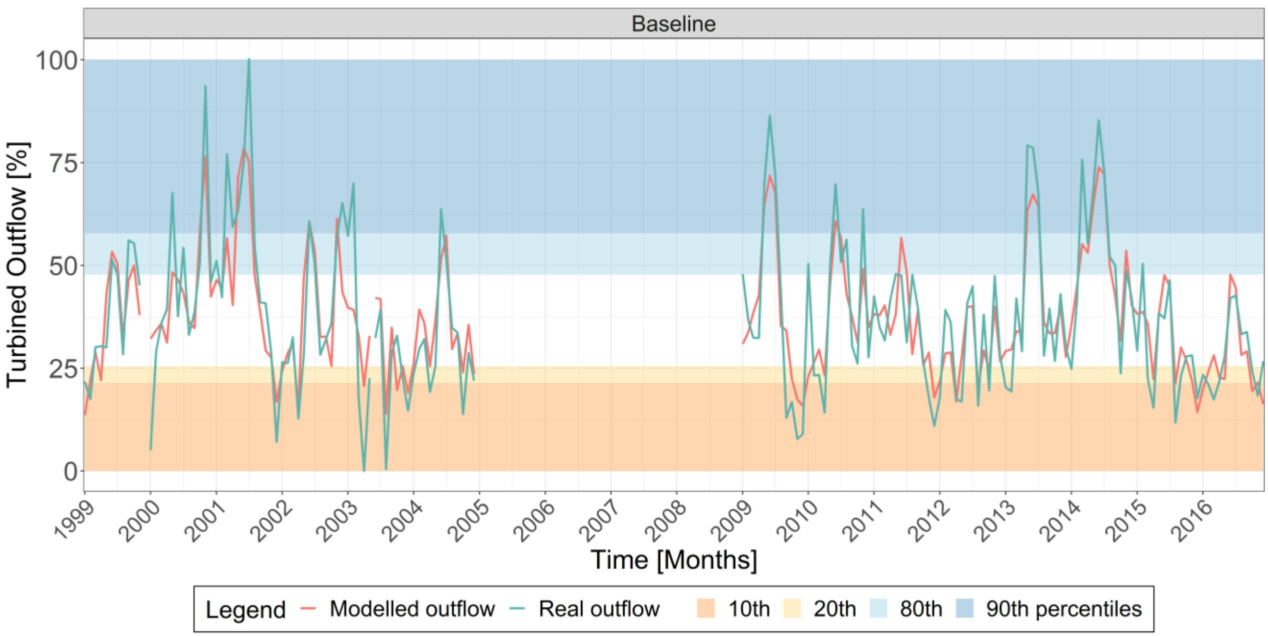
~~A~~a Monte Carlo approach was implemented to account for the uncertainty related to the simulations in future conditions. The water balance equation considered the lower and upper turbined outflow from the prediction bands to generate a range of simulated volume values. A set of ~~by randomly sampling from the simulated future water volume predictions and replicating possible reservoir critical state conditions more than~~ 1000~~0~~ replications of 30 years-length ~~times for~~ per each future climate scenario were generated by randomly sampling from the simulated volume values and their prediction bands. In addition, for each replication a subset was iteratively extracted considering a time-window of 14 years moving progressively at a monthly time step along the simulated 30 years of future volume. Extreme conditions metrics of frequency (absolute and relative), maximum duration and relative severity were calculated on the subset at each iteration. This procedure allowed to compare the calculated metrics of each subset replication with the 14 years of available data for the baseline volume (1999-2004, 2009-2016). By doing so, it was possible to account for the uncertainty related to the modelling and providing a wider range of low and high future volume values for a more robust characterization of their conditions.~~. In particular, the Monte Carlo approach~~

~~considered a moving sampling set having a time window of 14 years across the simulated 30 years of future water volume predictions per scenario to compare it with the available 14 years from the baseline.~~

3~~4~~ Results

3~~4~~.1 Baseline period

The linear mixed-effect model was used to replicate observations of ~~water~~ turbined water outflows ~~volumes stored in~~ from the S.Giustina reservoir (Figure 3~~Figure 4~~). The model was run at a daily time step and values aggregated and reported at monthly resolution to support reservoir management over long period considering climate change effects (Solander et al., 2016). The model gave an R^2= 0.75~~68~~, and mean RMSE of 16~~2~~.57~~12~~ Mm^3. Figure 3~~Figure 4~~ shows the modelled and real values, with y-scale ~~volume~~ ranging from 0% (i.e. no ~~usable volume~~turbined water) to 100% (i.e. maximum turbined water of 176 $Mm^3 \cdot month^{-1}$ for 31 days of full turbine operations). Coloured bands outline areas above or below the percentile values defining critical thresholds that were considered throughout the analysis.~~and a maximum level of 151.20~~ ~~Mm^3, or up to 159.30 Mm^3 in case of flood prevention. Simulated volume values greater than the maximum allowed for flood were limited to such a maximum value.~~



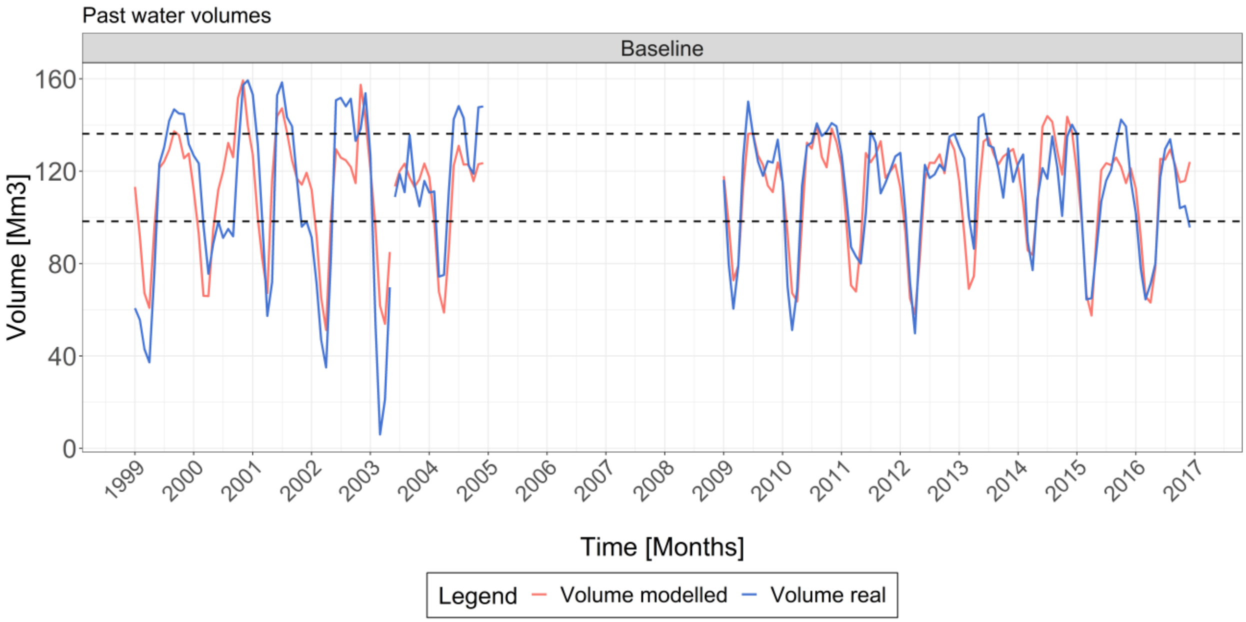


Figure 34 - S.Giustina water diverted to the turbines from 1999 to 2016. Modelled values (red line) and real (green line). Adjusted-R2= 0.75, mean RMSE= 16.57 Mm3. Coloured bands outline areas of values lower than the 10th, 20th and greater than the 80th and 90th percentiles. ~~time series of water volume. Measured (blue line) and modelled (red line) water stored in S.Giustina from 1999 to 2017. Adjusted-R2= 0.68, mean RMSE= 12.12·Mm3~~

The ~~same procedure was undertaken for simulating~~modelled ~~water~~ turbined water was then used in the iterative implementation of the water balance equation together with the operational rules for the minimum ecological flow and the emergency releases. ~~outflows (Figure 4Figure 5).~~shows ~~The maximum~~ the modelled and real volume ranging from 0 to 100% of stored volume (equal ~~a maximum level of 151.20 Mm^3, or up~~ to 159.30 Mm^3~~.~~, maximum volume allowed for ~~in case of~~ flood prevention), where the simulation of the stored volume resulted ~~. Simulated volume values greater than the maximum allowed for flood were limited to such a maximum value.discharge of water flow to the turbines is 176 Mm^3·month^{-1} for 31 days of full turbine operations. Equation 2 was applied to estimate the water turbined outflows used for hydropower production resulting~~ in a R^2= 0.60~~74~~, and mean RMSE of 19~~2~~.74~~35~~ Mm^3·month^{-1}. ~~In both cases, the water inflowing to the S.Giustina reservoir, and modelled using the GeoTransf hydrological model, played a key role influencing the water stored and hence the water turbined outflows. This influence of the inflow variable on both volume and turbined outflows is likely due to the low values of reservoir volume compared to the monthly inflow values, which was identified as the most important predictor (further information on model tests and performances are reported in the Supplementary material).~~

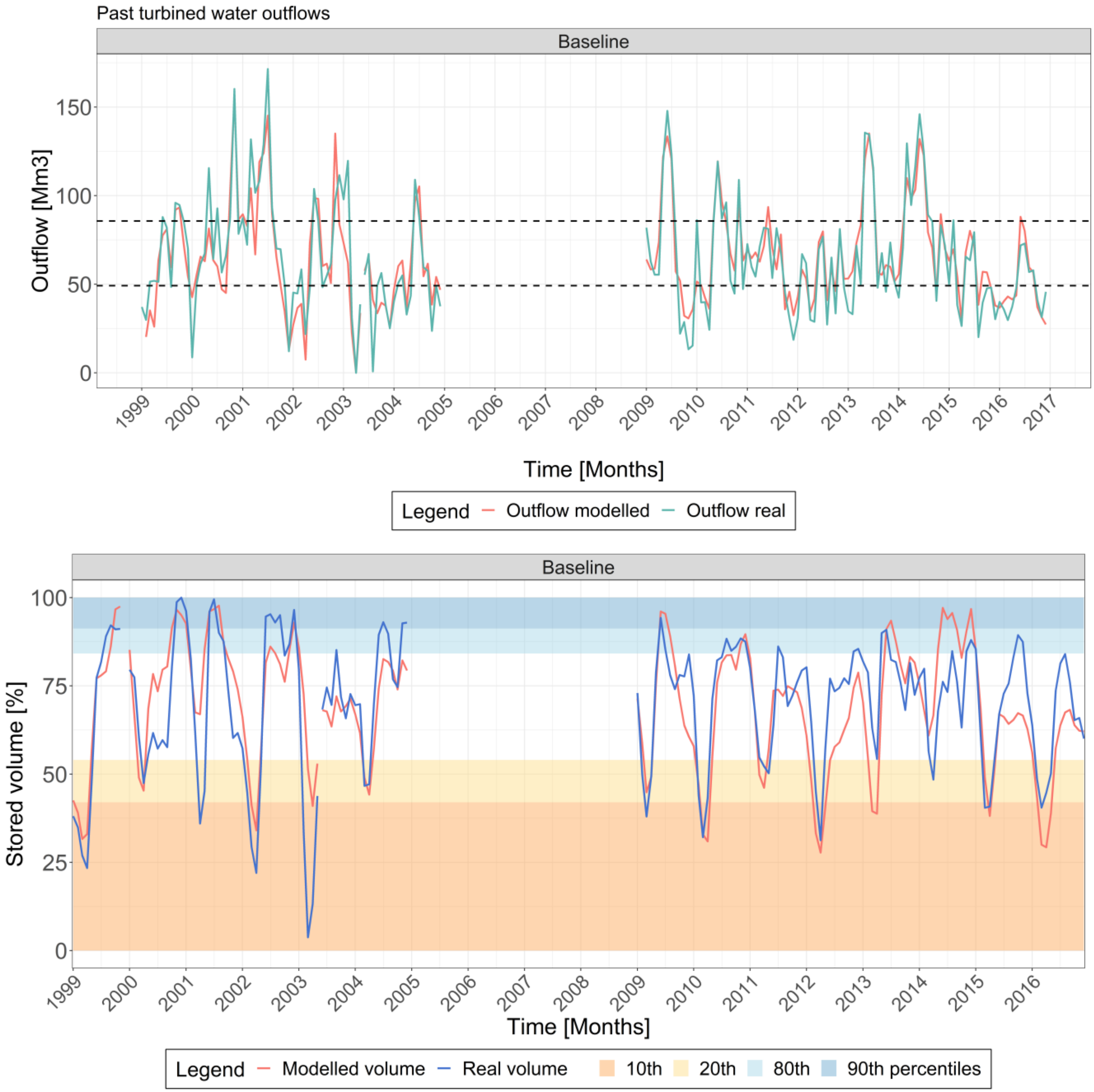


Figure 4~~5~~ - S.Giustina stored volume values from 1999 to 2016, modelled values (red line) and real (blue line). Adjusted-R^2= 0.60, RMSE= 19.74 Mm3. Coloured bands outline areas of values lower than the 10th, 20th and greater than the 80th and 90th percentiles.

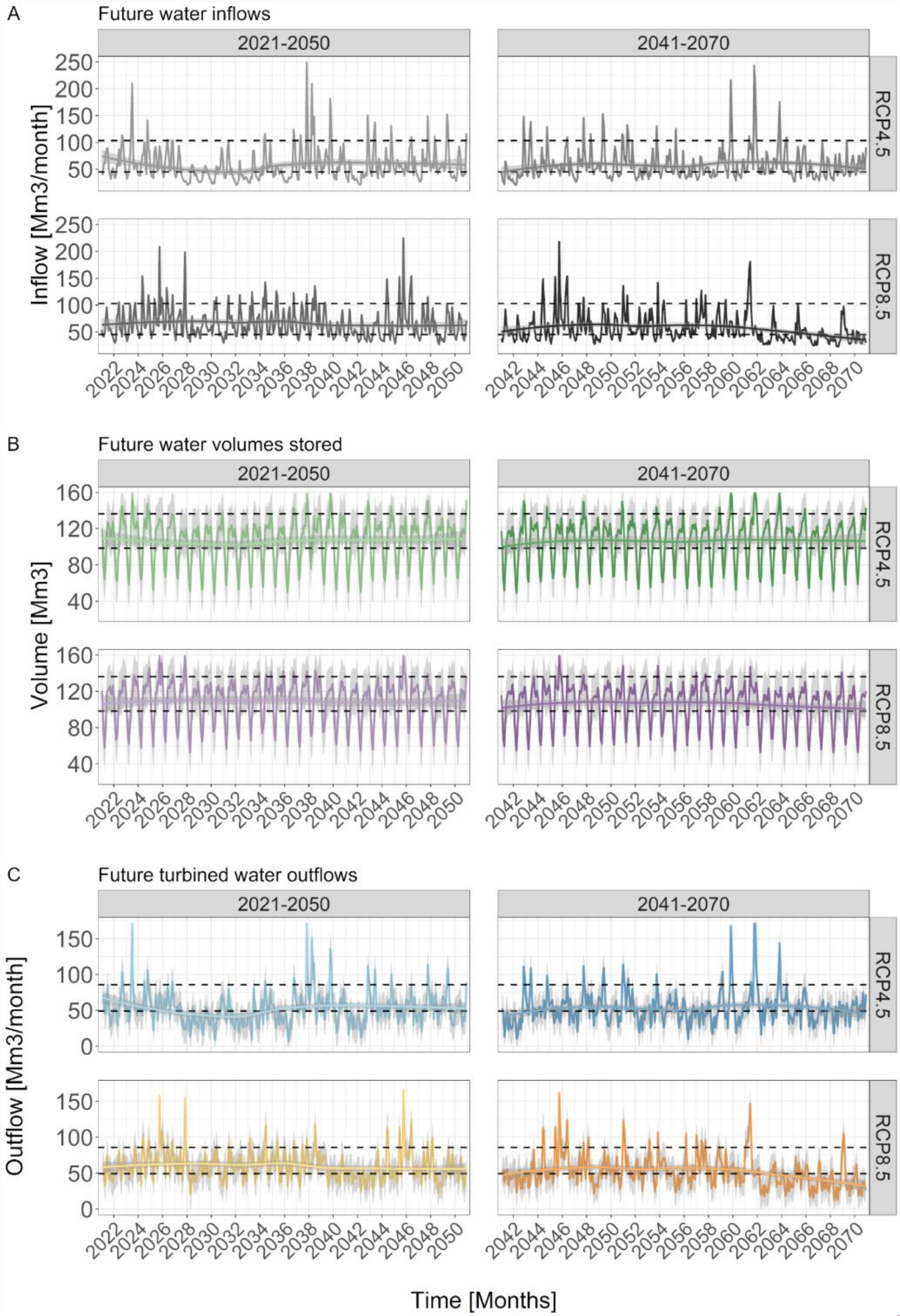
~~time-series of water diverted to the turbines. Measured (blue line) and modelled (red line) water outflowing from the S.Giustina reservoir from 1999 to 2017. Adjusted-R2= 0.74, RMSE= 12.35 Mm3~~

34.2 Future projections and statistical testing

Future GeoTransf model results forced by the COSMO-CLM climate projections depict a situation of general decreases in precipitation and water inflowing to the reservoir (Table 4~~Table 3~~ and Figure 5~~Figure 6~~). However, such decreases differ for the two climate change scenarios. ~~The short-term~~ RCP4.5 scenario shows a greater percentage reduction of inflow, outflow and volume (-19.74, -25.86 and -19.91% respectively) in the short-term compared to the long-term future where reductions are similar, but slightly lower (-18.50, -23.99 and -19.54%). Future conditions under RCP8.5 show greater differences between short- and long-term future. Inflow, outflow and volume reductions are lower for the short-term future (-7.78, -11.64, -10.24%) and are associated with the only case of precipitation increase (+1.4%), which points to the increase of evapotranspiration due to the relatively larger increase in temperature. In the long-term, results show the greatest increase of temperature (+60.1%), reduction of precipitation (-4.3%) as well as for inflow, outflow and volume (-21.25, -26.28, -20.80 %). ~~substantial decrease of precipitation compared to the baseline while RCP8.5 projects a slight increase of precipitation until 2050. However, such little increase seems to have no substantial consequences on the water flowing into the reservoir and consequently on the volume of water stored.~~

Table 4~~3~~ - A~~nnual a~~verage values of temperature and precipitation (COSMO-CLM projections), water inflow to the S.Giustina reservoir, turbined outflow, ~~volume~~ stored volume ~~and water turbined~~ (simulations)~~,~~ and their percentage differences compared to baseline values. †~~*~~Baseline period for climate data goes from 197~~5~~1 to 2005, while for water inflow and volume stored spans over 14 years from 1999 to 2004 and from 2008 to 201~~7~~6.

	Baseline	RCP4.5				RCP8.5			
	†~~*~~	2021-2050		2041-2070		2021-2050		2041-2070	
Variable	Value	Value	Δ [%]	Value	Δ [%]	Value	Δ [%]	Value	Δ [%]
Temperature [°C]	5.06	6.46	+27~~0~~.7~~5~~	7.5	+48~~0~~.~~9~~2	6.63	+31~~0.5~~	8.1	+60~~1~~.1
Precipitation [mm/year]	1495.1	1433.55	-4.1	1391.5	-6.9	1516.3	+1.~~5~~4	1430.7	-4.3
Inflow [Mm3/month]	71.5~~38~~	57.~~3~~4~~5~~	-19.7~~65~~	58.3~~25~~	-18.5~~40~~	65.90	-7.8~~67~~	56.~~28~~3	-21.3~~15~~
Turbined ~~O~~outflow [Mm3/month]	6~~5~~4.1~~04~~	48~~52~~.2~~33~~	-25~~19~~.~~54~~9	48~~53~~.7~~18~~	-24~~18.23~~	5~~9~~6.7~~95~~	-11~~7~~.~~82~~6	47~~51.54~~3	-2~~0~~6.~~76~~3
Stored ~~V~~volume [Mm3]	109~~11~~.6~~02~~	~~106~~87.~~10~~8	-19~~4~~.~~43~~9	~~106~~88.2~~46~~	-194.~~11~~5	98~~109~~.4~~15~~	-10.2~~69~~	86~~105~~.~~81~~8	-204.~~70~~8



A summary overview of future conditions for inflow, turbined water and stored volume is reported in Figure 5. For all variables, four coloured bands representing areas lower than the 10th, 20th and greater than the 80th and 90th percentile are reported as reference allowing to identify trends for the whole time series and in 5-year time slices. Values show a generalized decrease into the 20^{th} and 10^{th} percentile thresholds during the second half of the long-term RCP8.5 scenario. This trend is clearly visible for future water inflow, while values larger than boxplots whiskers can be identified in all inflow scenarios and hence pointing to single future conditions greater than baseline maximum recorded values (Figure 5 A). Future turbined outflows show boxplot values frequently lowered towards the 20^{th} percentile except for some cases in the short-term RCP8.5. Consistently with the results from Table 4, volume values show significant reductions already for RCP4.5 with many cases of 1^{st} quartile boxplot levels below with the 20^{th} and 10^{th} percentiles calculated from baseline (i.e. 1999-2004 & 2009-2016). These results were further investigated through the application of the Wilcoxon Rank Sum Test (Table 5), which provide more quantitative insights on the statistical significance of changes considering the whole time series of data for the baseline and the four scenarios (Figure 5) as well as considering monthly averaged values**10**. While p-values considering the whole time series are below the 0.05 threshold of significancy, monthly averages for short-term RCP8.5 scenario (2021-2050) provided non-significant results both for stored volume and turbined outflow.

Table 5 – Summary of the Wilcoxon Rank Sum Test application to stored volume and turbined outflow for the 4 scenarios compared to the baseline (1999-2004, 2009-2016). P-values are reported for the test considering the whole time series of future and baseline values and on paired monthly averages. Symbol '*', '', '***', '*****' refer to significant p-value ≤0.05, ≤0.01, ≤0.001 and ≤0.0001.**

		On the whole time series	**On monthly averages**
Compared scenarios	**Variable**	**P-value**	**P-value**
RCP4.5 2021-2050 vs Baseline	Stored volume	2.203e-15****	0.016*
	Turbined outflow	3.737e-12****	4.883e-4***
RCP4.5 2041-2070 vs Baseline	Stored volume	2.275e-16****	0.034*
	Turbined outflow	8.676e-12****	0.009**
RCP8.5 2021-2050 vs Baseline	Stored volume	1.120e-06****	0.092
	Turbined outflow	0.003**	0.095
RCP8.5 2041-2070 vs Baseline	Stored volume	5.006e-18****	0.012*
	Turbined outflow	1.381e-13****	0.007**

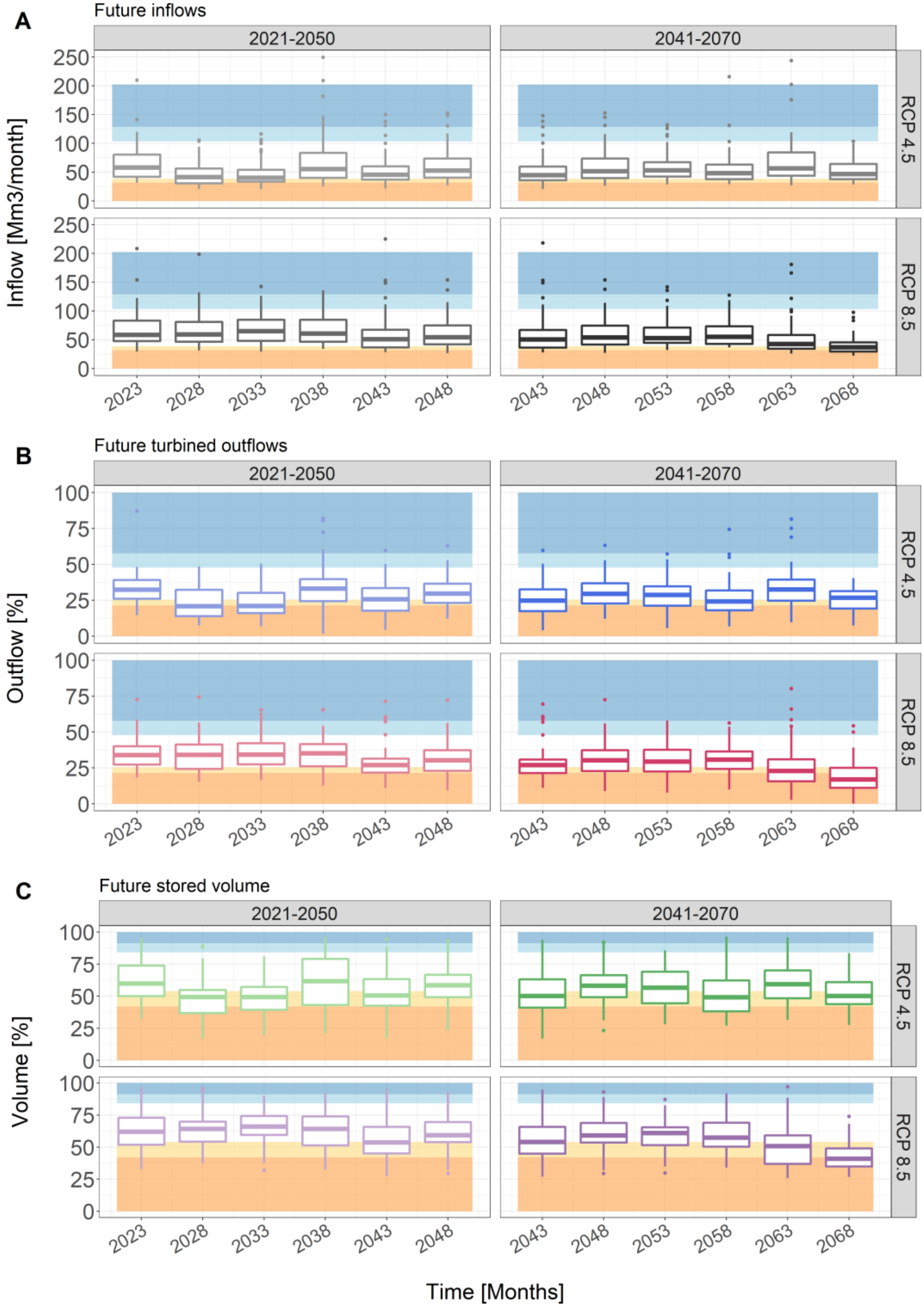
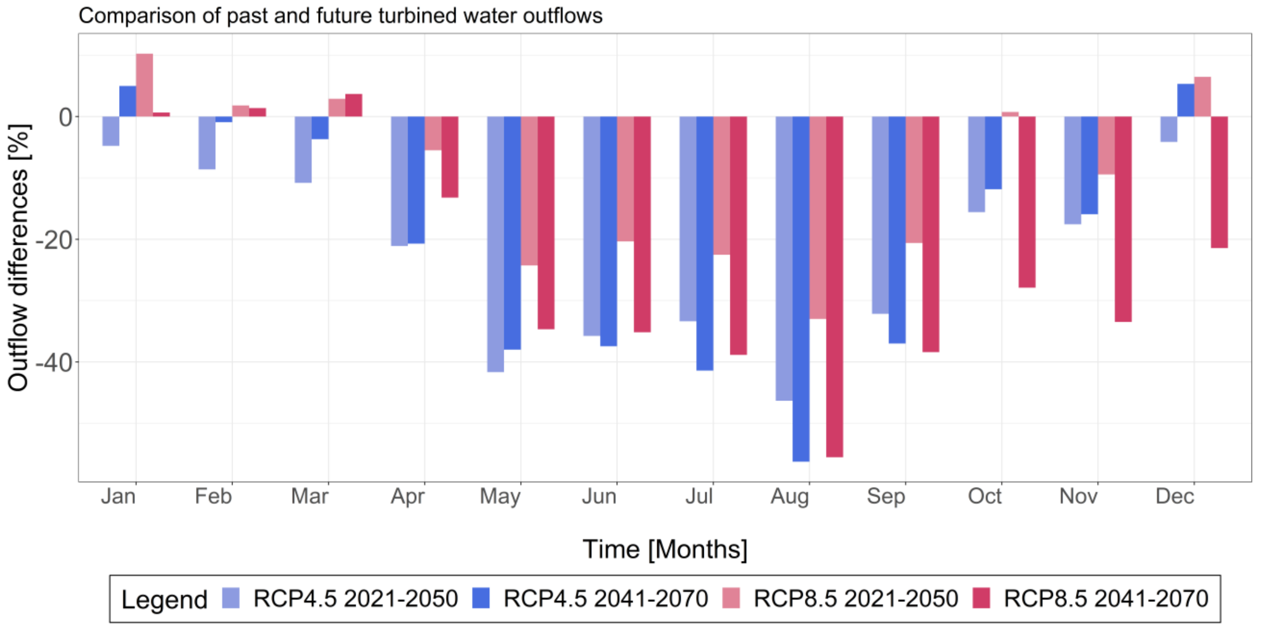


Figure 5~~6~~ - 5-years slice boxplots for future projections of: ~~Plots with future projections for:~~ A simulated water inflow to the S.Giustina reservoir, B simulated water turbined and C simulated future water volume stored in the S.Giustina reservoir. . Coloured

bands outline areas of baseline values lower than the 10th, 20th and greater than the 80th and 90th percentiles.~~Dotted lines indicate baseline 30th and 80th quantiles. Grey shaded represents the confidence interval for the simulated outflows and water volumes.~~

~~Considering average values over 30-year simulations, RCP4.5 results show a greater percentage reduction of inflow, outflow and volume (-19.65, -19.54 and -4.43% respectively) in the short-term compared to the long-term future, where reductions are similar, but slightly lower (-18.40, -18.23 and -4.11%). Future conditions under RCP8.5 show greater differences between short- and long-term future. Inflow, outflow and volume reductions are lower for the short-term future (-7.67, -7.53, -1.69%) and are associated with the only case of precipitation increase (+1.5%). While in the long-term results show the greatest increase of temperature (+1.1%), reduction of precipitation (-4.3%) as well as for inflow, outflow and volume (-21.15, -20.76, -4.70 %).~~

Results of future turbined outflows ~~at monthly temporal scale~~ are reported in Figure 6~~Figure 7~~ with values ~~and~~ averaged for each month over the 30-year simulation and compared to the baseline (i.e. percentage change~~; Figure 7~~). Negative reductions of outflows for all scenarios are reported for spring and summer, starting in April and until September with differences up to -56.3% in August for the RCP4.5 long-term scenario. All climate scenarios agree on a water flow reduction during November reaching a minimum of -33.5% of turbined outflow for RCP8.5 long-term scenario. In all other months, scenarios depict varying conditions of water flow. In particular, short-term RCP4.5 depicts conditions of negative differences for every month of the year. Increased number of positive differences are predicted for long-term RCP4.5 during January (+5%) and December (+5.3%). Short-term RCP8.5 shows larger positive differences during January (+10.3%), February (+1.8%), March (+2.9%), October (+0.8%) and December (+6.5%). Long-term RCP8.5 projects a negative trend from April until the end of the year reaching persistent negative conditions in summer down to -55.5% in August, overlapping with the summer electricity peak loads and calling for particular attention (Terna, 2019). Nevertheless, small but positive values are expected for January (+0.7%), February (+1.4%) and March (+3.7%), when the winter electricity peak load usually occurs (Terna, 2019).~~the general volume decrease in spring and summer down to a minimum of -16.1% for the RCP4.5 short-term case. Scenarios also agree on the negative trend in November where RCP8.5 in the long-term scenario reaches the lowest minimum of -6.5% of volume difference. However, scenarios disagree in terms of volume for January, February, March and October.~~



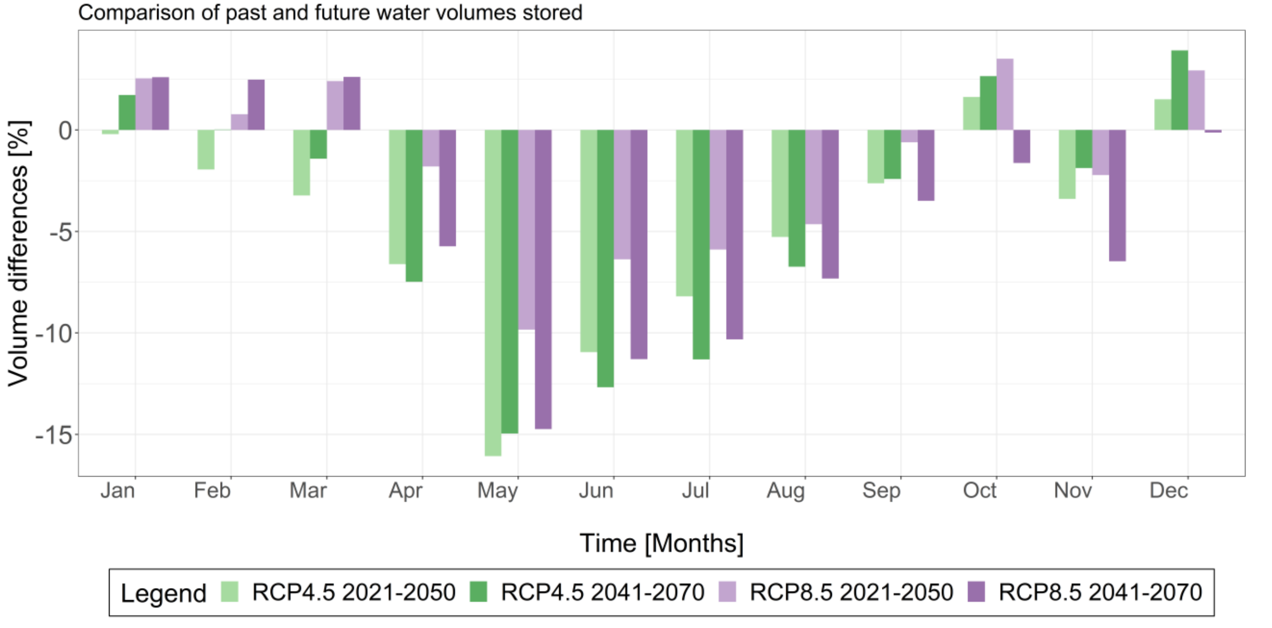


Figure 6~~7~~ - Percentage change of turbined water outflows ~~volume~~ [%] comparing the 4 climate scenarios to the baseline at monthly level

Comparative results with the baseline for monthly average over the 30-year simulation are reported for the stored volume in Figure 6. All climate scenarios agree on the general volume decrease from May until the end of the year. Short- and long-term RCP4.5 depicts conditions of minimum peaks in May (-43.8 and -40.6%) and June (-44.1 and -41.9%), while long-term RCP8.5 shows less negative minimum values although persistent negative values in November and December lower than the other scenarios (-26.8 and -19%). Scenarios agree on the positive variation during February and March with a maximum increase of +32.5% for the RCP8.5 short-term case. However, scenarios disagree in terms of stored volume for January, with RCP4.5 scenarios representing a positive variation both in the short- and long-term cases (+1.4 and +2.2%), while the RCP8.5 short-term case depicts a positive variation (+7.3%) but a negative one for the long-term (-7.1%). Conditions in April are reversed with RCP4.5 short-term depicting a decrease (-8.3%) and RCP8.5 increases for short- and long-term cases (+5.5% and +3.5%).

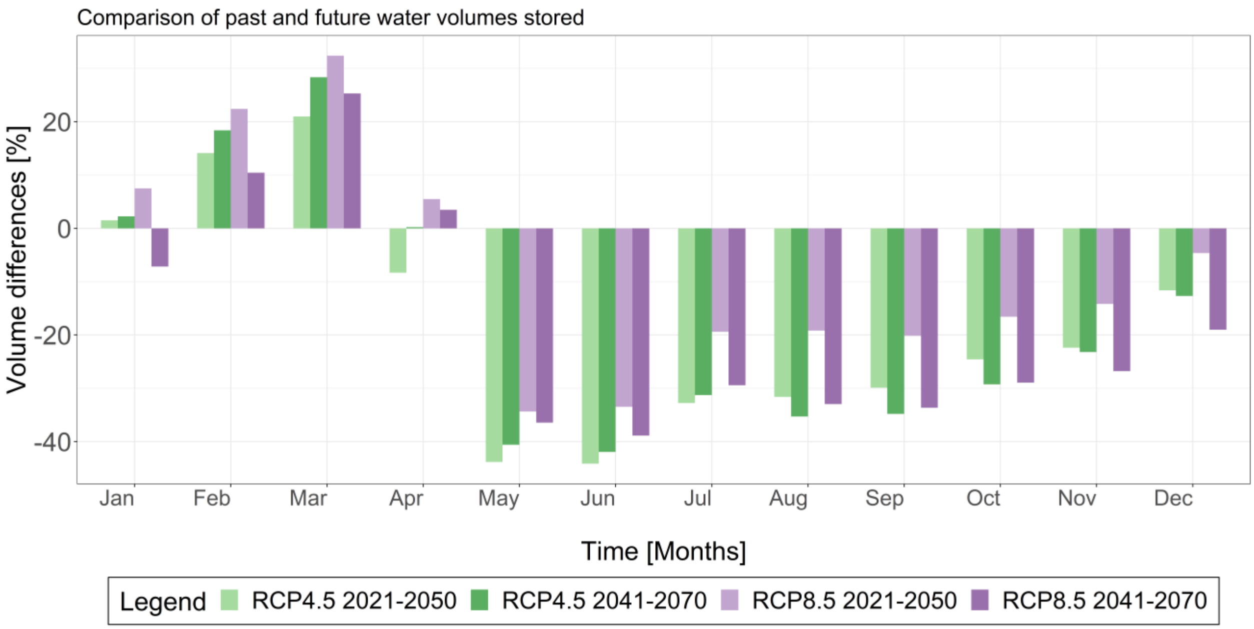


Figure 7 - Percentage change of volume [%] comparing the 4 climate scenarios to the baseline at monthly level

~~Such disagreement provides important information on the timing of potential reservoir management adaptation, while the small volume increases are insufficient to counterbalance spring and summer reductions. In particular, short-term RCP4.5 depicts conditions of continuous negative volume trends througout the year, which are associated with lower precipitation values compared with RCP8.5 in northern Italy (Bucchignani et al., 2016). Nevertheless, positive volume increases, albeit minor, are expected during October and December (+1.6 and +1.5%). Long-term RCP4.5 shows volume increases for January, February, October and December (+1.7, +0.02, +2.7% and +3.9%). Short-term RCP8.5 shows the most favourable conditions of water volumes, depicting positive differences in January (+2.5%) , February (+0.8%), March (+2.4), October (+3.5%),and December (+2.9%). While the long-term RCP8.5 envisages the first three months of the year having positive values (+2.6%, +2.5%, +2.6%) and the rest of the year with negative values down to -14.7% in May.~~

Months of positive variation and scenarios disagreement provide important information on the timing of potential reservoir management adaptation, while the small volume increases are insufficient to counterbalance persistent volume reductions.

Short-term RCP8.5 shows the most favourable conditions of water volumes, depicting positive differences in January (+7.3%), February (+22.5%), March (+32.5%) and April (+5.5%).

3.3 Future critical conditions characterization

~~Moreover, potentially~~ C~~c~~ritical conditions ~~states~~ of stored reservoir water volumes (both high and low) were explored to further understand how climate change may impact on long-term reservoir's ~~operations and its~~ vulnerability. A set of different metrics ~~The number of events lower than the 30th and greater than the 80th quantiles of stored volume~~ were calculated to characterize frequency, duration and severity of future critical volume conditions considering values lower than the 10th, 20th and higher than the 80th and 90th percentiles of stored volume (Figure 8 and Figure 9). The metrics were calculated from 1000 replications per scenario randomly sampled from the simulated future volume values and their prediction bands. Reductions showed to have similar trends across the metrics between the 10th and 20th as well as between the 80th and 90th percentiles with the 4 future scenarios having statistically significant differences compared to the baseline.

~~on future predictions considering a moving time-window of 14 years and comparing to the 14 years of the baseline (Figure 8).~~ Boxplots for low volume conditions (Figure 8) ~~of the 30th quantile threshold~~ show ~~an~~ increasing average values for all metrics and scenarios compared to the baseline: conditions of low volume are expected to become more frequent, having a longer duration and larger severity. In particular, for both values lower than the 10th and 20th percentile, short-term RCP4.5 shows the highest average increase. ~~number of low-volume events for RCP4.5 with a median of 64 events for the short-term and 57 for the long-term (+33.3% and +18.8% respectively compared to the baseline).~~ Frequency (absolute and relative) and relative severity are expected to have an higher increase for average values below the 10th percentile (+157% for frequency, from 23 to 59 months and +400% for severity, from 2 to 1%) compared to values below the 20th percentile (+105% for frequency, from 40 to 82 and +300% for severity, from 0,04 to 0,16%), while maximum duration is expected to have an higher increase for values below 20th percentile (+100%, from 5 to 10 months) compared to values below the 10th percentile (+75%, from 4 to 7 months). These results point to events of low volume conditions below the 10th percentile to be more frequent and with higher severity, while low volume events below the 20th percentile to last for longer time. RCP8.5 in the short-term depicts less negative conditions for both thresholds in line with results in Figure 6. For values below the 10th percentile: +39% in absolute and relative frequency (absolute requency from 23 to 32 months and relative frequency from 1,64 to 2,29 months/year), +0% in maximum duration (4 months) and +50% in relative severity (from 2 to 3%). For values below the 20th percentile: +38% in absolute frequency (from 40 to 55 months) and in relative frequency (from 2,86 to 3,93 months/year), +20% in maximum duration (from 5 to 6 months) and +75% in relative severity (from 4 to 7%).

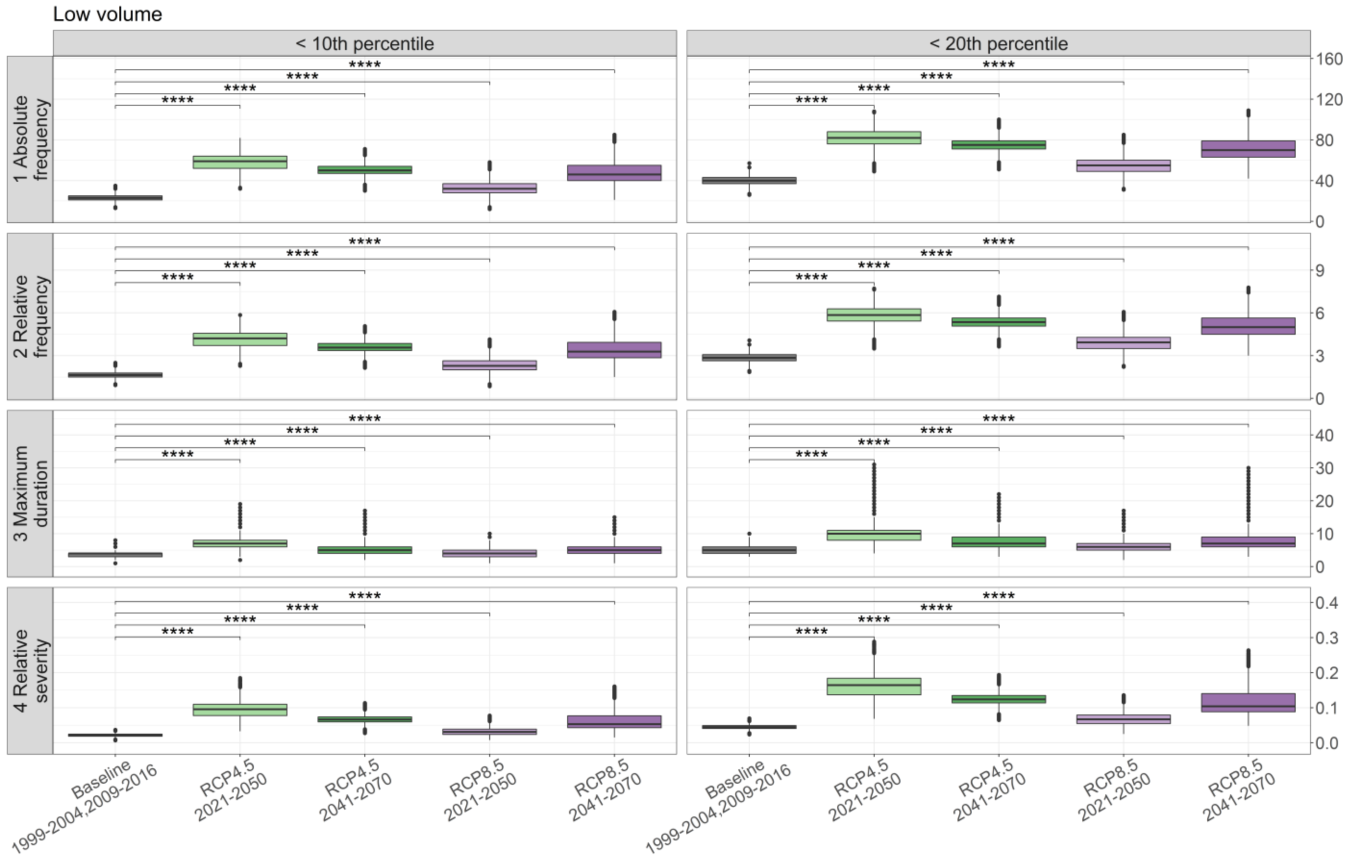
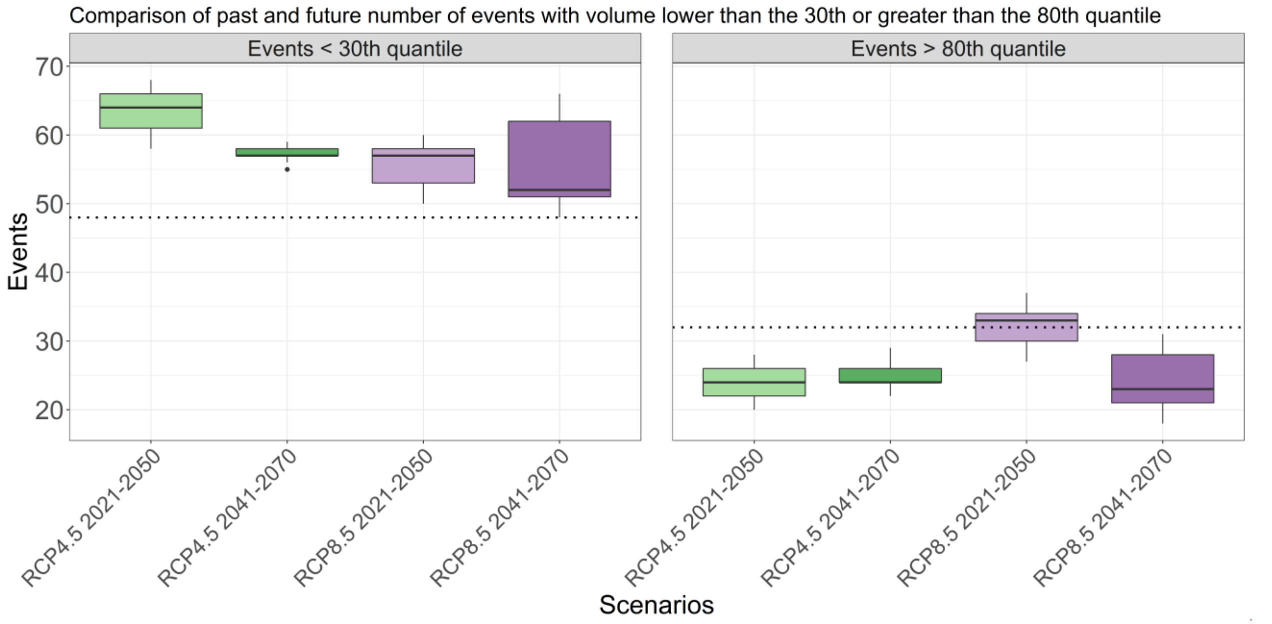


Figure 8 – Boxplots of frequency (absolute and relative), maximum duration and relative severity metrics calculated from volume values lower than the 10th and 20th percentiles. The simulated volume values used for the metrics calculation resulted from the Monte Carlo approach by randomly sampling from the volume prediction bands. Symbol '**' refers to p-value ≤0.0001.**

~~RCP8.5 shows an increase similar to that for the long-term RCP4.5, with a larger interquantile range towards lower values. Increased values are depicted for the long-term RCP8.5 with a median of 52 events (+8.3%) though lower compared to the other scenarios and having a wider interquantile range towards more low volume events.~~

~~Conditions for events greater than the 80th quantile show a decrease in the number of high volume events for RCP4.5 both short- and long-term (both with a median of 24 events) compared to the 32 events of the baseline. Consistent with previous considerations, RCP4.5 predicts a decrease in the number of high volume events, confirming the trend of water stored reduction both in terms of minimum and maximum volumes (-4.43% for the short-term and -4.11% for the long-term values, Table 3). Moreover, RCP8.5 depicts a small increase in the number of high volume events (33 events, +3.13%) in the short-term scenario, but also showing a strong decrease in the long-term scenario reaching 23 events (-28.13%).~~



~~Figure 8 – Number of events lower than the 30th and greater than the 80th baseline quantile for future scenarios of water volume in the S.Giustina reservoir using a Monte Carlo approach. The dotted line shows the number of events for the baseline~~

For values lower than the 20th percentile, a larger number of values outside the boxplots whiskers are depicted for all scenarios and especially towards higher number of months for absolute and relative frequency as well as maximum duration and relative severity, hence pointing to potential single conditions of lower volume stored in the future with respect to the represented median. These results point to the possibility of water scarcity conditions lasting longer than one hydrological year and pointing at chronic consequences of low stored volume, especially considering short-term RCP4.5 (maximum values of 19 months and 31 months for values below the 10th and 20th percentile) and long-term RCP8.5 (maximum values of 15 and 30 months for values below the 10th and 20th percentile) where the outliers highest values are expected.

Boxplots for high volume conditions also show a generalized decrease in all metrics of high stored volume for all scenarios and for both thresholds. Long-term RCP4.5 and RCP8.5 scenarios depict conditions of higher percentage reductions for absolute and relative frequency and maximum duration above the 90th percentile compared to the 80th percentile. On the contrary, relative severity reductions are expected to be higher for values above the 80th percentile (for RCP4.5 and RCP8.5, from 5% to 1%) compared to the 90th percentile (for RCP4.5 and RCP8.5, from 4% to 1%). Above the 90th percentile, values are expected to be less frequent than baseline conditions, while showing smaller severity reductions compared to values above the 80th percentile. Short-term RCP8.5 predicts a smaller decrease in all metrics in comparison with the other scenarios with -48% of absolute frequency (from 44 to 23 months) and of relative frequency (from 3,14 to 1,64 months/year), -50% of maximum duration (from 6 to 3 months) and -60% in relative severity (from 5 to 2%) for values above the 80th percentile compared to the baseline, as well as -56% of absolute frequency (from 32 to 14 months) and relative frequency (from 2,29 to 1 months/year), -60% of maximum duration (from 5 to 2 months) and -75% of relative severity (from 4 to 1%) for values above the 90th percentile compared to the baseline. A summary table with median, maximum, minimum and standard deviation values for low and high volume conditions is provided in the Supplementary material.

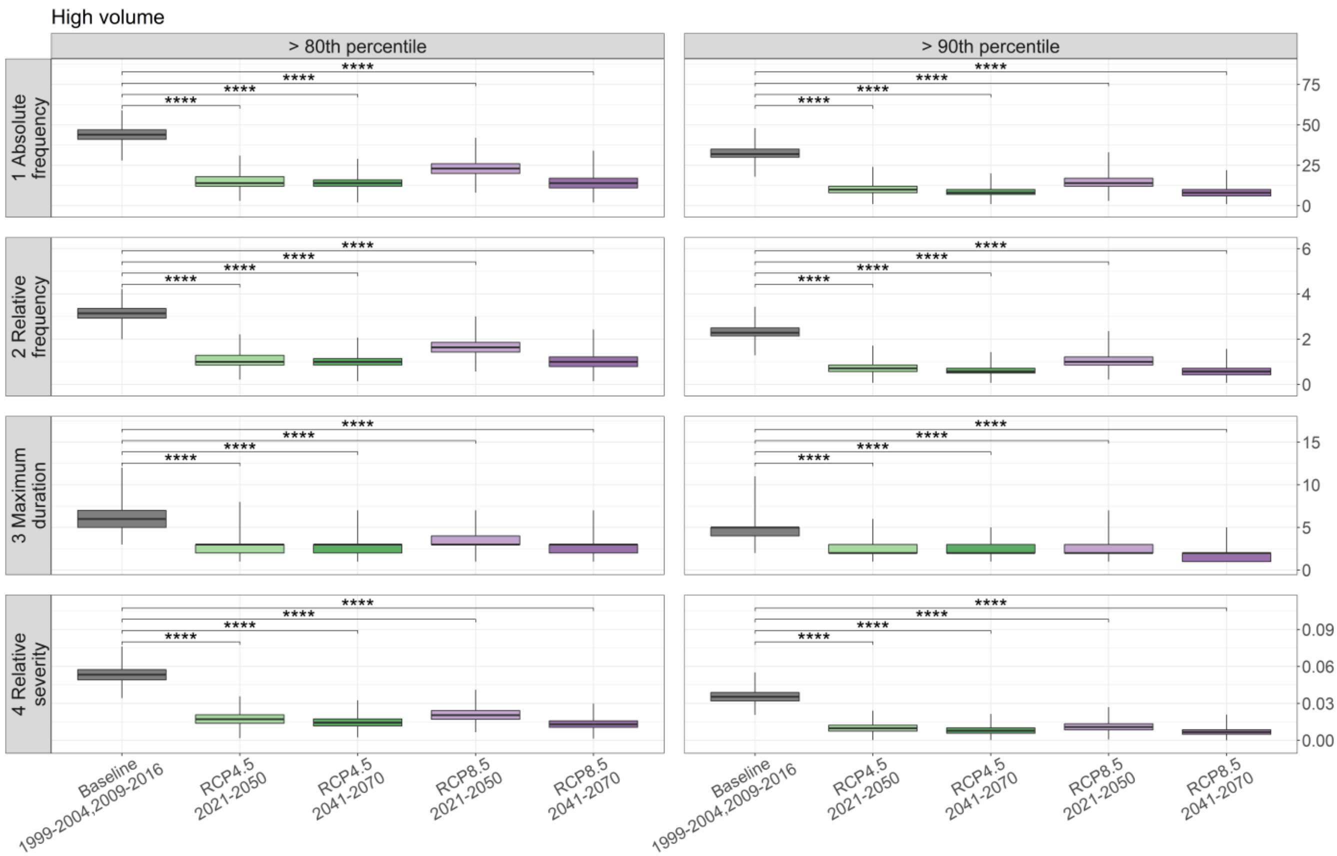
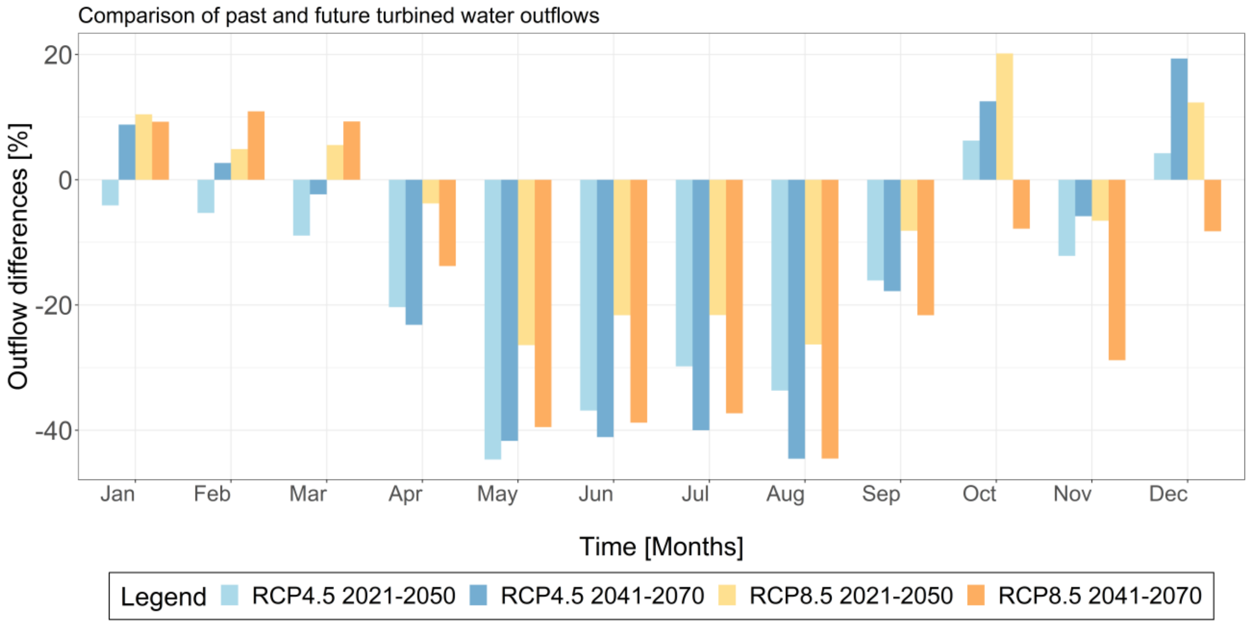


Figure 9 - Boxplots of frequency (absolute and relative), maximum duration and relative severity metrics calculated from volume values lower greater than the 80th and 90th percentiles. The simulated volume values used for the metrics calculation resulted from the Monte Carlo approach by randomly sampling from the volume prediction bands. Symbol '**' refers to p-value ≤0.0001.**

~~Future conditions of turbined water outflows considered a monthly average over the whole simulation period compared to the baseline (Figure 9). Highest reductions are reported for spring and summer with differences up to -44.7% for the RCP4.5 short-term scenario. All scenarios agree on a water flow reduction during November reaching a minimum of -28.8% of turbined outflow for RCP8.5 long-term scenario. In all other months, scenarios depict varying conditions of water flow. In particular, short-term RCP4.5 depicts conditions of negative differences for almost every month of the year except for October (+6.2%) and December (+4.2%). Increased number of positive differences are predicted for long-term RCP4.5 during January (+11.1%), February (+2.7%), October (+12.5%) and December (+19.3%). Short-term RCP8.5 shows larger positive differences during January (+10.4%), February (+4.9%), March (+5.5%) and October (+20.2%). Long-term RCP8.5 projects a negative trend for most of the year reaching persisting negative conditions in summer down to -44.5% for August, overlapping with the summer electricity peak loads and calling for particular attention (Terna, 2019). Nevertheless, positive~~

~~values are expected for January (+9.3%), February (+10.9%) and March (+9.3%), when the winter electricity peak load usually occurs (Terna, 2019).~~



~~Figure 109 - Percentage change of turbined water outflows [%] comparing the 4 climate scenarios to the baseline at monthly level~~

4~~5~~ Discussion

The SDM represents the overall trend of the system in terms of turbined outflow (water demand) and future conditions of reduced ~~characterized by conditions of high water demand for hydropower production and slow onset conditions of~~ water availability ~~variations~~ over a 30-year period. Changes ~~Such~~ in water availability can deeply ~~conditions~~ affect the actual turbined water ~~turbined and hence the hydropower production~~, which plays a strategic role in the economy of the province, as in the whole Alpine region. Moreover, reduction in the water streamflow can have consequences in terms of ecological hazards and water supply quality downstream of the reservoir.

The analysis considered the ~~Results show how the amount of~~ water flowing into the S.Giustina reservoir, and modelled using the GeoTransf hydrological model, as a key variable influencing the turbined water and hence the stored volume. A stochastic approach considered the simulated turbined outflows and its predictions bands as the main source of uncertainty to explore a wide range of possible outcomes in terms of turbined outflow and stored volume values.

Results show ~~is~~ how the amount of water flowing into the reservoir is deeply affecting ~~expected~~ both turbined outflows and hence the stored water, which are expected to reduce in the future ~~to negatively change with severe consequences~~ even under the short-term RCP4.5 scenario (-25.9%). In the case of long-term scenarios high reductions are also expected (-24% for RCP4.5 and -26.3% for RCP8.5).

~~Results during months of highest reduction of volume and turbined water outflows (i.e. from April to September) provide useful information on possible consequences coming from reservoir operations and climate change effects (i.e. -4.43% of volume, +33.3% in the number of events with low stored volume, -4.43% in the number of high-volume events and -19.54% of turbined water outflow). The SDM represents the overall trend of the system characterized by conditions of high-water demand for hydropower production and slow onset conditions of water availability variations over a 30-year period. Such conditions affect the actual water turbined and hence the hydropower production, which plays a strategic role in the economy of the province, as in the whole Alpine region. Moreover, reduction in the water streamflow can have consequences in terms of ecological hazards and water supply quality downstream of the reservoir.~~

~~Considering~~ Moreover, results on ~~those~~ monthly~~s~~ averages ~~of positive variations of volume and turbined water outflows (i.e. autumn and winter months, November excluded)~~ provide~~s~~ useful ~~insights~~ information on the ~~need~~ timing of possible consequences coming from reservoir operations and climate change effects. Considering those months of positive variation of volume (i.e. January, February, March and April, depending on the considered scenario) and turbined water outflows (i.e. December, January, February and March, depending on the considered scenario) provides insights on the need to plan adaptation and operational strategies to improve the management of the S.Giustina reservoir. ~~according to the timing of positive water volume changes aiming to prepare for more frequent negative volume variations in spring and summer.~~ Months of positive water volume changes need to be considered as periods of preparation to worsening conditions. Strategies of earlier water accumulation should be considered to face the persistent reductions throughout the last part of spring, summer, autumn and part of winter. Such a strategy could prevent downstream conditions of water shortages, while also preparing for reductions in turbined water for hydropower uses, especially during summer and winter months of high electricity peak loads. These results are in line with other findings in the Alps showing the need for earlier reservoir water accumulation during winter to prevent downstream conditions of water shortages during summer (Brunner et al., 2019; Hendrickx and Sauquet, 2013). Although positive percentage variations are expected to be lower and for fewer months than negative cases, earlier water accumulation strategies potentially reducing water scarcity conditions need to acknowledge and avoid flood events exacerbation. Additional storage for flood prevention needs to be ensured and managed together with the Civil protection department to prevent potential downstream floods.

~~Such n~~Negative stored volume variations are supported by the generalized trends ~~increasing number~~ of future water scarcity conditions characterized by an increase in frequency, maximum duration and severity of low stored volumes for values lower than the 10^{th} and 20^{th} percentiles and for both RCP4.5 and 8.5.~~of high and low volumes stored, especially in a long-term perspective. At the same time, high volume events decrease in number, confirming previous results of a general negative trend of water stored.~~ These results point at higher percentage increases in frequency and severity for values below the 10th percentile, while volume values below the 20th percentile are expected to last longer. ~~Results~~ At the same time, high volume conditions decrease in terms of frequency, duration and severity with higher reductions for volume above the 90^{th} percentile compared to the percentage decrease for events above the 80^{th} percentile. Only in case of relative severity, reductions are expected to be higher for values above the 80^{th} percentile compared to those above the 90^{th} percentile for long-term RCP4.5

and 8.5 scenarios. Above the 90th percentile, values are expected to be less frequent than in baseline conditions, while showing smaller severity reductions compared to values above the 80th percentile. Within this context, the calculation of a set of metrics in terms of low and high volume conditions through a Monte Carlo approach considering a moving window of data (Figure 8 and) allowed to generate a set of possible future volume time series derived from the simulation prediction bands. By doing so, the analysis prevented any potential bias associated with limited data and provided statistically tested information on increases of low volume and reductions of high volume values showed as boxplots for S.Giustina over four 30-years climate scenarios.

~~on the increase in the number of low-volume states are in agreement with the predictions reported in Majone et al., (2016) on future reductions of medium and low flows. Moreover, Monte Carlo results (Figure 8) provide additional information on the substantial reduction of high volume values for S.Giustina for long-term climate scenarios.~~

In general, the results suggest exacerbated risks to reservoir operation due to persistent stored volume and turbined outflow reductions in late ~~with acute water reductions in~~ spring and summer, autumn, and early winter ~~, but~~ that can potentially lead to ~~also~~ chronic ~~reductions~~ consequences lasting more than one hydrological year and hence ~~lasting throughout autumn and part of winter,~~ threatening water supply security, hydropower production, and ecosystem services in the valley. ~~Results should be considered in future plans to change S.Giustina management practices to reduce climate change impacts on reservoir operations. The findings presented reinforce the Alpine 'water tower' region's vulnerability to supply water and ensure its use for power production.~~

~~5~~4.1 Limitations of the study

The applied SDM is mainly considering outputs from the GeoTransf applications integrating the COSMO-CLM climate projections. However, several assumptions and limitation in this study are noted.

Accounting for the GeoTransf application means relying on a very accurate water ~~evaluation~~ streamflow within the catchment (Bellin et al., 2016), but also considering one climate model (i.e. COSMO-CLM) for future projections. A wider range of inflow values driven by a set of climate models could provide a larger set of results that can be used for further stochastic analysis of turbined water and stored volume. Nevertheless, the climate ~~This~~ model has been demonstrated to well represent conditions in mountain regions (Montesarchio et al., 2013) and differently from other climate models depicts general conditions of decreased precipitation over the catchment (Table 4~~Table 3~~). Hence it provides conservative information on possible impacts on streamflow and volume management. The results from the GeoTransf application assumed a conservative condition of upstream water use set at the maximum licensed withdrawals values. This information was kept unchanged for future scenarios, although possible variations in the future (e.g. from agricultural and touristic uses) may affect river water flows.

Moreover, the presented study considered precipitation, water flow and volume trends over a 30-year period considering their monthly average values, important for long-term large reservoir management. For this reason, ~~, focusing on long-term~~

~~variations, but potentially missing more intense (i.e. short duration)~~conditions of high volume with a very short duration might have been potentially underrepresented. ~~precipitation episodes.~~

~~As reported in section 3.4, the available data on the reservoir volume was limited, hence affecting the model predicting performance. To compensate for these limitations, more advanced validation techniques were investigated and employed (i.e. forward time-window approach), contributing to a better understanding of the model error and performance.~~

The statistical models are a quick and effective tool to replicate past observations of water volume and turbined water outflows. Applying such a regression to future conditions of predictors, reservoir management in terms of turbined outflow as well as minimum ecological flows was assumed to be stationary over time. Nevertheless, such a constraint is justified by the high uncertainty associated to future changes in hydropower production patterns affected by societal conditions (e.g. energy price fluctuations~~;)~~ ~~(~~Gaudard et al., 2014; Ranzani et al., 2018). Moreover, the minimum ecological flow was always set to the values established by law, although critical conditions in water availability (e.g. streamflow) may lead to extraordinary changes in minimum flow which can affect the stored volume as well as the turbined outflow.

Finally, the selected models considered ~~only a~~ few tested and selected variables. Although other variables play important roles within the management of the reservoir at different temporal resolution (e.g. hourly energy market price), the simulation on monthly aggregated values ~~monthly simulation step allowed~~ supported the objective of analysing long-term variations of stored volume for the large S.Giustina reservoir~~to represent variation over a long term perspective~~.

5~~6~~ Conclusions

The S.Giustina reservoir plays a crucial role in buffering water variations in the Noce catchment and downstream. Due to its size, type and position it is strategic for hydropower regulation and hydrologically disconnecting upstream with downstream river flow.

The modelling chain from ~~combination of outputs from~~ climate change projections to the ~~and~~ hydrological model~~s~~ water flow output and their use into the ~~with a~~ stochastic SDM ~~proved~~ provided to be a quick and effective tool to explore trends conditions of the S.Giustina reservoir volume and turbined outflows~~looking at their critical conditions~~.

~~In particular,~~ R~~r~~esults of both stored volume and turbined outflow suggest that even under RCP4.5 in the short-term scenario reductions in terms of volume and turbined outflow will be severe with monthly average reductions for outflow and volume values respectively from April and May onwards and persisting throughout the year. This period of negative variations should be considered for the adoption of adaptation strategies focusing on water demand reduction, while considering months of expected increases in water availability as preparation periods, implementing strategies of earlier reservoir water accumulation while preparing for persistent conditions of lower availability compared to the baseline period. Such a strategy could prevent downstream conditions of water shortages during summer, autumn and part of winter, while also preparing for reductions in turbined water for hydropower especially during summer and winter months of high electricity peak loads. Adaptation strategies should consider the results on generalized future conditions with increase in frequency of months, maximum number of consecutive months and relative severity for all scenarios of low volume below 10^{th} and 20^{th} percentiles. Consistently with these projections, frequency, duration and severity metrics for high volume events below 80^{th} and 90^{th} percentiles are expected to decrease. These results call for a~~of acute reductions on water stored and turbined outflows in spring and summer call for adaptation strategies of earlier reservoir water accumulation during autumn and winter, months of expected increases in water availability. Such a strategy could prevent downstream conditions of water shortages during summer, while also preparing for reductions in hydroelectric production especially during summer months of high electricity peak loads. A~~daptation strategies of coordinated actions across those socio-economic sectors relying on abundant water demands (e.g. for agriculture) to face more frequent and longer periods of higher reduction of stored volume compared to the past. ~~should consider the chronic effects of volume and outflow reductions during autumn and winter, causing long periods of negative variations and hence calling for reductions in electricity and downstream water demands (e.g. for agricultural and domestic uses).~~

Future model expansions will include water demand from multiple human activities (e.g. agriculture and domestic) and their effects on water availability reduction from upstream to downstream. By doing so, SDM models can support the understanding of criticalities connected to unsustainable water demands and anticipate critical conditions, to inform dam managers and local authorities on the timing and importance of climate change adaptation strategies. Moreover, the use of open codes and libraries for the assessment of variables interactions through statistical models make SDM transferrable to other cases at interregional / transnational scale in combination with available water flows datasets and open hydrological models (e.g. Copernicus, LISFLOOD model).

Finally, this analysis sheds light on the need to consider future changes in water availability and their consequences on already existing human activities relying on abundance water resources, and hence unprepared to quickly adapt to future climate impacts. Results should be considered in future plans to change S.Giustina management practices to reduce climate change impacts on reservoir operations. The findings presented reinforce the Alpine 'water tower' region's vulnerability to supply water and ensure its use for power production. This is the first step for more comprehensive water scarcity assessments in order to provide policy-makers with information in line with the European Water Framework Directive on potential adaptation strategies to gain systemic leverage effects ~~in line with the European Water Framework Directive~~ on sustainable water management and climate change adaptation in the Alps (Alpine convention, 2013; European Commission, 2018, 2021).

Code availability

The source code for data processing and analysis developed in this study is freely available at https://github.com/Sterzi/SGiustina_future_SDM.

Author contribution

Stefano Terzi: conceptualization, data curation, formal analysis, methodology, software, validation, visualization, writing – original draft preparation. **Janez Susnik**: conceptualization, formal analysis, methodology, writing – review & editing; **Stefan Schneiderbauer**: visualization, supervision, writing – review & editing; **Silvia Torresan**: visualization, supervision, writing – review & editing, **Andrea Critto**: supervision, writing – review & editing.

Competing interests

The authors declare that they have no conflict of interest.

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