Università
Ca'Foscari
Venezia

Corso di Dottorato di ricerca
in Scienze Ambientali
ciclo 32

Tesi di Ricerca

Multi-risk assessment within the context of climate change in mountain regions

SSD: CHIM/12

Coordinatore del Dottorato
ch. prof. Enrico Bertuzzo

Supervisore
ch. prof. Andrea Critto

Supervisori esterni
Dr. Silvia Torresan
Dr. Stefan Schneiderbauer

Dottorando
Stefano Terzi
Matricola
956301

Abstract

Mountain regions are facing multiple impacts due to climate change and anthropogenic activities. While shifts in precipitation and temperature are affecting the available water, current water demand for economic activities still rely on large quantity of water making mountain regions particularly susceptible to water scarcity.

These conditions call for innovative methodologies accounting for such complex interplays involved in multi-risk processes and describing climate-related water issues so to understand and adapt to future climate change impacts.

For these reasons, a literature review considered five innovative modelling approaches (i.e. Bayesian networks, agent-based models, system dynamic models, event and fault trees, and hybrid models), exploring their advantages and limitations in multi-risk assessments and providing a roadmap to enhance methodological and technical implementations for climate change adaptation.

Among these methodologies, System Dynamics Modelling (SDM) was selected and applied to explore multiple interactions and feedback loops associated to hydrological processes and human demands in the Alpine Noce river catchment in the Province of Trento (Italy).

The first application explored the vulnerability of the S.Giustina dam reservoir in the Noce catchment in terms of water stored and turbined considering conditions of water availability and demand for future climate change scenarios. By doing so, the aim was to assess the climate-related risk for the hydropower sector considering impacts of different climate change scenarios and of anthropogenic management.

The SDM model was then extended including multiple water demanding sectors of the Noce catchment to evaluate the risks of potential mismatch in future water availability and demand conditions for hydropower production, agricultural production, domestic, and ecological flow.

Results show a precipitation decrease affecting river streamflow with consequences on water stored and turbined in all dam reservoirs of the Noce catchment, especially for long-term climate change scenarios. Moreover, temperature scenarios will increase the amount of water used for agricultural irrigation from upstream to downstream. Nevertheless, decreasing population projections will have a beneficial reduction of water demand from residents, hence partially counterbalancing an increasing demand from the other sectors. Such conditions have relevant effects on the Noce catchment as a whole, considering upstream high water availability areas to downstream high water demand areas.

These results call for the need to prepare to future water availability and water demand conditions in different areas of the Noce catchment. Adaptation strategies should consider a different timely of water storing patterns together with a reduction of consumptive.

Finally, the assessment aimed to identify critical states coming from a systemic perspective of water availability and water demand in three sub-catchment areas discussing possible climate adaptation strategies to inform local decision makers and prepare for future multi-risk conditions of water scarcity.

Table of contents

“I am a short-term pessimist, but a long-term optimist”

Zygmunt Baumann

Introduction

Climate change effects are already visible and leading to severe impacts in vulnerable areas of the world (IPCC, 2018). While the number and intensity of natural hazards is changing, land-use and socio-economic changes are increasing exposure and vulnerability hence exacerbating the overall risk conditions. The interactions among multiple hazardous events, evolving exposure and vulnerability conditions can generate multi-risk processes (Kappes *et al.*, 2012; Gallina *et al.*, 2016; Tilloy *et al.*, 2019). Assessing the dynamics of multi-risk requires unravelling both the bio-physical interactions that can trigger multiple natural hazards through cascading, synergic or antagonistic effects (Gill and Malamud, 2014, 2016; Xu, Meng and Xu, 2014; Kumasaki *et al.*, 2016), and the socio-economic relations exposed to multiple climate hazards that can generate cascading effects on other anthropogenic processes due to their interdependent vulnerabilities (Gill and Malamud, 2017; Zio, 2016; Petit et al., 2015; Rinaldi et al., 2001).

However, current risk assessments often account for a one-hazard perspective or a static representation of vulnerabilities, without considering their interactions and misrepresenting the real multi-risk (Bell and Glade, 2004; Marzocchi *et al.*, 2009, 2012; Kappes *et al.*, 2012; Harrison *et al.*, 2014; Forzieri *et al.*, 2016; Gill and Malamud, 2016; Mehran *et al.*, 2017; Tilloy *et al.*, 2019).

The importance of addressing multi-risk is internationally recognized by the Unites Nations Sendai Framework for Disaster Risk Reduction and the International Panel on Climate Change as necessary for disaster risk reduction (UNISDR, 2015; IPCC, 2018).

This is particularly relevant in mountain regions where climate change is already having significant impacts (UNESCO, 2010; Zebisch *et al.*, 2011). In the European Alps climate change is threatening their role as “water towers” affecting water availability currently used for several activities such as large hydropower plants and intensive agriculture (Majone et al., 2016; Beniston and Stoffel, 2014; Permanent Secretariat of the Alpine Convention, 2013). Moreover, since different human activities rely on the same resource such conditions can potentially propagate impacts across multiple areas and across different sectors (Viviroli and Weingartner, 2004; Mountain Partnership, 2014).

Previous studies mainly focus on specific aspects of water management in mountains (Farinotti *et al.*, 2012; Bellin *et al.*, 2016; Etter *et al.*, 2017; Wever *et al.*, 2017; Huss and Hock, 2018) without adopting an integrated multi-risk perspective.

These conditions call for applications unravelling this complexity, considering such interplays and system behaviours and describing the factors involved in climate-related water issues towards climate adaptation strategies identification.

Starting from a better comprehension and representation of multi-risk characteristics, different modelling approaches were selected and reviewed looking at their advantages and limitations in addressing distinctive features of multi-risk assessments with a specific focus on mountain regions.

Among them, System Dynamics Model (SDM) has already been applied in the water-food-energy Nexus research field looking at the interactions of different sectors (Kotir *et al.*, 2016; Ansell and Cayzer, 2018; Sušnik *et al.*, 2018). It represents a suitable approach to investigate the spreading of hazards consequences to environmental and anthropogenic elements at risk and interacting with each other (Simonovic, 2015; Halbe, 2016).

For these reasons, this thesis aims to advance the current perspectives on multi-risk assessments developing and implementing a SDM for the Noce catchment (Province of Trento, Italy) to investigate how climate- and human-induced changes in water availability and demand can lead to mismatch between water availability and demand, hence leading to multiple impacts.

The SDM model was initially tailored to replicate the S.Giustina dam reservoir assessing the climate-related risk for the hydropower sector considering impacts of different climate change scenarios and of anthropogenic management. The SDM was then extended to account for multiple water demanding sectors in different areas of the catchment. In particular, hydropower, agriculture, domestic and ecological water demand were evaluated in three sub-areas of the Noce catchment, selected according to their morphological features. By doing so it was possible to evaluate the risks affecting multiple interrelated sectors considering potential mismatch in water availability and demand from high water availability upstream areas to high water demand downstream areas.

The SDM application considered climate change RCP4.5 and 8.5 short and long-term simulating future conditions of water availability in terms of volume stored in different reservoirs and river streamflow. Moreover, water demand was replicated considering the hydropower needs in terms of water turbined, agricultural need in terms of water for irrigation, domestic demand for inhabitants and tourism presences, and finally ecological flow demand to sustain the existing mountain Noce river ecosystems.

Final outcomes explored potential unbalanced conditions of water use in the three sub-catchment areas looking at their future conditions that can potentially lead to water scarcity with multiple effects on different economic activities. In particular, results show a precipitation decrease affecting river streamflow with consequences on water stored and turbined in all dam reservoirs of the Noce catchment, especially for long-term climate change scenarios. Moreover, temperature scenarios will increase the amount of water used for agricultural irrigation from upstream to downstream. Nevertheless, decreasing population projections will have a beneficial reduction of water demand from residents, hence partially counterbalancing an increasing demand from the other sectors. Such conditions have relevant effects on the Noce catchment as a whole, considering upstream high water availability areas to downstream high water demand areas.

These results can foster the discussion at local level supporting dam managers and decision-makers to implement European policies to make our water management systems more resilient through climate adaptation strategies at regional and local level (European Parliament & Council, 2000; Alpine convention, 2013; European Commission, 2013).

Scope and objectives

This thesis aims to advance the current knowledge on multi-risk assessments adopting a systems thinking perspective. This perspective aims to account for dynamical interactions among variables involved in risk processes for the assessment of multi-risk conditions. In particular, the water-energy-food Nexus perspective was here transferred to unravel complex interplays characterizing multi-risk processes towards a more comprehensive assessment of risk.

The thesis structure is based on three research papers exploring multi-risk processes and the use of an integrated System Dynamics Modelling approach to address climate and anthropogenic impacts on water availability and demand. All the papers are connected together to address multi-risk assessments within the climate change context in mountain regions.

Moreover, each paper is characterised by specific research questions defining the goal and boundaries of the study. For each research question, different sub-questions were identified to better characterize the research objectives.

The first paper investigated the current challenges related to multi-risk assessments exploring the current definitions and proposing an innovative framework that integrate multiple relations among the main components of the risk equation. Starting from such a definition, a literature review on different methodological applications (i.e. Bayesian networks, agent-based modelling, System Dynamics, event and fault trees and hybrid model) was implemented addressing multi-risk assessments with a specific focus on mountain regions. This explorative study aimed to clarify what a multi-risk assessment means and what are the available tools to address it.

Research questions paper 1:

- *What are the essential characteristics of a multi-risk process?*
- *How can multi-risk processes be modelled in order to represent their essential characteristics (e.g. spatial, temporal variation and uncertainty)?*
- *What are the available and innovative methodologies to support multi-risk assessments for climate change adaptation?*

Within these research questions, we aimed to fulfil two main objectives:

Objectives paper 1:

- *To explore and better characterise multi-risk assessments definition*
- *To identify and analyse advantages and drawbacks of 5 available methodologies for multi-risk assessments within the climate change context in mountain regions*

Starting from the paper 1 findings, we identified SDM as a suitable methodology providing innovative insights on dynamic variable interactions and feedback loops. This approach has already been applied by the water-food-energy Nexus community and we transferred and extended such perspective to the multi-risk assessments field. A System Dynamics Model was then applied to characterise the vulnerability of the S.Giustina mountain dam reservoir in the Italian Alps looking at how climate change effects and hydropower operations may lead to potential water scarcity issues due to a high water demand for hydropower production. This risk assessment application involved a case with only one sector (i.e. hydropower demand) exposed to future climate change projections. In particular, a System Dynamics model was coupled with probabilistic assessments of variables dynamic interactions providing useful insights on dam functioning and the water volume stored.

Research question paper 2:

- *How well System Dynamics Modelling can account for dynamical interactions of climate change and water demand to assess long-term risk of water scarcity for a mountain dam reservoir in the Noce catchment (province of Trento, Italy)?*

Considering these research questions, we aimed to fulfil two main objectives:

Objectives paper 2:

- *To explore the use of System Dynamics Modelling for a risk assessment considering its potentialities and limitations*
- *To integrate statistical assessments within a SDM considering multiple sources of data for climate risk assessments*

The third study transferred and expanded the knowledge and findings gained in the two previous applications into an integrated multi-risk assessment evaluating water scarcity effects on different economic sectors (i.e. hydropower, agricultural, domestic and ecological). A systemic perspective was hence considered encompassing interactions of climate change and anthropogenic activities and their effects on both water availability and demand for future climate scenarios. This is of particular importance for mountain regions where climate change is causing severe impacts on glacier melting and snowfall reduction, while anthropogenic activities and their demand is growing. Moreover, the high connectivity between upstream and downstream areas plays a significant role for a sustainable water resource management. Multi-risk conditions can propagate spatially due to the lack of an integrated management triggering impacts from upstream to downstream areas. For these reasons, the

SDM developed in the second paper was further expanded including a cross-sectoral and spatially explicit assessment of bio-physical and socio-economic interactions involved in unsustainable conditions of water use within the Noce river catchment. This methodological application represents an initial step to work at intra-regional level addressing water scarcity and drought events intensification providing useful information for policy-makers.

Research question 3:

- *How well can System Dynamics Modelling integrate biophysical and socio-economic dynamic variables interactions to assess potential multiple-risk conditions due to water scarcity in the mountain Noce catchment (province of Trento, Italy)?*

Within these research questions, we aimed to fulfil two main objectives:

Objective 3:

- *To develop a cross-sectoral and spatially explicit System Dynamics Model to assess multi-risk conditions*
- *To contribute to improve water management in a mountain case study preparing for future conditions of water scarcity*

Finally, Figure 1 depicts the thesis structure representing the consequentiality of each paper aiming to explore the current challenges of multi-risk assessments within the context of climate change in mountain regions.

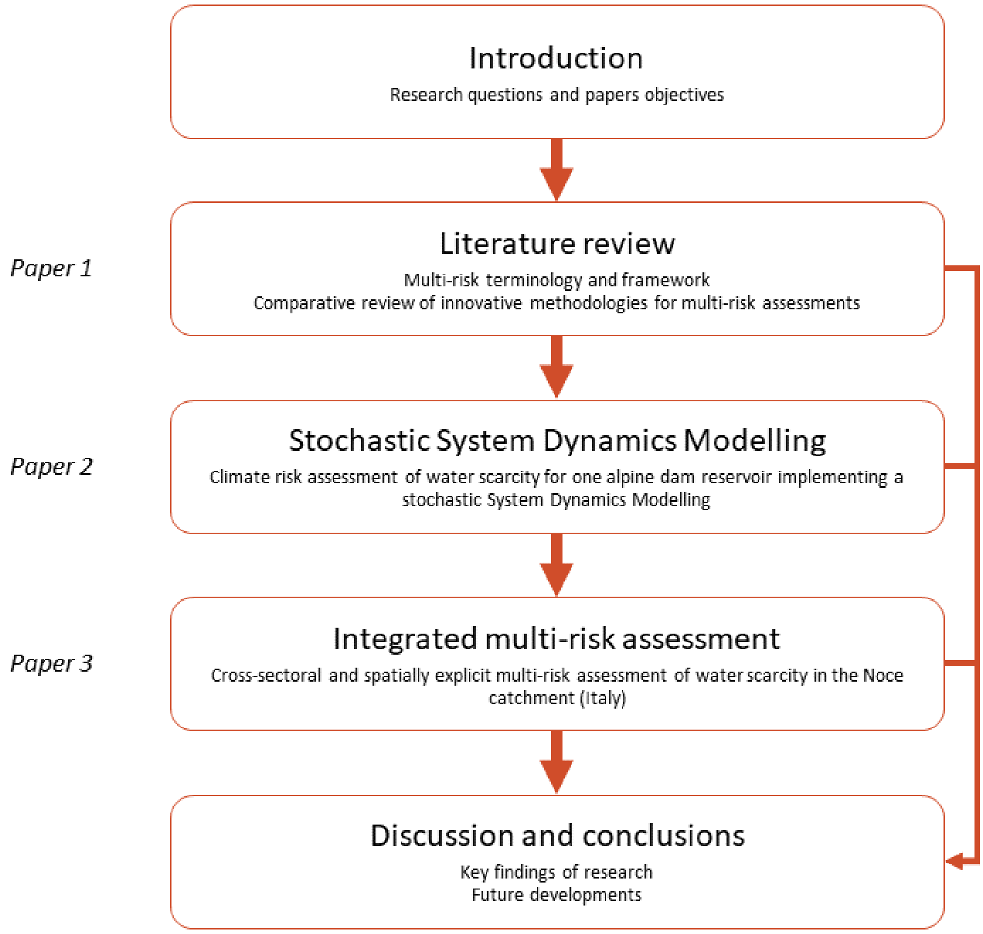

Figure 1 - Thesis structure

References

Alpine convention (2013) ‘Guidelines for Climate Change Adaptation at the local level in the Alps’, p. 44. Available at: http://www.alpconv.org/en/publications/alpine/Documents/guidelines_for_climate_change_EN.pdf

Ansell, T. and Cayzer, S. (2018) ‘Limits to growth redux: A system dynamics model for assessing energy and climate change constraints to global growth’, Universe. Elsevier Ltd, 120(May), pp. 514–525. doi: 10.1016/j.enpol.2018.05.053.

Bell, R. and Glade, T. (2004) ‘Multi-hazard Analysis in Natural Risk Assessments’, Risk Analysis IV, 77, p. 10. Available at: https://www.witpress.com/elibrary/wit-transactions-on-ecology-and-the-environment/77/14298.

Bellin, A. et al. (2016) ‘A continuous coupled hydrological and water resources management model’, Environmental Modelling and Software. Elsevier Ltd, 75, pp. 176–192. doi: 10.1016/j.envsoft.2015.10.013.

Beniston, M. and Stoffel, M. (2014) ‘Assessing the impacts of climatic change on mountain water resources’, Science of the Total Environment. Elsevier B.V., 493, pp. 1129–1137. doi: 10.1016/j.scitotenv.2013.11.122.

Convention, A. (2009) ‘Report on the State of the Alps Alpine Signals - Special Edition 2’, Water and water management issues, 2, p. 235.

Etter, S. et al. (2017) ‘Climate change impacts on future snow, ice and rain runoff in a Swiss mountain catchment using multi-dataset calibration’, Journal of Hydrology: Regional Studies. Elsevier, 13(February), pp. 222–239. doi: 10.1016/j.ejrh.2017.08.005.

European Commission (2013) ‘Adapting infrastructure to climate change: An EU Strategy on adaptation to climate change’, pp. 1–37. doi: COM(2018) 738 final.

European Parliament & Council (2000) ‘DIRECTIVE 2000/60/EC’, Analytical Proceedings, 21(6), p. 196. doi: 10.1039/AP9842100196.

Farinotti, D. et al. (2012) ‘Runoff evolution in the Swiss Alps: Projections for selected high-alpine catchments based on ENSEMBLES scenarios’, Hydrological Processes, 26(13), pp. 1909–1924. doi: 10.1002/hyp.8276.

Forzieri, G. et al. (2016) ‘Multi-hazard assessment in Europe under climate change’, Climatic Change. Climatic Change, 137(1–2), pp. 105–119. doi: 10.1007/s10584-016-1661-x.

Gallina, V. et al. (2016) ‘A review of multi-risk methodologies for natural hazards: Consequences and challenges for a climate change impact assessment’, Journal of environmental management. Elsevier, 168, pp. 123–132.

Gill, J. C. and Malamud, B. D. (2014) ‘Reviewing and visualizing the interactions of natural hazards’, Reviews of Geophysics, 52(4), pp. 680–722. doi: 10.1002/2013RG000445.

Gill, J. C. and Malamud, B. D. (2016) ‘Hazard interactions and interaction networks (cascades) within multi-hazard methodologies’, Earth System Dynamics, 7(3), pp. 659–679. doi: 10.5194/esd-7-659-2016.

Gill, J. C. and Malamud, B. D. (2017) ‘Anthropogenic processes, natural hazards, and interactions in a multi-hazard framework’, Earth-Science Reviews. The Authors, 166, pp. 246–269. doi: 10.1016/j.earscirev.2017.01.002.

Halbe, J. (2016) ‘Governance of Transformations towards Sustainable Water, Food and Energy Supply Systems Facilitating Sustainability Innovations through Multi-Level Learning Processes’, p. 194. Available at: https://repositorium.uni-osnabrueck.de/handle/urn:nbn:de:gbv:700-2017022715609.

Harrison, P. A. et al. (2014) ‘Cross-sectoral impacts of climate change and socio-economic change for multiple, European land- and water-based sectors’, Climatic Change, 128(3–4), pp. 279–292. doi: 10.1007/s10584-014-1239-4.

Huss, M. and Hock, R. (2018) ‘Global-scale hydrological response to future glacier mass loss’, Nature Climate Change. Springer US, 8(2), pp. 135–140. doi: 10.1038/s41558-017-0049-x.

IPCC (2018) 'Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change',.

Kappes, M. S. et al. (2012) 'Challenges of analyzing multi-hazard risk: A review', Natural Hazards, pp. 1925–1958. doi: 10.1007/s11069-012-0294-2.

Kotir, J. H. et al. (2016) 'A system dynamics simulation model for sustainable water resources management and agricultural development in the Volta River Basin, Ghana', Science of the Total Environment. Elsevier B.V., 573, pp. 444–457. doi: 10.1016/j.scitotenv.2016.08.081.

Kumasaki, M. et al. (2016) 'Anatomy of cascading natural disasters in Japan: main modes and linkages', Natural Hazards. Springer Netherlands, 80(3), pp. 1425–1441. doi: 10.1007/s11069-015-2028-8.

Majone, B. et al. (2016) 'Impact of climate change and water use policies on hydropower potential in the south-eastern Alpine region', Science of the Total Environment. Elsevier B.V., 543, pp. 965–980. doi: 10.1016/j.scitotenv.2015.05.009.

Marzocchi, W. et al. (2009) Principles of multi-risk assessment, Environment. Available at: http://cordis.europa.eu/documents/documentlibrary/106097581EN6.pdf.

Marzocchi, W. et al. (2012) 'Basic principles of multi-risk assessment: A case study in Italy', Natural Hazards, 62(2), pp. 551–573. doi: 10.1007/s11069-012-0092-x.

Mehran, A. et al. (2017) 'Compounding Impacts of Human-Induced Water Stress and Climate Change on Water Availability', Scientific Reports. Springer US, 7(1), pp.1–9. doi: 10.1038/s41598-017-06765-0.

Mountain Partnership (2014) 'Why mountains matter for energy: A Call for Action on the Sustainable Development Goals (SDGs)', p. 4. Available at: http://www.mountainpartnership.org/publications/publication-detail/fr/c/218384/.

Petit, F. et al. (2015) 'Analysis of Critical Infrastructure Dependencies and Interdependencies'.

Rinaldi, B. S. M., Peerenboom, J. P. and Kelly, T. K. (2001) 'Identifying, Understanding, and Analyzing critical infrastructure interdependencies', pp. 11–25. doi: 10.1109/37.969131.

Simonovic, S. P. (2015) 'Systems approach to management of disasters: methods and applications', Journal of Integrated Disaster Risk Management, 5(2), pp. 70–83. doi: 10.5595/idrim.2015.0099.

Sušnik, J. et al. (2018) 'Multi-stakeholder development of a serious game to explore the water-energy-food-land-climate nexus: The SIM4NEXUS approach', Water (Switzerland), 10(2). doi: 10.3390/w10020139.

Tilloy, A. et al. (2019) 'A review of quantification methodologies for multi-hazard interrelationships', Earth-Science Reviews. Elsevier, 196(June), p. 102881. doi: 10.1016/j.earscirev.2019.102881.

UNESCO (2010) 'Climate Change Impacts on Mountain Regions of the World'.

UNISDR (2015) Sendai Framework for Disaster Risk Reduction 2015 - 2030.

Viviroli, D. and Weingartner, R. (2004) 'The hydrological significance of mountains: from regional to global scale', Hydrology and Earth System Sciences, 8(6), pp. 1017–1030. doi: 10.5194/hess-8-1017-2004.

Wever, N. et al. (2017) 'Simulating the influence of snow surface processes on soil moisture dynamics and streamflow generation in an alpine catchment', Hydrology and Earth System Sciences, 21(8), pp. 4053–4071. doi: 10.5194/hess-21-4053-2017.

Xu, L., Meng, X. and Xu, X. (2014) 'Natural hazard chain research in China: A review', Natural Hazards, 70(2), pp. 1631–1659. doi: 10.1007/s11069-013-0881-x.

Zebisch, M. et al. (2011) Assessment of vulnerability to natural hazards and climate change in mountain environments – examples from the Alps, Measuring vulnerability to natural hazards: Towards disaster resilient societies (2 nd edn) United Nations University Press.

Zio, E. (2016) 'Challenges in the vulnerability and risk analysis of critical infrastructures', Reliability Engineering and System Safety. Elsevier, 152, pp. 137–150. doi: 10.1016/j.ress.2016.02.009.

Paper 1 - Multi-risk assessment in mountain regions: a review of modelling approaches for climate change adaptation

Introduction

Future scenarios of climate change show an increase of frequency and magnitude of natural hazards that will affect our society and the environment (IPCC, 2014a, 2014b; European Environmental Agency, 2017). The need to prepare and adapt to multiple climate events is internationally recognised as a fundamental step towards the development of resilient societies (UNISDR, 2015). Assessing the dynamics of multi-risk processes and climate change requires unravelling the magnitude and frequency of different hazardous events over space and time, and exploring how these extremes interact with dynamic social and economic fabrics and processes.

Various possible combinations generating climate risk are characterised by non-linear interactions and feedback loops among three crucial components: (i) climate hazards (e.g. heat waves, droughts, floods, landslides, avalanches), (ii) territorial elements exposed to risk (e.g. built-up areas, critical infrastructures, agriculture, tourism) and (iii) cross-sectoral and dynamic vulnerabilities of the exposed elements (e.g. people mobility, education levels and technology diffusion) (Gallina et al., 2016; Kappes et al., 2012; Carpignano et al., 2009). In particular, the interactions among environmental variables constitute the mechanism triggering potential cascading, synergic or antagonistic effects of different natural hazards (Gill and Malamud, 2014, 2016; Xu, Meng and Xu, 2014; Kumasaki *et al.*, 2016). In addition, socio-economic activities can be exposed to multiple climate hazards or generate cascading effects on others anthropogenic processes due to their characteristics of high interdependent vulnerability (Gill and Malamud, 2017; Zio, 2016; Petit et al., 2015; Rinaldi et al., 2001).

Mountain regions represent significant vulnerable areas with specialized natural and human systems (e.g. alpine species, valley population density, tourism-based economy) exposed and susceptible to climate change (Zebisch *et al.*, 2011; United Nations, 2012). Modifications in snow precipitation and glaciers melting trigger consequences in the management of water used for hydropower production and for agricultural irrigation, calling for climate change adaptation measures to avoid future cascading impacts on different sectors (Beniston and Stoffel, 2014; Fuhrer et al., 2014; Balbi, 2012).

Currently, holistic assessments of future climate change impacts in mountain environments are still in their infant phase. Pioneering multi-layer single hazard/risk analysis integrating cause-effect matrices, vulnerability indices and fragility curves have been recently used as first step toward multi-risk assessment (Forzieri et al., 2016; Kappes et al., 2012; Marzocchi et al., 2012, 2009; Delmonaco et al., 2006; Bell and Glade, 2004;).

However, they show some limits in modeling the dynamic interdependencies and cascading effects among (and within) the risk components and can result in misleading assessments of potential impacts.

Therefore, there is the need to identify cutting-edge modeling approaches and tools able to: consider correlations among multiple (conjoint or cascading) hazard events; evaluate the multiple risk pathways for natural and human systems under current or future climate and anthropogenic pressures (e.g. land use changes).

Bayesian networks, agent-based models, system dynamic models, event and fault trees, and hybrid models have been recognised as suitable methodologies in addressing a wide range of complex environmental problems. These methodologies have been used in integrated environmental modelling through the combination of qualitative and quantitative information (Mallampalli et al., 2016; Hamilton et al., 2015; Kelly et al., 2013; Jakeman et al., 2006), in climate change impact studies through uncertainty analysis (UK Climate Impacts Programme, 2003; Maani, 2013) and in the critical infrastructures field through the analysis of interdependencies and cascading effects (Ouyang, 2014; Satumtira and Duenas-Osorio; 2010 Eusgeld et al., 2008).

However, previous applications of these methodologies addressing multi-risk assessments, climate and future changes for vulnerable regions are limited in number (Sperotto et al., 2017; Gallina et al., 2016; Nadim et al., 2013; Environment Agency, 2007).

This study profiles five broad categories of methodologies analysing their contributions and limitations in addressing critical aspects of multi-risk modelling within the context of climate change. We explored their applications for vulnerable environments with a focus on mountain regions distressed by climate change impacts (e.g. temperature increase, precipitation variation) and direct anthropogenic pressures (e.g. socio-economic development, population growth, land-use change).

After introducing a conceptual framework showing the complexity and challenges of multi-risk components in mountain regions (Section 1); the paper discusses the main methodological and technical features of multi-risk assessments (Section 2) and finds out benefits and limitations of five distinguished modelling approaches (Bayesian networks, agent-based models, system dynamic models, event and fault trees, and hybrid models) for climate change multi-risk assessment in mountains (Section 3). Finally, Section 4 synthetizes the main findings of the review highlighting the future challenges to represent climate change effects on multi-risk processes for an effective implementation of climate adaptation strategies.

1. Multi-risk and climate change in mountain regions

At an international level, the fifth Assessment Report (AR5) of the IPCC Working Group II (WGII) has defined the key components that lead to climate-risk events: hazard, exposure and vulnerability. While climate change exacerbates the development of hazards, the number of elements exposed and their degree of vulnerability are affected by socioeconomic processes (Figure 1).

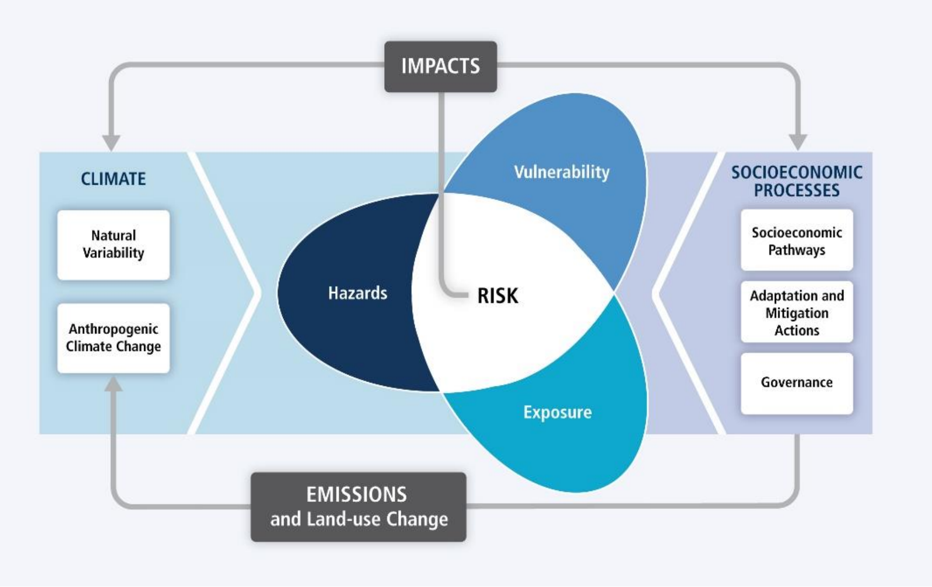

Figure 1 - IPCC AR5 components leading to risk of climate related impacts (IPCC, 2014a)

Even if the IPCC diagram provides a general conceptual basis for climate risk assessment, it does not represent the multi-faceted relationships typical of multi-risk processes (e.g. chain of impacts and feedback loops) (Zscheischler *et al.*, 2018). As recently endorsed by the United Nations Sendai Framework (UNISDR, 2015), it is important to integrate the concepts of multi-hazard and multi-sectoral assessments to strengthen risk reduction practices. According to recent literature (Kappes *et al.*, 2012; Gallina *et al.*, 2016) the adoption of a multi-risk perspective requires the consideration of a specific glossary including new concepts such as multi-hazard, multi-vulnerability and multi-hazard risk. In particular, as explained in Gallina et al. (2016), it is necessary to expand the traditional risk components (hazard, exposure and vulnerability) into multi-hazard, exposure and multi-vulnerability dimensions in order to represent the complex multi-risk interactions.

Here we show the application of the multi-risk paradigm in climate change impact and adaptation assessments, with an illustrative example of a conceptual framework for mountain regions (Figure). As discussed in the following sections, within the figure is possible to identify the variables to be analysed for each multi-risk component and their interactions (e.g. floods triggering erosion and landslides). However, other important features of multi-risk assessments, such as feedback loops and cross-components relations (e.g. the double effects of urban-land regulations on both the number of element exposed and the hydrological conditions linked to hazards development), are still difficult to be represented in a diagram, and require further level of analyses through innovative modelling approaches.

1.1. Mountain multi-hazard

Multi-hazard refers to the different interacting hazardous events that can lead to greater impact than the sum of the single hazard effects. The nature and combination of these interactions (e.g. cascade events, increase/decrease of probability and spatio-temporal coincidence) has already been analysed by different authors (Gill and Malamud, 2014, 2016; Xu, Meng and Xu, 2014; Kumasaki *et al.*, 2016; Mignan, Scolobig and Sauron, 2016). However, this framework focus on potential cascading effects in mountain environments, therefore shifting the attention from a multi-layer single hazard approach to a multi-risk perspective. Blue boxes outline hazard factors and biophysical processes that affect hydrogeological extreme events (e.g. landslides, floods, avalanches). Although spatio-temporal dynamics are not represented in the description of risk processes, both interactions and feedback loops show the high connectivity of multiple consecutive events, for example the landslide-flood cascade. In addition, climate change and socio-economic processes act as external drivers on the biophysical multi-hazard processes affecting both their probability of occurrence and magnitude, as also shown in the IPCC AR5 diagram.

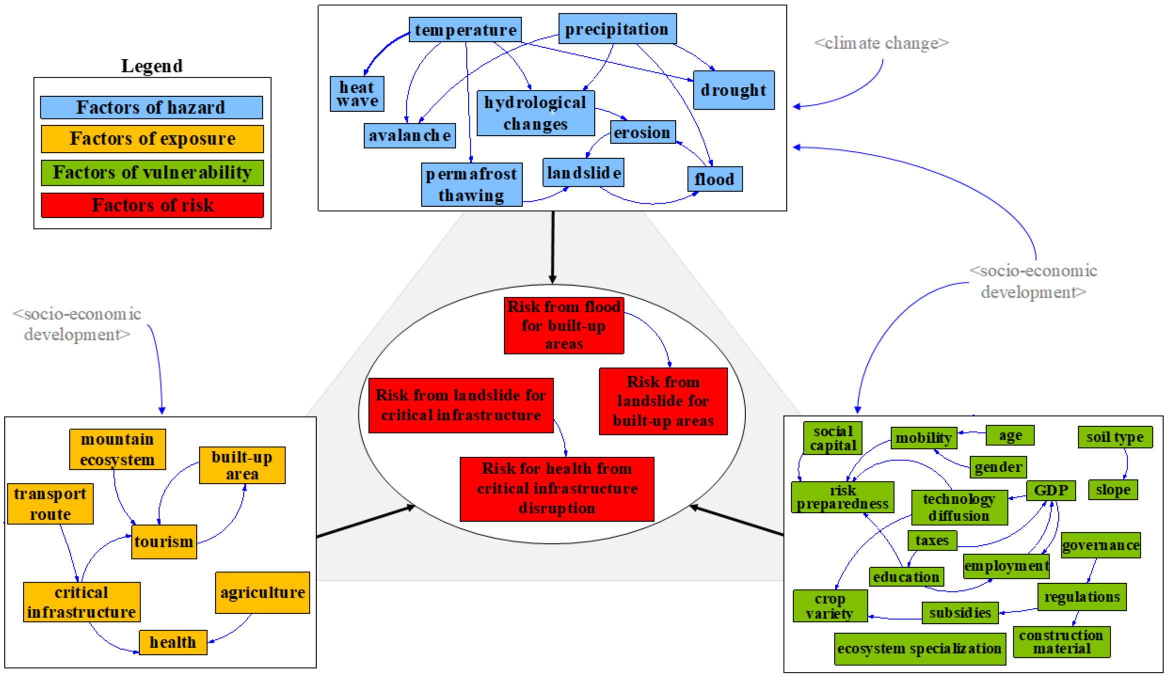

Figure 2 - Conceptual framework for mountain regions expanding the risk components into multi-hazard, exposure, multi-vulnerability and multi-risk.

1.2. Exposure and multi-vulnerability

IPCC (2014a) defined exposure as “the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected”. Moreover, the IPCC also defines vulnerability as “the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt”.

To extend these concepts towards multi-risk assessments it is important to refer to a multi-vulnerability perspective as the ensemble of interconnected and dynamic vulnerabilities among different exposed elements (Jurgilevich et al., 2017;Connelly et al., 2015).

Mountain ecosystems, built-up areas, transport route, tourism, critical infrastructures, agriculture and health are possible exposed macro-categories represented in orange boxes, while factors of sensitivity, coping and adaptive capacity are reported in green boxes (e.g. age, technology diffusion, ecosystem specialization), in the multi-vulnerability component. Blue arrows highlight the presence of interdependencies on different exposed elements, such as the increase of tourism fluxes sustaining the creation of new built-up areas, or the connection between a transportation route and a critical infrastructure (e.g. a hospital). Dependencies are also shown within the multi-vulnerability box reporting connections involved both in the susceptibility variables (e.g. age→mobility→risk preparedness) and in the coping or adaptive capacity (e.g. governance→regulations→subsidies→crop variety). Moreover, exposure and multi-vulnerability are strictly related. Critical infrastructures represent a clear example of these relations, providing services to other sectors (e.g. tourism and health) and having consequences on the vulnerability of other elements if affected (e.g. mountain road interruption due to a landslide can increase health vulnerability for elders). Finally, the various combinations of vulnerability factors and exposed elements in the multi-risk issues call for a joint analysis of these two components integrating competences and information coming from different fields (i.e. social, economic, and environmental).

1.3. Multi-risk

The comprehension of the multi-risk concept is based on the multi-hazard and multi-vulnerability pillars (Gallina *et al.*, 2016). In particular, the multi-hazard refers to all the possible interacting hazards that can affect the same elements exposed, while the multi-vulnerability considers dynamic and connected vulnerabilities of different elements exposed. Therefore, as depicted in Figure , multi-risk stem from the multi-faceted combinations and interactions among multi-hazard, exposure and vulnerability, determining multiple "risk pathways", pictured by the shaded grey triangle in figure.

Considering the complexity of representing all the possible combinations of risk pathways, in Figure we reported few examples illustrating two possible multi-risk configurations due to: (i) dependent vulnerabilities among elements exposed for the left red boxes (i.e. a landslide damaging a critical infrastructure and affecting the access to health services), or due to (ii) the presence of multiple hazards affecting the same elements exposed, for the right boxes (e.g. a flood and a landslide hitting the same built-up areas).

Despite the inclusion of a multi-hazard perspective, Figure still demonstrates limitations in capturing the complexity of multi-risk processes both providing little information on the sequence of risk dependencies and neglecting feedback loops and interactions among risk components.

The number of components, interactions and combinations of risks make the study of climate change issues of particular complexity. Although it is internationally recognised to adopt multi-risk governance principles, it is still not clear how to assess the combination of multiple effects and integrate effective strategies.

A clear analysis of multi-risk processes calls for the application of innovative methods that are able to represent distinctive features of risk such as cross-disciplinary features, spatial and temporal dynamics and possible future scenarios of impacts.

2. Challenges of modelling multi-risk in mountain regions

Once we recognised the components and the complexity of multi-risk processes, two main questions emerged: (i) what are the distinctive features of multi-risk processes? (ii) what are the available tools to address them?

The aim of this section is to identify and describe the methodological and technical distinctive features (i.e. criteria) characterizing a comprehensive multi-risk assessment. Seven criteria were chosen to explore the suitability of each model to address: (i) uncertainty management, (ii) feedback loops, (iii) temporal dynamics, (iv) spatial analysis, (v) cross-sectoral assessment, (vi) stakeholder engagement and (vii) adaptation strategies integration. In addition to these, (viii) data input and (ix) level of complexity provided technical information on models suitability.

2.1. Uncertainty management

Dealing with interactions of natural hazards with society in the context of climate change means handling frequency of occurrence and joint probabilities of multiple impacts (Warren, 2011). Considering that various chains of events can lead to the evaluation of direct and indirect impacts propagation, the uncertainty assessment is challenging but fundamental for the comprehension of future climate impacts.

This criterion was selected to account for the uncertainty surrounding risk modelling in short and long-term: from the uncertainty of occurrence of future natural hazards where there have never been (e.g. water scarcity in mountain regions) to that of socio-economic dynamics influencing the number of exposed elements and their vulnerabilities (e.g. population concentration in flood-prone valley bottoms).

Finally, the integration of uncertainty analysis in a model offers a support for risk modellers and analysts in selecting suitable approaches and fostering informed and transparent decision processes.

2.2. Feedback loops

Natural hazards, socio-economic systems and climate change are characterized by non-linear interactions and feedback loops within and across them (European Environmental Agency, 2017; Dawson, 2015).

The identification of interactions distinctive of mountain environments underpins a comprehensive assessment of the causes, cascading effects and adaptation strategies of risk processes (Gallina et al., 2016; Birkmann et al., 2013).

This criterion was selected to provide information on the reinforcing and balancing characteristics of interactions within and across mountain hydrogeological processes leading to hazard phenomena (e.g. glaciers melting→smaller glaciers creation→increase of glaciers melting). Moreover, it considers socio-economic fabrics looking at potential interactions influencing the vulnerabilities of elements exposed in a risk perspective (e.g. economic subsidies to high water consuming agricultural practices triggering water issues for domestic use).

2.3. Temporal dynamics

One of the challenges posed by multi-risk events is the representation of their dynamics in space and time. For this reason, the concept should incorporate dynamic changes of vulnerability for different categories of exposed elements and connected among each other (Gallina *et al.*, 2016). This concept brings about the necessity of representing evolving interactions of both socio-economic and biophysical dynamics which contribute to the development of risk processes (Fuchs *et al.*, 2013).

This criterion addresses the methodological integration of dynamical processes to describe both slow-onset projections (e.g. permafrost melting, demographic increase) and rapid changes in the risk assessment chain (e.g. rock-fall preventive evacuation). Specific information on the simulation time length and steps adopted are provided for each application in Table 1 of the Supplementary Material.

2.4. Spatial analysis

Spatially explicit risk assessments can help planners and decision-makers to estimate the risks identifying the most exposed areas (Grêt-Regamey and Straub, 2006; Gallina *et al.*, 2016). Characterizing the overlapping hazards, the number and category of elements threatened by multiple events, and their future scenarios can foster the prioritization of adaptation strategies.

In our review, the spatial analysis refers to the integration of remotely sensed data on land use and cover at valley bottoms and on slopes, potential hazard extensions and locations of affected population and infrastructures using geographic information systems. Finally, the use of hotspots indicators provide information on the type of territorial systems exposed to overlapping hazards, connecting spatial data to social and economic fabrics potentially affected.

2.5. Cross-sectoral assessment

The importance of analysing future climate impacts spanning across different sectors has been introduced in Gallina et al. (2016) in order to “systematically estimate the chain from greenhouse gases emissions, climate change scenarios and cascading impacts affecting simultaneously multiple natural systems and socio-economic sectors”. This criterion moves away from the perspective of independent single sectors causing misrepresentation of climate impacts and hence of possible adaptation measures (Harrison *et al.*, 2016).

Here we consider interactions and feedbacks among mountain hydrogeological features and socio-economic characteristics (e.g. water availability-hydropower production-industrial production), exploring if the applications achieve a cross-sectoral assessment and which sectors have been considered (e.g. biophysical, social and economic).

2.6. Stakeholder engagement

The cross-disciplinary nature of climate-risk issues and their consequences on human-environment systems need the integration of experts and stakeholder knowledge (van Aalst, Cannon and Burton, 2008; Döll and Romero-Lankao, 2017). Although a hazards probability assessment is usually performed through expert knowledge and quantitative modelling, a collaborative approach integrating qualitative information from the social and environmental fields can improve the understanding of risk processes and adaptation measures effectiveness (Komendantova *et al.*, 2014; Döll and Romero-Lankao, 2017). For this reason, this criterion considers the engagement of stakeholders for model design, implementation and for communication of results (Table 1). Finally, for each application specific information on the modality of stakeholder involvement is demonstrated according to the use of surveys, workshop, conferences or role games in Table 1 of the Supplementary Material

2.7. Adaptation strategies integration

The final aim of climate-risk studies often involves the identification of effective adaptation strategies robust to future changes in climate and socio-economic conditions (Harrison *et al.*, 2016). Misleading risk assessments can lead to the implementation of maladaptation practices, for example reducing the risk to one hazard can actually increase the risk to another hazard (e.g. adaptation strategy of moving houses from an area exposed to flood to an area exposed to landslide), or ignoring the effects of one hazard on the adaptation strategies again another hazard (e.g. earthquake damaging river levees that collapse during a flooding event (Grünthal *et al.*, 2006)). Hence, multi-risk assessments should evaluate the efficiency of adaptation options and strategies through consideration of cross-sectoral interactions and cascading effects (Birkmann, 2011; Dawson, 2015).

For these reasons, this criterion is here used to explore which studies have assessed climate-risk implementing and evaluating the effectiveness of adaptation strategies both structural (e.g. flood barriers, rock protection nets) and non-structural (e.g. evacuation routes, preventive behaviours). This distinctive feature of multi-risk assessments moves the attention from an impact assessment perspective towards active strategies that can be put in place to make our communities more resilient. For each model description, different types of adaptation strategies have been analysed, highlighting the feasibility of including them into each modelling technique.

2.8. Data required

The choice of a modelling technique often has to consider the quantity and quality of available data. Similarly to Kelly et al. (2013) and Eusgeld et al. (2008), this criterion takes into account the various input data ranging from surveys with stakeholders providing qualitative indicators, to quantitative measurable observed parameters. For this reason, two classes of data have been identified:

- Qualitative: considers data coming from local stakeholder and expert involvement, providing opinions and semi-quantitative values (e.g. ordinal rankings), for example, on hazards extension and vulnerability perception. This class embraces risk perceptions of local population and their evaluation on the need or the effectiveness of territorial risk reduction practices.
- Quantitative: refers to measurable data used as input for the modelling approaches. Quantitative data provides precise information of variables of interest, which can be used for simulations of hazards and vulnerable systems dynamics for risk management purposes. Among others, it included land use data, population census data, time series and future scenarios of temperature and rainfall data.

2.9. Level of complexity

Similarly to Mallampalli et al. (2016) and Ouyang (2014), this indicator provides concise information on the resources (i.e. quantity and quality of input data), time and ease of use needed for the application of modelling approaches. In order to cover the wide differences in complexity, we have characterised three levels: low, medium and high.

- Low complexity accounts for an intuitive graphical representation fostering the integration of stakeholder information within the model. Although this process speeds up the creation of a model and can include local knowledge and needs (e.g. from mountain communities), a low complex model shows limitations in representing spatial and temporal dynamics.
- Medium complexity encompasses the use of either spatial or temporal representation, provides accurate information on a mono-sectoral perspective and usually integrates quantitative data.
- High complexity includes elements of sectoral interdependency, spatial and temporal dynamics of risk. According to the aim of the analysis, different models can be combined working in synergy at macro- and micro- levels with both socio-economic and environmental information towards an integrated risk assessment.

3. Reviewing five modelling approaches for climate multi-risk assessments

The need to explore new approaches to model multi-risk, climate change impacts and vulnerability fostered the analysis of different methodologies (Kappes *et al.*, 2012; Gallina *et al.*, 2016). This review does not claim to cover all the available methodologies for multi-risk assessments, but it profiles Bayesian networks (BNs), agent-based models (ABMs), system dynamic models (SDMs), event and fault trees (EFTs) as well as hybrid models (HMs), since they have been used to address a wide range of complex environmental problems:

- in integrated environmental modelling through the combination of qualitative and quantitative information (Mallampalli et al., 2016;Hamilton et al., 2015; Kelly et al., 2013; Jakeman et al., 2006),

- in climate change impact studies through uncertainty analysis (UK Climate Impacts Programme, 2003; Maani, 2013) and
- in the critical infrastructures field through the analysis of interdependencies and cascading effects (Ouyang, 2014; Satumtira and Duenas-Osorio, 2010; Eusgeld et al., 2008).

Moreover, Sperotto et al. (2017), Gallina et al. (2016), Dawson (2015), Nadim et al. (2013) and Environment Agency (2007) recommended the application of these approaches as a feasible way in addressing complex risk assessments.

For each approach a general description is provided, followed by an overview of applications in multi-risk assessments based on the benchmarks established in the multi-risk distinctive criteria (Section 2). Finally, the main drawbacks and advantages for the application of each modelling approach for multi-risk assessment mountain areas are discussed, providing a roadmap for future research in this field. Whereas studies on mountain risk processes were not found, the review included references to risk assessments in different environments (e.g. urban, coastal, plains) whose considerations can be extended to specific aspects of mountain risk analysis (e.g. water management consequences for lowlands). A qualitative synthesis of limitations and benefits for each methodology can be found in Table 1, while a discussion on each methodology's application according to more specific criteria is demonstrated in Table 1 of the Supplementary Material.

3.1. Bayesian networks

General description

Bayesian networks (BNs) are a tool explicitly dealing with probabilities of occurrence and uncertainty analysis. They represent a set of random variables and their conditional dependencies according to the definition of Directed Acyclic Graph (DAG) (Pearl, 1988). Each node in the graph is associated with a random variable, while the edges between the nodes represent probabilistic dependencies among the corresponding random variables.

Mountain applications

BN studies have been applied to perform decision-making in risk assessments for a wide range of environmental issues (Vogel et al., 2014; Uusitalo, 2007;). However, BNs applications considering climate and multi-risk are still limited, especially in mountain regions. In particular, Song et al. (2012), Balbi et al. (2016) and Grêt-Regamey & Straub (2006) are reported and analysed for their specific focus on mountain risk assessments. Song et al. (2012) considered a potential interaction of two hazards (i.e. earthquake triggering multiple landslides) analysing the most influential parameters involved in landslide generation. Balbi et al. (2016) considered flood risk coupling quantitative and semi-quantitative data for the assessment of potential human impacts and effectiveness of early warning systems. Grêt-Regamey & Straub (2006) performed an avalanche risk assessment at local level in Switzerland considering potential impacts for people, buildings and transportation means.

Multi-risk criteria fulfilment

The graphical representation makes BN suitable for application in decision-support for the management of complex environmental issues through the involvement of experts and stakeholders (Cain, 2001; Aguilera *et al.*, 2011). Although their use in describing relations and uncertainty in multi-risk perspective is not yet largely diffused, Nadim et al. (2013) presented and discussed the advantages of BN applications in addressing multi-risk issues within the European FP7 MATRIX project. Their inherent management of uncertainties make them a suitable tool for studying the occurrence of multiple events and climate change projections characterized by high degree of uncertainty (Sperotto *et al.*, 2017).

Moreover, Liu et al. (2016a), van Verseveld et al. (2015) and Song et al. (2012) represented the interactions of multiple hazards striking on the same exposed territorial systems accounting for potential cascading effects among hazards. In particular, Liu et al. (2016a) and van Verseveld et al. (2015) respectively considered two independent hazards and four simultaneous hazards, while Song et al. (2012) carried out a multi-hazard assessment, focusing on the landslides distribution and assessing the factors influencing earthquake-induced landslides.

Despite the fact that BN are acyclic graphs, and hence cannot represent feedback loops among their nodes, it is possible to overcome this limitation introducing a time step approach. Through this particular technique, also known as “dynamic Bayesian network”, feedback loops are considered as connections at a precise time step (Sperotto *et al.*, 2017). In particular, Molina et al. (2013) implemented a time step approach to evaluate future impacts of climate change scenarios on groundwater resource in SE Spain, assessing potential adaptation strategies in vulnerable aquifer systems. Moreover, Catenacci & Giupponi (2009) reviewed the effectiveness of BN in addressing future scenarios of climate change for adaptation policies. Although some applications explored dynamic simulations, the temporal dynamic integration still represents one of the main weaknesses of BN, bringing an increase of complexity and computation time in case of time steps management (Aguilera *et al.*, 2011).

In addition to temporal dynamics, a multi-risk perspective can make use of spatial analysis and characterisation to support decision makers. However, BN cannot autonomously manage spatial evaluations, but it can be combined with GIS software to deal with the assessment of hydrogeological hazard extension and exposed mountain territorial elements. Within this context, Balbi et al. (2016) described the probability of direct injury for people exposed to flooding events working with a GIS polygons approach. In the same way, Grêt-Regamey & Straub (2006) assessed mountain avalanche risk in Switzerland using a GIS cell-by-cell method. Moreover, in both these publications, risk adaptation strategies (i.e. evacuation and early warning system) have been included in the models, allowing the assessment of risk reduction practices and their uncertainty.

BN can also integrate nodes representing indicators on potential elements exposed and their vulnerability from a socio-economic point of view as implemented by Balbi et al. (2016) and Liu et al. (2016a). These cross-sectoral information contributed to a better description of vulnerability dynamics and a more accurate quantification of the impacts of natural hazard (Liu, Siu and Mitchell, 2016a).

The flexibility to integrate experts’ opinion, indicators and qualitative information with empirical data makes BN suitable for participation of stakeholders and experts in the whole model development process. However, the degree of participation of stakeholders depends on their knowledge and comprehension of the conditional probability concept (Cain, 2001; Aguilera *et al.*, 2011).

Finally, BN can be used to communicate results to experts and assist the decision-making process considering the uncertainty associated to the results (Balbi *et al.*, 2016).

Different studies on natural hazards have also adopted a data-driven learning approach for the creation of BNs starting from historical data and their dependencies (Vogel *et al.*, 2014; van Verseveld *et al.*, 2015).

Although this approach provides a quantitative identification of the relations, it also requires a high amount of input-data. In these cases the complexity can easily increase, especially if integrates a dynamic Bayesian method, where conditional probabilities have to be update at each time step.

Future challenges

BNs applications demonstrated already existing knowledge dealing with mountain environment and multi- risk assessments. The explicit management of uncertainty in this method makes it a suitable tool to study potential interactions of hazards accounting for their probability of occurrence. Applications mainly involved quantitative information, nevertheless Pope & Gimblett (2015) engaged the population for a bottom-up network creation, showing their use in case of poor quantitative data and stakeholder engagement. However, integration of feedback loop, spatial and temporal dynamics represent the future challenge to be explored to enhance the effectiveness of this method for climate change adaptation.

3.2. Agent-based models

General description

Social interactions and dynamics towards the representation of emergent phenomena at macro level (Gilbert and Troitzsch, 2005; Janssen, 2005). Within this field, agent-based models (ABMs) are used for the description of the ensemble dynamics of a system and are composed of three elements: the agents, the environment and time. These elements interact according to natural and social sciences rules (i.e. physical based and behavioural theories) creating an overall dynamic which is not just the aggregation of the individual entities.

Mountain applications

When dealing with complex systems in mountain regions, ABMs were applied to understand the emergent behaviour in case of climate change scenarios. In particular, Balbi et al. (2013) applied an agent-based approach to assess the socio-economic consequences at local level looking at behaviours of winter and summer tourists for different snow cover scenarios in the Alps. Moreover, Girard et al. (2015) considered a mountain environment to understand salamander population distribution and dynamics in case of temperature and water availability variation due to climate change.

Multi-risk criteria fulfilment

Due to their abilities of representing collective social dynamics, ABMs have also been applied for the study of different conditions of social and policies choices during disasters (Eid *et al.*, 2017; Mashhadi Ali, Shafiee and Berglund, 2017). These characteristics make ABMs suitable to trace behavioural features, social interactions and feedback loops among agents subjected to physical pressures from natural hazards in different spatial and social contexts (e.g. mountain regions, social and economic networks) (Sobiech, 2013).

Often a conceptual framework is developed before their implementation. This step is used for a clear definition of the dynamics and to visualize the overall model structure. For this purpose, Acosta et al. (2014) and Balbi et al. (2013) applied the unified modelling language (UML), coming from computer science techniques, but other “class diagrams” are also available (Müller et al., 2013; Grimm et al., 2006). In particular, guidelines and techniques to improve the application of ABMs were introduced by Grimm et al. (2006), Grimm et al. (2010) and Müller et al. (2013) in order to review the standard protocol, to describe agent’s behaviours and define human decision-making rules.

Due to its characteristics of explicit temporal dynamic description, ABMs were applied to look at future scenarios of human-environment interactions. In particular, Mashhadi Ali et al. (2017), Haer et al. (2016) and Girard et al. (2015) integrated future scenarios of climate change representing social dynamics and interactions with the environment for risk assessment purposes. In addition to climate change scenarios, Acosta et al. (2014) and Balbi et al. (2013) also considered future economic changes as main drivers of social emergent behaviours, assessing potential consequences at local level.

Another important characteristic of ABMs is the ability to reproduce movements and changes over a space grid, importing geographic information from GIS software and working on a cell-by-cell basis (Eid et al., 2017; Acosta et al., 2014; Filatova et al., 2013; Dawson et al., 2011). The grid-based maps outputs of the simulations can also integrate vulnerability changes over time, accounting for human behaviours during flood events and providing guidance for decision making strategies as in Dawson et al. (2011) and Haer et al. (2016).

Moreover, structural and non-structural adaptation measures can also be implemented and tested within the model, evaluating their effectiveness in the whole risk assessment chain: from emergency strategies to reduce the number of exposed targets, to preventive actions for hazards extension containment and post-events impact evaluation (Balbi et al., 2013; Sobiech, 2013; Balbi and Giupponi, 2009).

One limitation of ABMs is their lack to explicitly assess uncertainty, which make them a deterministic method and can lead to the “truth-machine” misinterpretation (Balbi and Giupponi, 2009; Sobiech, 2013). However, simulations through Monte Carlo analysis remain a common approach for the management of uncertainties (Mallampalli et al., 2016; Kelly et al., 2013).

On the other side, their high potentiality for stakeholder involvement make them suitable for identification and description of agent’s behaviour rules through the use of workshops and public surveys. In particular, Becu et al. (2016) showed how the application of immersive game theory for stakeholder involvement can foster social learning on coastal risk prevention measures. Although this application focuses on coastal environment, the game approach can be extended to engage inhabitants in mountain environment, collecting risk perception information on gravitational processes, enhancing risk awareness and giving credibility to risk reduction behaviours.

However, dealing with behavioural rules also means to collect and work with a big amount of data related to agents profile characterization and complex social and physical interactions (Balbi *et al.*, 2013; Acosta *et al.*, 2014). In case qualitative data are collected through stakeholder involvement, it has to be translated into a semi-quantitative or quantitative input for the ABMs simulation. For this reason, a trade-off between an extensive characterisation of environment and agents’ profiles, and the complexity of the system under study needs to be considered to overcome a high level of complexity and time required for its implementation.

Future challenges

ABMs demonstrated their capabilities in addressing climate change actions involving interdisciplinary information across environmental, social and economic fields. However, mountain applications are still limited in number although their characteristics make it a promising method for risk assessment integrating micro-level interactions among agents and the environment with explicit spatio-temporal references.

3.3. System dynamic models

General *description*

System dynamic models (SDMs) include a wide group of approaches to represent non-linear behaviour of complex systems on a macro-level. Among these, the “stock-and-flow” approach introduced by Forrester in 1971 to deal with macro analysis of socio-economic processes, it is composed of quantities accumulation (i.e. stock) and quantity changes during time between stocks (i.e. flow). SDMs representation is based on the analysis of the aggregated dynamics of systems components whose systemic behaviour cannot be explained in terms of the sum of the single components (Simonovic, 2015). SDMs have been used to describe dependencies and interactions among different elements of a complex system in order to find the leverage points: parts of the system to act on in order to trigger changes on the system as a whole. By doing so, it is possible to identify the key points of a system and seek for possible measures to change its status.

Mountain applications

None of the applications here considered involve multi-risk assessments or mountain regions studies, but some of their considerations can be extended also for mountain regions applications.

Multi-risk criteria fulfilment

One of the main advantages of using SDMs models is the explicit representation of feedback loops demonstrating the reinforcing and balancing effects among the elements of a system. The use of feedbacks loops contributes to improve the comprehension of nonlinearities and complexity of the considered system (Li & Simonovic 2002). Consequently, applications of SDMs are frequent for macro analysis of social and ecological systems, which are characterized by a high degree of complexity (Elsawah et al., 2017; Armenia et al., 2014). However, although multiple risk processes are characterised by interdependencies, feedback loops and high complexity, risk assessments for mountain environment involving SDMs need to be further explored. Deterministic representations of uncertain behaviours of a system and models validation are among the limitations that needs to be overcome through external methods, such as Monte Carlo simulations and model testing (Barlas, 1996).

Although SDMs well grasp temporal dynamics of the system, it shows limitations in representing spatial characteristics (Simonovic and Ahmad, 2005; Ahmad and Simonovic, 2004). Improvements have been reached through the combination of SDMs with GIS software. Sahin & Mohamed (2014) and Maxwell (2011) showed cases where the spatial analysis was combined with SDMs model for a spatio-temporal assessment of sea level rise and storm surge risks. Although the considered issues refer to coastal environments, the methodological process could be extended to address hazard characteristics in mountain regions and potential climate impacts on vulnerable exposed. In particular, Maxwell (2011) integrated economic, social, environmental and cultural indices analysing the dependencies among different sectors exposed. In the same way, Simonovic & Ahmad (2005) integrated socio–economic information for the assessment of the major factors influencing human behaviour during flood evacuations. In this case, the acquisition of socio-economic qualitative and semi-quantitative data was performed through field surveys with the affected communities representing the characteristics of the population and their risk perception. By doing so, it was possible to translate data from the survey into input for the SDMs model and improve policy choices related to evacuation warning dissemination (Simonovic & Ahmad 2005).

The integration of participatory approaches can strongly enhance the assessment of potential adaptation measures looking at both structural and non-structural strategies for risk adaptation (Simonovic and Ahmad, 2005; Stave, 2010). Although the translation and comparison of qualitative to quantitative information is still an open-problem for risk modellers, the participation of heterogeneous stakeholders can improve the effectiveness and credibility of adaptation strategies. Moreover, stakeholder involvement aims at promoting social learning and identifying leverage points for policy making purposes (Stave, 2010). Duran-Encalada et al. (2017) integrated several policy adaptation measures (i.e. better infrastructures for water supply, water consumption reduction and virtual water reduction) under different anthropic and climate change scenarios, extending their assessments to future patterns of water use and availability.

The use of qualitative data in the model can represent a problem for accurate simulations. In particular, whenever data is assumed by the modellers becomes difficult to find a correct way for its calibration, affecting the accuracy of the simulation’s results. For this reason, SDMs are mostly applied to foster the comprehension of the elements interactions within the system improving a system-thinking approach.

Future challenges

The level of complexity of SDMs depends on the system under study and the representation of its spatial-temporal interactions. Higher number of connections and feedback loops can limit non-experts participation, increasing the computational time and having consequences on leverage points identification. SDMs have been used to depict intertwined socio-ecological system and the impacts on natural resources, such as in water resource management under climate scenarios (Mereu *et al.*, 2016). However, their limited use in describing the interaction of multiple events and the cascading impacts on exposed systems represents a future challenge to tackle forthcoming climate issues in vulnerable environment.

3.4. Event and fault trees

General description

Event and fault trees (EFTs) methodologies have found wide applications in the field of safety engineering, dealing with causes of infrastructure failures and the best ways to reduce them (Ruijters and Stoelinga, 2015; Rosqvist et al., 2013; Clifton and Ericson, 2005). Fault trees have been used to trace the events that can contribute to an accident or failure, while event trees consider the consequences due to an accident, hence the identification of mitigation strategies (Sebastiaan *et al.*, 2012). Similarly to BN, these logic diagram are composed of nodes connected by means of branches identifying different events scenarios. Each event is characterised by a defined probability of occurrence, making these tools useful in identifying and modelling chains of events that lead to risk processes (Dalezios, 2017).

Mountain applications

Applications in mountain environments for multi-hazard assessments purposes are presented by Lacasse et al. (2008), Marzocchi et al. (2012), Sandri et al. (2014) and Neri et al. (2008). In particular, Lacasse et al. (2008) addressed the potential risk arising from a rock-slide triggering a tsunami, scrutinizing different potential early warning systems with the involvement of different stakeholders. Moreover, the characteristic of mutually exclusive logic has been mostly used in a multi-hazard perspective to evaluate chains of hazards originated from volcanic eruptions (Sandri et al., 2014; Marzocchi et al., 2012; Neri et al., 2008).

Multi-risk criteria fulfilment

In case of non-linear systems, EFTs show limitations in representing feedback loops and bi-directional relationships (Sebastiaan *et al.*, 2012). Similarly to BN, they evaluate the probability of occurrence of events using a probability density function, providing information on the uncertainty of potential risk and considering temporal dynamics, through the “dynamic tree” method (Nadim *et al.*, 2013). Within this context, Frieser (2004) applied a dynamic event tree to assess flood prediction and coordination of people evacuation. His application considered a probabilistic evacuation decision-making model based on minimization of the overall costs (i.e. evacuation and flood damage). Specifically, the evacuation decision-making process relied on flood level information updated on a time step basis. Few applications considered EFTs together with spatial analysis. Marzocchi et al. (2012) integrated a spatial analysis of the tephra fall hazard maps for Mount Vesuvius reporting the percentiles of the annual probability per map pixel. Similarly, Sandri et al. (2014) mapped on 1x1 and 5x5 km grid the yearly annual probability for different hazards triggered by a volcanic explosion. Finally, Neri et al (2008) integrated percentiles of hazard probability based on a broad segmentation of the volcano area due to the topography characteristics.

Moreover, the flexibility of EFTs to incorporate qualitative and quantitative data makes them a suitable tool for stakeholders and experts involvement. Participatory approaches can be included throughout models design and for the identification of potential mitigation strategies. In particular, Lacasse et al. (2008) and Rosqvist et al. (2013) involved stakeholders and experts through workshops, for an inclusive decision-making process on the risk perceived and the assessment of countermeasures. Rosqvist et al. (2013) introduced an economic evaluation of the losses caused by different future scenarios of flooding events, hence assessing the costs and benefits of flood protection measures.

Other examples of adaptation strategies integration can be found in Peila & Guardini (2008), where they considered different structural passive protection installations against rock falls for the assessment of the yearly fatality risk reduction on a road. Furthermore, Lacasse et al. (2008) involved scientists from different field of expertise to examine the most important factors characterizing effective early warning systems against a rockslide. In this context, EFTs showed to be an intuitive technique to set risk assessment with participatory purposes. In case of complex systems, they show limitations in grasping non-linear behaviours and an increase in data required, with difficulties for the involvement of public stakeholders and limiting the participation to experts only.

Future challenges

A possible layout for EFTs application is the bow-tie method. This approach, largely used in industry risk assessments, integrates together EFTs for a comprehensive investigation of the upstream conditions triggering an event, and the consequences downstream (Cockshott, 2005; Weber, 2006; Shahriar, Sadiq and Tesfamariam, 2012; Ravankhah, Schmidt and Will, 2017). Overall, applications in mountain regions showed the suitability of EFTs in assessing chains of natural hazards. However, this methodology has been mostly used to assess scenarios of hazard occurrence rather than vulnerability factors. For this reason, the inclusion of spatio-temporal dynamics to fully represent risk processes represent a future challenge for this methodology.

3.5. Hybrid models

General description

One of the main challenges in multi-risk assessment is the integration of information coming from different fields and with different scales into one single assessment (Poljanšek *et al.*, 2017). Although social and environmental sectors play a fundamental role in risk approaches (i.e. categories of elements exposed and their multi-vulnerabilities), often risk assessments consider a multi-hazard risk perspective for physical and economic losses evaluation (Gallina *et al.*, 2016; Poljanšek *et al.*, 2017). The combination of two models (i.e. hybrid model, HM) represents one possible path towards a better comprehension and description of the multi-risk processes from different levels and sectors of analysis. The studies here analysed regard mainly biophysical and socio-ecological processes linked with water issues (i.e. floods, drought and water quality problems), looking at social and economic components for an integrated risk assessment.

Mountain applications

Also for hybrid models, specifically applications involving multi-risk assessments or mountain regions studies are very limited. For this reason, here we analyse studies that can be extended for mountain regions applications.

Multi-risk criteria fulfilment

Existing studies considered the combination of a probabilistic evaluation performed by BN with one deterministic approach, like SDMs or ABM (Bertone, et al. 2016; Phan et al. 2016; Wang et al. 2016; Pope & Gimblett 2015; Kocabas & Dragicevic 2013b). Advantages of this “hybridization” include the capacity of dealing with a high degree of uncertainty, the use of feedback loops and the integration of quantitative and qualitative data.

Qualitative-data driven BN involving a participatory approach through stakeholder involvement allows a quick creation of a model and the inclusion of local information to better characterise people's perception on risk areas and legitimate risk reduction measures (Pope and Gimblett, 2015; Phan, Sahin and Smart, 2016).

Moreover, Wang et al. (2016), Pope & Gimblett (2015) and Kocabas & Dragicevic (2013) performed a spatial analysis together with discrete temporal representation, looking at changes of systems variables and creating output maps. In addition to that, Pope & Gimblett (2015) also extended the analysis to future scenarios of climate change, assessing water scarcity impacts across different sectors (i.e. social, ecological and biophysical). Another example of evaluation for future conditions is carried out by Kocabas & Dragicevic (2013) considering future increase of population and land use change in urban environment. They incorporated agent’s behaviour and different decision-options into a land-use hybrid model combining social and environmental perspectives.

The second “hybridization” category was applied by Martin & Schlüter (2015) combining ABM and SDM. In this case, the hybrid model integrated emergent patterns of micro-level decision-making with the analysis of the feedbacks and dynamics at systemic level. In this way, they worked on the connections between environmental and socio-economic sectors looking to the emergent dynamics. Specifically, they considered the ecological problem of anthropic pressures on a shallow lake, simulating different human behaviours in terms of emissions and time needed for the lake ecological restoration.

The evaluation of ecological dynamics and social processes allowed performing a cross-disciplinary assessment of the sewage water pollution, unpacking the complexity of the socio-ecological system. Moreover, they included a temporal assessment of the lake restoration dynamic based on a public survey in order to understand the social conditions leading to the implementation of ecosystem management measures.

Future challenges

As reported in Section 3.3 on system dynamics models, the amount of data required can be very large according to the level of details used for the representation of the system. Overall, hybrid models are highly complex due to the integration of methodologies working at aggregated or disaggregated scales that need to communicate (Martin & Schlüter 2015, Kelly et al. 2013).

Table 1- Decision matrix with five selected methodologies in the rows and nine criteria of multi-risk analysis in the columns. Qualitative information is provided for each cell and colours correspond to the degree of fulfilment of the criteria: green= very suitable; yellow= suitable but with limitations; red= not suitable

	Uncertainty management	**Feedback loops**	**Temporal dynamics**	**Spatial analysis**	**Cross-sectoral assessment**	**Stakeholders involvement**	**Adaptation strategies integration**	**Data required**	**Level of complexity**	**Literature references**
Bayesian networks	Considering conditional probabilities among variables	Implementation of a time step approach	Implementation of a time step approach	Not common, although possible if the model is integrated with GIS software	Integration of socio-economic parameters	Stakeholder involvement through workshops at different stages: model design, application and results communication	The model can integrate uncertainty assessment of adaptation policies	Model able to deal with limited and large amount of quantitative data. It can include qualitative information through participatory processes	Medium complexity depending on the amount and quality of data considered. Time and data needed can increase in case of continuous conditional probability update	(Döll and Romero-Lankao, 2017; Liu et al., 2016a; Balbi et al., 2016; van Verseveld et al., 2015; Molina et al., 2013; Song et al., 2012; Grêt-Regamey and Straub, 2006; Cain, 2001)
Agent-based model	Implementation of Monte Carlo simulations	The model represents interactions and feedbacks among agents, environment and future scenarios	The model exhibit the dynamics of the simulated system	The model works with grid maps	Integration of socio-economic parameters and rules of interactions	Stakeholder involvement in workshops to simulate emergence collective plans and actions	The model represents social adaptation behaviours through agents interactions representation	The model requires a large amount of quantitative data to determine agents' behaviours and changes in the environment	High complexity due to the big amount of quantitative and cross-sectoral data as input	(Eid et al., 2017; Mashhadi Ali et al., 2017; Becu et al., 2016; Haer et al., 2016; Girard et al., 2015; Acosta et al., 2014; Balbi et al., 2013; Dawson et al., 2011)
System dynamic models (stock & flow)	Implementation of Monte Carlo simulations	Considering both reinforcing and balancing feedback loops	The model describes changes of stock over time	Not common, although possible if the model is integrated with GIS software	Used to describe physical, social and economic processes	Stakeholder involvement in the model design, application and results communication	The model can include adaptation strategies affecting the level of stocks	The model can be developed using qualitative information and improving the system thinking, or need large amount of quantitative data for simulating changes of stocks over time	Medium-high complexity depending on the type of data and the number of feedback loops considered for the simulation	(Duran-Encalada et al., 2017; Mereu et al., 2016; Armenia et al., 2014; Sahin and Mohamed, 2014; Hartt, 2011; Stave, 2010; Simonovic and Ahmad, 2005; Li and Simonovic, 2002)
Event and fault trees	Considering probability of occurrence for each event	The model considers mutually exclusive events in a domino effect	If the model implements a "dynamic fault trees" approach	Not common, although possible if the model is integrated with GIS software	Integration of socio-economic parameters	Stakeholder involvement in the development stage and results communication	The model can integrate uncertainty assessment of adaptation policies	The model uses quantitative data for probabilistic assessment, but it can provide solutions also in the event of limited qualitative data	Low complexity, they are easy to learn and understand, albeit proper application depends on the level of detail of the represented system	(Sandri et al., 2014; Rosqvist et al., 2013; Marzocchi et al., 2012; Lacasse et al., 2008;; Neri et al., 2008; Peila and Guardini, 2008; Frieser, 2004)
Hybrid models	Implementation of Monte Carlo simulations	Hybrid models can investigate interactions and feedbacks between the involved models	Through exchange of information between methods working at different temporal level	Through exchange of information between methods working at different spatial level	Often the final goal of hybrid models, but it requires suitable connections among models	Depending on the selected models	Adaptation strategies can be included in the models design and/or can emerge from outcome analysis	Generally high amount of data due to methods working at different scale of analysis	High complexity due to the integration of models working at different scales of analysis	(Bertone et al., 2016b; Phan et al., 2016; Wang et al., 2016; Pope and Gimblett, 2015; Martin and Schlüter, 2015; Kocabas and Dragicevic, 2013)

4. Discussion and conclusions

This review represents the starting point for risk modellers interested in exploring and selecting methods for multi-risk assessment and climate change adaptation in mountain regions. The interactions among biophysical variables in the hydrogeological processes, the consequences of anthropogenic activities, and the uncertainty associated with future climatic and socio-economic changes make the assessment of multi-risk processes particularly complex.

The high non-linearity of these processes has also been reinforced by the evaluation of the multi-risk framework developed following the IPCC AR5 risk definition. For these reasons, it is necessary to work towards an improved comprehension and representation of the multi-risk characteristics. Starting from this need, we first identified nine distinctive features as the current challenges for comprehensive multi-risk assessments. They were chosen to explore models suitability in representing risk analysis looking at both the methodological and technical characteristics of each modelling technique. Successively, we reviewed risk and climate change impact studies involving five modelling categories: Bayesian networks, agent-based models, system dynamic models, event and fault trees and hybrid models. For each approach, qualitative information on the fulfilment of the criteria for a full multi-risk assessment was reported as a decision matrix in *Table 1*. Moreover, for each application we identified information on potential applicability of the five approaches in the mountain region, shedding light on potentialities and drawbacks in addressing additional and more specific features of multi-risk assessment (Table 1 of Supplementary Material).

In particular, Bayesian networks provide an explicit representation of the probability, dealing with uncertainty management of hazards occurrence and future land-use scenarios. Although they are limited in representing spatio-temporal references or feedback loops, they offer a reliable statistical method also in case of limited data availability that can include bottom-up qualitative information for a quick participatory creation of the model. Similarly, event and fault trees explicitly manage the probability of occurrence when working on mutually exclusive events, which is particularly useful in case of impact chains. Their extensive applications in the industrial field have supported the use in natural hazards contexts, although their limitations in representing spatial outputs and in feedback loops have affected their diffusion. If the objective of the multi-risk assessment is to focus on the collective behaviours emerging from the interactions of agents among them and with the surrounding environment, then agent-based models are a valuable tool. Applications rely on simple behavioural rules definition for the agents, which account for a high amount of information to develop agents choices scenarios.

If agent-based models work at the micro-level, system dynamic models can be used to evaluate changes over time at macro-level on the system accounting for the interactions and feedback loops among aggregated variables. This method offers the opportunity for interdisciplinary modelling and is used to improve the general understanding of a system. The lack of a spatial analysis and of uncertainty assessment are among its main limitations that need to be explored in the future. In those cases where the analysis aims to integrate information from different disciplines a combination of modelling techniques can be more appropriate. This configuration overcomes the limitations of a single model application and support interdisciplinary research in those cases where a high amount of data is available.

Indexes and expert-based approaches were not included in the review, although they represent a large percentage of currently used approaches dealing with natural hazards and risk assessments. This choice was justified considering indexes as a synthesis of information rather than a methodology itself; hence, being applied in the analysis of models output. Moreover, this study has provided an overview of approaches commonly used to tackle interplaying biophysical and socio-economic processes extending their use for mountain applications and going beyond mono-disciplinary expert-based models.

In summary, results showed the wide range of problems these approaches are used for, but also highlighted the limited number of models applications dealing with climate impacts in mountain environments (Grêt-Regamey and Straub, 2006; Lacasse *et al.*, 2008; Marzocchi *et al.*, 2012; Balbi *et al.*, 2013, 2016; Girard *et al.*, 2015). This gap is particularly clear for system dynamic models and hybrid models, highlighting potential room for further applications and methodological improvements. The analysis also showed the limitations of each methodology to address a thorough multi-risk assessment, especially because of the combination of information from the social and environmental fields as well as spatial and temporal dynamics. Although single approaches are still widely applied, the increase of data availability and speed of processing can foster models combination, therefore addressing the distinctive features of multi-risk assessments identified in this review. For this reason, better understanding of anthropogenic and climate change in mountain regions involve the integration of models able to grasp spatio-temporal dynamics, combination of deterministic and stochastic approaches as well as quantitative and qualitative data to tackle future climate-risk challenges.

References

Acosta, L., Rounsevell, M., Bakker, M., Van Doorn, A., Gómez-Delgado, M., Delgado, M., 2014. An Agent-Based Assessment of Land Use and Ecosystem Changes in Traditional Agricultural Landscape of Portugal. Intell. Inf. Manag. 55–80. https://doi.org/10.4236/iim.2014.62008

Aguilera, P.A., Fernández, A., Fernández, R., Rumí, R., Salmerón, A., 2011. Bayesian networks in environmental modelling. Environ. Model. Softw. 26, 1376–1388. https://doi.org/10.1016/j.envsoft.2011.06.004

Ahmad, S., Simonovic, S.P., 2004. Spatial System Dynamics : New Approach for Simulation of Water Resources Systems. J. Comput. Civ. Eng. 3801, 331–341. https://doi.org/10.1061/(ASCE)0887-3801(2004)18

Armenia, S., Carlini, C., Tsaples, G., Cavallini, S., Volpe, M., D’Alessandro, C., Assogna, P., Brein, E., 2014. CrisAdmin project - CRitical Infrastructure Simulation of ADvanced Models on Interconnected Networks resilience - Final report.

Balbi, S., 2012. Climate change and Tourism in the Alps: a position paper in view of the upcoming Alpine Convention Fourth Report on the State of the Alps on Sustainable Tourism. https://doi.org/10.2139/ssrn.2014045

Balbi, S., Giupponi, C., 2009. Reviewing agent-based modelling of socio-ecosystems: a methodology for the analysis of climate change adaptation and sustainability. Soc. Sci. Res. 93, 2873–2886. https://doi.org/10.2139/ssrn.1457625

Balbi, S., Giupponi, C., Perez, P., Alberti, M., 2013. A spatial agent-based model for assessing strategies of adaptation to climate and tourism demand changes in an alpine tourism destination. Environ. Model. Softw. 45, 29–51. https://doi.org/10.1016/j.envsoft.2012.10.004

Balbi, S., Villa, F., Mojtahed, V., Tessa Hegetschweiler, K., Giupponi, C., 2016. A spatial Bayesian network model to assess the benefits of early warning for urban flood risk to people. Nat. Hazards Earth Syst. Sci. 16, 1323–1337. https://doi.org/10.5194/nhess-16-1323-2016

Barlas, Y., 1996. Formal aspects of model validity and validation in system dynamics. Syst. Dyn. Rev. 12, 183–210. https://doi.org/10.1002/(SICI)1099-1727(199623)12:3<183::AID-SDR103>3.0.CO;2-4

Becu, N., Amalric, M., Anselme, B., Beck, E., Bertin, X., Delay, E., Long, N., Manson, C., Nicolas, M., Pignon-Mussaud, C., Rousseaux, F., 2016. Participatory simulation of coastal flooding: building social learning on prevention measures with decision-makers. 8th Int. Congr. Environ. Model. Softw. 1167–1178.

Bell, R., Glade, T., 2004. Multi-hazard Analysis in Natural Risk Assessments. Risk Anal. IV 77, 10.

Beniston, M., Stoffel, M., 2014. Assessing the impacts of climatic change on mountain water resources. Sci. Total Environ. 493, 1129–1137. https://doi.org/10.1016/j.scitotenv.2013.11.122

Bertone, E., Sahin, O., Richards, R., Mengersen, K., Roikod, A., 2016a. Managing water quality related health risks from extreme events : A coupled Bayesian Network and System Dynamics modelling approach. Final Rep. – WaterRA Proj. 1071-12.

Bertone, E., Sahin, O., Richards, R., Roiko, A., 2016b. Modelling with stakeholders : a systems approach for improved environmental decision making under great uncertainty. Int. Environ. Model. Softw. Soc.

Birkmann, J., 2011. First- and second-order adaptation to natural hazards and extreme events in the context of climate change. Nat. Hazards 58, 811–840. https://doi.org/10.1007/s11069-011-9806-8

Birkmann, J., Cardona, O.D., Carreño, M.L., Barbat, A.H., Pelling, M., Schneiderbauer, S., Kienberger, S., Keiler, M., Alexander, D., Zeil, P., Welle, T., 2013. Framing vulnerability, risk and societal responses: The MOVE framework. Nat. Hazards 67, 193–211. https://doi.org/10.1007/s11069-013-0558-5

Cain, J., 2001. Planning improvements in natural resources management. Cent. Ecol. Hydrol. 44.

Carpignano, a., Golia, E., Di Mauro, C., Bouchon, S., Nordvik, J., 2009. A methodological approach for the definition of multi-risk maps at regional level: first application. J. Risk Res. 12, 513–534. https://doi.org/10.1080/13669870903050269

Catenacci, M., Giupponi, C., 2009. Potentials of Bayesian Networks To Deal With Uncertainty in Climate Change Adaptation. https://doi.org/10.2139/ssrn.1557088

Clifton, A., Ericson, I., 2005. Event Tree Analysis. Hazard Anal. Tech. Syst. Saf. 223–234. https://doi.org/10.1002/0471739421.ch12

Cockshott, J.E., 2005. Probability Bow-Ties. Process Saf. Environ. Prot. 83, 307–316. https://doi.org/10.1205/psep.04380

Connelly, A., Carter, J.G., Handley, J., 2015. State of the Art Report (4) - Vulnerability Assessment.

Dalezios, N.R., 2017. Environmental Hazards Methodologies for Risk Assessment and Management. https://doi.org/10.2166/9781780407135

Dawson, R., 2015. Handling Interdependencies in Climate Change Risk Assessment. Climate 3, 1079–1096. https://doi.org/10.3390/cli3041079

Dawson, R., Peppe, R., Wang, M., 2011. An agent-based model for risk-based flood incident management. Nat. Hazards 59, 167–189. https://doi.org/10.1007/s11069-011-9745-4

Delmonaco, G., Margottini, C., Spizzichino, D., 2006. Report on new methodology for multi-risk assessment and the harmonisation of different natural risk maps. Rapp. Final 1–4.

Döll, P., Romero-Lankao, P., 2017. How to embrace uncertainty in participatory climate change risk management - a roadmap. Earth’s Futur. https://doi.org/10.1002/2016EF000411

Duran-Encalada, J.A., Paucar-Caceres, A., Bandala, E.R., Wright, G.H., 2017. The impact of global climate change on water quantity and quality: A system dynamics approach to the US?Mexican transborder region. Eur. J. Oper. Res. 256, 567–581. https://doi.org/10.1016/j.ejor.2016.06.016

Eid, M.S., Asce, S.M., El-adaway, I.H., Asce, M., 2017. Integrating the Social Vulnerability of Host

Communities and the Objective Functions of Associated Stakeholders during Disaster Recovery Processes Using Agent-Based Modeling 1–15. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000680.

Elsawah, S., Pierce, S.A., Hamilton, S.H., van Delden, H., Haase, D., Elmahdi, A., Jakeman, A.J., 2017. An overview of the system dynamics process for integrated modelling of socio-ecological systems: Lessons on good modelling practice from five case studies. Environ. Model. Softw. 93, 127–145. https://doi.org/10.1016/j.envsoft.2017.03.001

Environment Agency, 2007. Risk assessment for flood incident management: Understanding and application of complex system risk assessment models.

European Environmental Agency, 2017. Climate change, impacts and vulnerability in Europe: An indicator-based report. https://doi.org/10.2800/534806

Eusgeld, I., Henzi, D., Wolfgang, K., 2008. Comparative Evaluation of Modeling and Simulation Techniques for Interdependent Critical Infrastructures.

Filatova, T., Verburg, P.H., Parker, D.C., Stannard, C.A., 2013. Spatial agent-based models for socio-ecological systems: Challenges and prospects. Environ. Model. Softw. 45, 1–7. https://doi.org/10.1016/j.envsoft.2013.03.017

Forzieri, G., Feyen, L., Russo, S., Vousdoukas, M., Alfieri, L., Outten, S., Migliavacca, M., Bianchi, A., Rojas, R., Cid, A., 2016. Multi-hazard assessment in Europe under climate change. Clim. Change 137, 105–119. https://doi.org/10.1007/s10584-016-1661-x

Frieser, B., 2004. Probabilistic Evacuation Decision Model for River Floods in the Netherlands, Faculty of Civil Engineering and Geosciences.

Fuchs, S., Keiler, M., Sokratov, S., Shnyparkov, A., 2013. Spatiotemporal dynamics: The need for an innovative approach in mountain hazard risk management. Nat. Hazards 68, 1217–1241. https://doi.org/10.1007/s11069-012-0508-7

Fuhrer, J., Smith, P., Gobiet, A., 2014. Implications of climate change scenarios for agriculture in alpine regions - A case study in the Swiss Rhone catchment. Sci. Total Environ. 493, 1232–1241. https://doi.org/10.1016/j.scitotenv.2013.06.038

Gallina, V., Torresan, S., Critto, A., Sperotto, A., Glade, T., Marcomini, A., 2016. A review of multi-risk methodologies for natural hazards: Consequences and challenges for a climate change impact assessment. J. Environ. Manage. 168, 123–132. https://doi.org/10.1016/j.jenvman.2015.11.011

Gilbert, N., Troitzsch, K.G., 2005. Simulation for the Social Scientist.

Gill, J.C., Malamud, B.D., 2017. Anthropogenic processes, natural hazards, and interactions in a multi-hazard framework. Earth-Science Rev. 166, 246–269. https://doi.org/10.1016/j.earscirev.2017.01.002

Gill, J.C., Malamud, B.D., 2016. Hazard interactions and interaction networks (cascades) within multi-hazard methodologies. Earth Syst. Dyn. 7, 659–679. https://doi.org/10.5194/esd-7-659-2016

Gill, J.C., Malamud, B.D., 2014. Reviewing and visualizing the interactions of natural hazards. Rev. Geophys. 52, 680–722. https://doi.org/10.1002/2013RG000445

Girard, P., Levison, J., Parrott, L., Larocque, M., Ouellet, M.-A., Green, D.M., 2015. Modeling cross-scale relationships between climate, hydrology, and individual animals: generating scenarios for stream salamanders. Front. Environ. Sci. 3, 1–13. https://doi.org/10.3389/fenvs.2015.00051

Grêt-Regamey, A., Straub, D., 2006. Spatially explicit avalanche risk assessment linking Bayesian networks to a GIS. Nat. Hazards Earth Syst. Sci. 6, 911–926. https://doi.org/10.5194/nhess-6-911-2006

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., 2006. A standard protocol for describing individual-based and agent-based models. Ecol.

Modell. 198, 115–126. https://doi.org/10.1016/j.ecolmodel.2006.04.023

Grimm, V., Berger, U., DeAngelis, D.L., Polhill, J.G., Giske, J., Railsback, S.F., 2010. The ODD protocol: A review and first update. Ecol. Modell. 221, 2760–2768. https://doi.org/10.1016/j.ecolmodel.2010.08.019

Grünthal, G., Thieken, A.H., Schwarz, J., Radtke, K.S., Smolka, A., Merz, B., 2006. Comparative risk assessments for the city of Cologne - Storms, floods, earthquakes. Nat. Hazards 38, 21–44. https://doi.org/10.1007/s11069-005-8598-0

Haer, T., Botzen, W.J.W., de Moel, H., Aerts, J.C.J.H., 2016. Integrating Household Risk Mitigation Behavior in Flood Risk Analysis: An Agent-Based Model Approach. Risk Anal. https://doi.org/10.1111/risa.12740

Hamilton, S.H., ElSawah, S., Guillaume, J.H.A., Jakeman, A.J., Pierce, S.A., 2015. Integrated assessment and modelling: Overview and synthesis of salient dimensions. Environ. Model. Softw. 64, 215–229. https://doi.org/10.1016/j.envsoft.2014.12.005

Harrison, P.A., Dunford, R.W., Holman, I.P., Rounsevell, M.D.A., 2016. Climate change impact modelling needs to include cross-sectoral interactions. Nat. Clim. Chang. 6, 885–890. https://doi.org/10.1038/nclimate3039

Hartt, M.D., 2011. Geographic Information Systems and System Dynamics - Modelling the Impacts of Storm Damage on Coastal Communities. https://doi.org/10.20381/ruor-4460

IPCC, 2014a. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth As- sessment Report of the Intergovernmental Panel on Climate Change., Headline statements from the Summary for Policymakers. https://doi.org/10.1017/CBO9781107415324

IPCC, 2014b. Climate Change 2014 Synthesis Report Summary Chapter for Policymakers. Ipcc 31. https://doi.org/10.1017/CBO9781107415324

Jakeman, A.J., Letcher, R.A., Norton, J.P., 2006. Ten iterative steps in development and evaluation of environmental models. Environ. Model. Softw. 21, 602–614. https://doi.org/10.1016/j.envsoft.2006.01.004

Janssen, M., 2005. Agent-based modelling. Model. Ecol. Econ. 1–9. https://doi.org/10.1016/j.patrec.2007.06.021

Jurgilevich, A., Räsänen, A., Groundstroem, F., Juhola, S., 2017. A systematic review of dynamics in climate risk and vulnerability assessments. Environ. Res. Lett. 12, 013002. https://doi.org/10.1088/1748-9326/aa5508

Kappes, M.S., Keiler, M., von Elverfeldt, K., Glade, T., 2012. Challenges of analyzing multi-hazard risk: A review. Nat. Hazards. https://doi.org/10.1007/s11069-012-0294-2

Kelly, R.A.. B., Jakeman, A.J.., Barreteau, O., Borsuk, M.E.., ElSawah, S.., Hamilton, S.H.., Henriksen, H.J.., Kuikka, S.., Maier, H.R.., Rizzoli, A.E.., van Delden, H.. I., Voinov, A., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. Softw. 47, 159–181. https://doi.org/10.1016/j.envsoft.2013.05.005

Kocabas, V., Dragicevic, S., 2013. Bayesian networks and agent-based modeling approach for urban land-use and population density change: A BNAS model. J. Geogr. Syst. 15, 403–426. https://doi.org/10.1007/s10109-012-0171-2

Komendantova, N., Mrzyglocki, R., Mignan, A., Khazai, B., Wenzel, F., Patt, A., Fleming, K., 2014. Multi-hazard and multi-risk decision-support tools as a part of participatory risk governance: Feedback from civil protection stakeholders. Int. J. Disaster Risk Reduct. 8, 50–67. https://doi.org/10.1016/j.ijdrr.2013.12.006

Kumasaki, M., King, M., Arai, M., Yang, L., 2016. Anatomy of cascading natural disasters in Japan: main modes and linkages. Nat. Hazards 80, 1425–1441. https://doi.org/10.1007/s11069-015-2028-8

Lacasse, S., Eidsvig, U., Nadim, F., Høeg, K., Blikra, L.H., 2008. Event tree analysis of Aknes rock slide hazard. 4th Can. Conf. Geohazards From Causes to Manag. 2, 551–558.

Li, L., Simonovic, S.P., 2002. System dynamics model for predicting floods from snowmelt in north American prairie watersheds. Hydrol. Process. 16, 2645–2666. https://doi.org/10.1002/hyp.1064

Liu, B., Siu, Y.L., Mitchell, G., 2016. A quantitative model for estimating risk from multiple interacting natural hazards: an application to northeast Zhejiang, China. Stoch. Environ. Res. Risk Assess. 1–22. https://doi.org/10.1007/s00477-016-1250-6

Maani, K., 2013. Decision-making for climate change adaptation: a systems thinking approach.

Mallampalli, V.R., Mavrommati, G., Thompson, J., Duveneck, M., Meyer, S., Ligmann-Zielinska, A., Druschke, C.G., Hychka, K., Kenney, M.A., Kok, K., Borsuk, M.E., 2016. Methods for translating narrative scenarios into quantitative assessments of land use change. Environ. Model. Softw. 82, 7–20. https://doi.org/10.1016/j.envsoft.2016.04.011

Martin, R., Schlüter, M., 2015. Combining system dynamics and agent-based modeling to analyze social-ecological interactions—an example from modeling restoration of a shallow lake. Front. Environ. Sci. 3, 1–15. https://doi.org/10.3389/fenvs.2015.00066

Marzocchi, W., Garcia-Aristizabal, A., Gasparini, P., Mastellone, M.L., Ruocco, A. Di, 2012. Basic principles of multi-risk assessment: A case study in Italy. Nat. Hazards 62, 551–573. https://doi.org/10.1007/s11069-012-0092-x

Marzocchi, W., Mastellone, M., Di Ruocco, A., Novelli, P., Romeo, E., Gasparini, P., 2009. Principles of multi-risk assessment, Environment.

Mashhadi Ali, A., Shafiee, M.E., Berglund, E.Z., 2017. Agent-based modeling to simulate the dynamics of urban water supply: Climate, population growth, and water shortages. Sustain. Cities Soc. 28, 420–434. https://doi.org/10.1016/j.scs.2016.10.001

Mereu, S., Sušnik, J., Trabucco, A., Daccache, A., Vamvakeridou-Lyroudia, L., Renoldi, S., Virdis, A., Savić, D., Assimacopoulos, D., 2016. Operational resilience of reservoirs to climate change, agricultural demand, and tourism: A case study from Sardinia. Sci. Total Environ. 543, 1028–1038. https://doi.org/10.1016/j.scitotenv.2015.04.066

Mignan, D., Scolobig, A., Sauron, A., 2016. Using reasoned imagination to learn about cascading hazards: a pilot study. Disaster Prev. Manag. https://doi.org/10.1108/09574090910954864

Molina, J.-L., Pulido-Velázquez, D., García-Aróstegui, J.L., Pulido-Velázquez, M., 2013. Dynamic Bayesian Networks as a Decision Support tool for assessing Climate Change impacts on highly stressed groundwater systems. J. Hydrol. 479, 113–129. https://doi.org/10.1016/j.jhydrol.2012.11.038

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., Schwarz, N., 2013. Describing human decisions in agent-based models - ODD+D, an extension of the ODD protocol. Environ. Model. Softw. 48, 37–48. https://doi.org/10.1016/j.envsoft.2013.06.003

Nadim, F., Liu, Z., Woo, G., Zschau, J., 2013. Framework for multi-risk assessment.

Neri, A., Aspinall, W.P., Cioni, R., Bertagnini, A., Baxter, P.J., Zuccaro, G., Andronico, D., Barsotti, S., Cole, P.D., Esposti Ongaro, T., Hincks, T.K., Macedonio, G., Papale, P., Rosi, M., Santacroce, R., Woo, G., 2008. Developing an Event Tree for probabilistic hazard and risk assessment at Vesuvius. J. Volcanol. Geotherm. Res. 178, 397–415. https://doi.org/10.1016/j.jvolgeores.2008.05.014

Ouyang, M., 2014. Review on modeling and simulation of interdependent critical infrastructure systems.

Reliab. Eng. Syst. Saf. 121, 43–60. https://doi.org/10.1016/j.ress.2013.06.040

Pearl, J., 1988. Probabilistic Reasoning in Intelligent Systems. Morgan Kaufmann Publ. San Mateo, Calif. 552. https://doi.org/10.2307/2026705

Peila, D., Guardini, C., 2008. Use of the event tree to assess the risk reduction obtained from rockfall protection devices. Nat. Hazards Earth Syst. Sci. 8, 1441–1450. https://doi.org/10.5194/nhess-8-1441-2008

Petit, F., Verner, D., Brannegan, D., Buehring, W., Dickinson, D., Guziel, K., Haffenden, R., Phillips, J., Peerenboom, J., 2015. Analysis of Critical Infrastructure Dependencies and Interdependencies.

Phan, T.D., Sahin, O., Smart, J.C., 2016. System Dynamics and Bayesian Network Models for Vulnerability and Adaptation Assessment of a Coastal Water Supply and Demand System. https://doi.org/10.13140/RG.2.1.1464.7285

Poljanšek, K., Marin Ferrer, M., De Groeve, T., Clark, I., 2017. Science for Disaster Risk Management 2017: knowing better and losing less. https://doi.org/10.2788/842809

Pope, A.J., Gimblett, R., 2015. Linking Bayesian and Agent-based Models to Simulate Complex Social-ecological Systems in Semi-arid Regions. Front. Environ. Sci. 3, 1–9. https://doi.org/10.3389/fenvs.2015.00055

Ravankhah, M., Schmidt, M., Will, T., 2017. Multi-hazard disaster risk identification for World Cultural Heritage sites in seismic zones. J. Cult. Herit. Manag. Sustain. Dev. 7, 272–289. https://doi.org/10.1108/JCHMSD-09-2015-0032

Rinaldi, B.S.M., Peerenboom, J.P., Kelly, T.K., 2001. Identifying, Understanding, and Analyzing critical infrastructure interdependencies 11–25. https://doi.org/10.1109/37.969131

Rosqvist, T., Molarius, R., Virta, H., Perrels, A., 2013. Event tree analysis for flood protection - An exploratory study in Finland. Reliab. Eng. Syst. Saf. 112, 1–7. https://doi.org/10.1016/j.ress.2012.11.013

Ruijters, E., Stoelinga, M., 2015. Fault tree analysis: A survey of the state-of-the-art in modeling, analysis and tools. Comput. Sci. Rev. 15, 29–62. https://doi.org/10.1016/j.cosrev.2015.03.001

Sahin, O., Mohamed, S., 2014. Coastal vulnerability to sea-level rise: A spatial-temporal assessment framework. Nat. Hazards 70, 395–414. https://doi.org/10.1007/s11069-013-0818-4

Sandri, L., Thouret, J.C., Constantinescu, R., Biass, S., Tonini, R., 2014. Long-term multi-hazard assessment for El Misti volcano (Peru). Bull. Volcanol. 76, 1–26. https://doi.org/10.1007/s00445-013-0771-9

Satumtira, G., Duenas-Osorio, L., 2010. Synthesis of Modeling and Simulation Methods on Critical Infrastructure Interdependencies Research. Sustain. Resilient Crit. Infrastruct. Syst. Simulation, Model. Intell. Eng. 1–51. https://doi.org/10.1007/978-3-642-11405-2_1

Schneiderbauer, S., Zebisch, M., Kass, S., Pedoth, L., 2013. Assessment of vulnerability to natural hazards and climate change in mountain environments, Measuring vulnerability to natural hazards: Towards disaster resilient societies (2 nd edn) United Nations University Press.

Sebastiaan, N.J., van Gelder, P., Horst, W. ter, van Erp, N., 2012. Fault Trees and Event Trees - An Extension of the Modeling Toolkit based on Fault Trees and Event Trees for Environmental Risks.

Shahriar, A., Sadiq, R., Tesfamariam, S., 2012. Risk analysis for oil & gas pipelines: A sustainability assessment approach using fuzzy based bow-tie analysis. J. Loss Prev. Process Ind. 25, 505–523. https://doi.org/10.1016/j.jlp.2011.12.007

Simonovic, S.P., 2015. Systems approach to management of disasters: methods and applications. J. Integr. Disaster Risk Manag. 5, 70–83. https://doi.org/10.5595/idrim.2015.0099

Simonovic, S.P., Ahmad, S., 2005. Computer-based model for flood evacuation emergency planning. Nat. Hazards 34, 25–51. https://doi.org/10.1007/s11069-004-0785-x

Sobiech, C., 2013. Agent-based simulation of vulnerability dynamics - A case study of German north sea coast. https://doi.org/10.1007/978-3-642-32365-2

Song, Y., Gong, J., Gao, S., Wang, D., Cui, T., Li, Y., Wei, B., 2012. Susceptibility assessment of earthquake-induced landslides using Bayesian network: A case study in Beichuan, China. Comput. Geosci. 42, 189–199. https://doi.org/10.1016/j.cageo.2011.09.011

Sperotto, A., Molina, J.-L., Torresan, S., Critto, A., Marcomini, A., 2017. Reviewing Bayesian Networks potentials for climate change impacts assessment and management: A multi-risk perspective. J. Environ. Manage. 202, 320–331. https://doi.org/10.1016/j.jenvman.2017.07.044

Stave, K., 2010. Participatory system dynamics modeling for sustainable environmental management: Observations from four cases. Sustainability 2, 2762–2784. https://doi.org/10.3390/su2092762

UK Climate Impacts Programme, 2003. Climate adaptation : Risk , uncertainty and decision-making.

UNISDR, 2015. Sendai Framework for Disaster Risk Reduction 2015 - 2030.

United Nations, 2012. The Future We Want: Outcome document of the United Nations Conference on Sustainable Development.

Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecol. Modell. 203, 312–318. https://doi.org/10.1016/j.ecolmodel.2006.11.033

van Aalst, M.K., Cannon, T., Burton, I., 2008. Community level adaptation to climate change: The potential role of participatory community risk assessment. Glob. Environ. Chang. 18, 165–179. https://doi.org/10.1016/j.gloenvcha.2007.06.002

van Verseveld, H.C.W., van Dongeren, A.R., Plant, N.G., Jäger, W.S., den Heijer, C., 2015. Modelling multi-hazard hurricane damages on an urbanized coast with a Bayesian Network approach. Coast. Eng. 103, 1–14. https://doi.org/10.1016/j.coastaleng.2015.05.006

Vogel, K., Riggelsen, C., Korup, O., Scherbaum, F., 2014. Bayesian network learning for natural hazard analyses. Nat. Hazards Earth Syst. Sci. 14, 2605–2626. https://doi.org/10.5194/nhess-14-2605-2014

Wang, G., Wang, S., Kang, Q., Duan, H., Wang, X., 2016. An integrated model for simulating and diagnosing the water quality based on the system dynamics and Bayesian network. Water Sci. Technol. 74, 2639–2655. https://doi.org/10.2166/wst.2016.442

Warren, R., 2011. The role of interactions in a world implementing adaptation and mitigation solutions to climate change. Philos. Trans. A. Math. Phys. Eng. Sci. 369, 217–241. https://doi.org/10.1098/rsta.2010.0271

Weber, M., 2006. Some Safety Aspects on the Design of Sparger Systems for the. Process Saf. Prog. 25, 326–330. https://doi.org/10.1002/prs

Xu, L., Meng, X., Xu, X., 2014. Natural hazard chain research in China: A review. Nat. Hazards 70, 1631–1659. https://doi.org/10.1007/s11069-013-0881-x

Zio, E., 2016. Challenges in the vulnerability and risk analysis of critical infrastructures. Reliab. Eng. Syst. Saf. 152, 137–150. https://doi.org/10.1016/j.ress.2016.02.009

Zscheischler, J., Westra, S., van den Hurk, B.J.J.M., Seneviratne, S.I., Ward, P.J., Pitman, A., AghaKouchak, A., Bresch, D.N., Leonard, M., Wahl, T., Zhang, X., 2018. Future climate risk from compound events. Nat. Clim. Chang. 1. https://doi.org/10.1038/s41558-018-0156-3

Paper 2- Stochastic system dynamics modelling for climate change impact assessment and adaptation in the alpine case study of the Noce river (Italy)

Introduction

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

The European Alps are among those mountain regions where water abundance triggered the increase of several activities such as large hydropower plants and intensive agriculture, exposing them to future impacts due to water availability changes (Majone et al., 2016; Beniston and Stoffel, 2014; Permanent Secretariat of the Alpine Convention, 2013). Moreover, water scarcity issues have been considered less likely to happen in such regions, and hence can have larger impacts on unprepared systems when occurring (Di Baldassarre et al., 2018).

For these reasons, 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 glaciers melting and runoff (Huss and Hock, 2018; Farinotti et al., 2012), and snowpack and runoff (Etter *et al.*, 2017; Wever *et al.*, 2017).

However, the tangle of interplays connecting natural processes and socio-economic activities, sometimes known as sociohydrology (Sivapalan, Savenije and Blöschl, 2012; Di Baldassarre *et al.*, 2015) call for further research. There is a need to implement methodologies with the ability to unravel this complexity, dynamically describing such interplays and system behaviours in order to find which and how adaptation strategies across economic sectors can effectively tackle climate-related water issues.

System Dynamics Modelling (SDM) is a methodology created to improve the understanding of complex systems and their dynamic interactions. Previous applications of SDM often rely on deterministic assumptions (Sušnik *et al.*, 2013; Sahin and Mohamed, 2014; Mereu *et al.*, 2016), while statistical analysis of variables trends and interactions are of great importance in the context of climate change and risk assessments (Terzi *et al.*, 2019). These conditions call for probabilistic system dynamics assessments to better understand the dependencies between the anthropogenic activities and the stochastic environmental processes that can lead to multiple impacts, water disputes and crisis. For these reasons, statistical methods combined with SDM present an innovative and powerful opportunity to overcome the current limitations involved in deterministic assessments.

Hence, this study explores the vulnerability of a major reservoir in the Noce catchment (Province of Trento, Italy) considering the current situation and future climate change effects influencing the water stored and flow diverted to reservoir hydropower turbines and the amount of water remaining for other activities. By doing so, the aim is to test and demonstrate a probabilistic SDM assessment expanding the information coming from a hydrological model as a quick and effective tool on reservoir future conditions for climate change risk assessment and adaptation planning.

In section 2, the concepts behind SDM and the innovation of its applications are described. Section 3 focuses on the case study characteristics and the recently arisen water management challenges. Section 4 describes the methodology, data and scenario used for the simulations. Section 5 focuses on the results of such SDM application for both the baseline and future projections simulations. Section 6 involves the discussion of the analysis results and its limitations. Future developments and applications are described in section 7, towards more integrated climate risk assessments including future scenarios of socio-economic pressures for climate adaptation strategies identification.

1. System dynamics modelling background

System dynamics modelling (SDM) is an approach used to foster the understanding of complex system behaviour. SDM allows the exploration of variable interactions and feedback loops in order to find the leverage points: parts of the system to act upon in order to trigger maximum influence on the system as a whole. Since system-wide complexity can be modelled, indirect impacts of changes can be assessed and delay and emergent processes may be identified. SDM was originally developed by Jay Forrester (Forrester, 1971) to improve industrial business processes and then successfully applied to model global human and natural resources interactions in the publication "Limits to Growth" (Meadows *et al.*, 2018). Moreover, SDM applications span a wide range of problems, from climate change risk assessments (Duran-Encalada *et al.*, 2017; Gohari, Mirchi and Madani, 2017; Masia *et al.*, 2018), water management issues (Davies and Simonovic, 2011; Gohari, Mirchi and Madani, 2017), disasters studies (Simonovic, 2001, 2015), water-energy-food Nexus studies (Sušnik et al., 2018; Davies and Simonovic, 2008) and applications fostering participatory modelling (Stave, 2010; Malard *et al.*, 2017).

It is therefore the ideal tool to study complex interactions and dynamic behaviour in a wide variety of complex systems (Ford, 2010), such as climate impacts on water management in the Noce catchment.

SDM software makes use of three main modelling elements connected to each other: stocks (system state variables) – stocks 'store' or accumulate material (e.g. water in a reservoir); flows (variable's rate of change) – flows move material into and out of stocks (e.g. river inflow and outflow, evaporation losses) and converters (parameters influencing the flow rates, e.g. evaporation rates modulated by seasonal variation). The combination of these elements is applied to represent temporal changes in system elements accounting for both endogenous and exogenous influences on the overall system behaviour. This concept encourages a system thinking approach, splitting large systems into sub-systems and progressively increasing their interactions and complexity (Mereu *et al.*, 2016; Gohari, Mirchi and Madani, 2017). 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.

However, SDM also shows some limitations, such as (i) the limited spatial representation since it works with lumped regions, although some research has recently coupled SDM to GIS to account for spatially explicit system dynamics (Neuwirth, Hofer and Peck, 2015; Xu *et al.*, 2016) ; (ii) the reduced accuracy in comparison with dedicated physically based models; (iii) applications usually accounts for deterministic approaches, although recently, stochastic analysis have been used for probabilistic SDM output (Sušnik *et al.*, 2018); (iv) ease of creating very complex what-if scenarios that can be difficult to validate, but which are useful for exploration of indicative system behaviour under different potential futures, giving general ideas of likely system trajectories.

This study focuses on a novel refinement of previous SDM applications implementing a stochastic assessment of variables interactions for a more robust validation of their uncertainties and trends, particularly useful in the risk assessments field. In particular, conceptual diagram of system variables interactions were elaborated using the Stella software (https://www.iseesystems.com/) while statistical correlations and dependencies between variables were analysed in R (R Core Development Team, 2013). This innovative combination contributes to improving SDM analysis accounting for the uncertainty associated with past and future water flow data. Moreover, the modular nature of SDM allows to lay the foundation for future expansion of the systemic model to include different other anthropogenic activities (e.g. agriculture and domestic) and their consequences on the system as a whole.

2. Case study

The Noce river is in the Province of Trento (Italy) in the south-eastern part of the Alps (Figure 2) and it is one tributary of the Adige river, the second longest river in Italy. The Noce river basin is a typical Alpine basin characterized by intensive anthropogenic activities: from hydropower plants in the upper part of the catchment mostly relying on glacier melting, to intensive apple orchards shaping the landscape of valley bottoms, and tourism flows with high water demands mainly during winter and summer time for sport activities (i.e. skiing, hiking and kayaking).

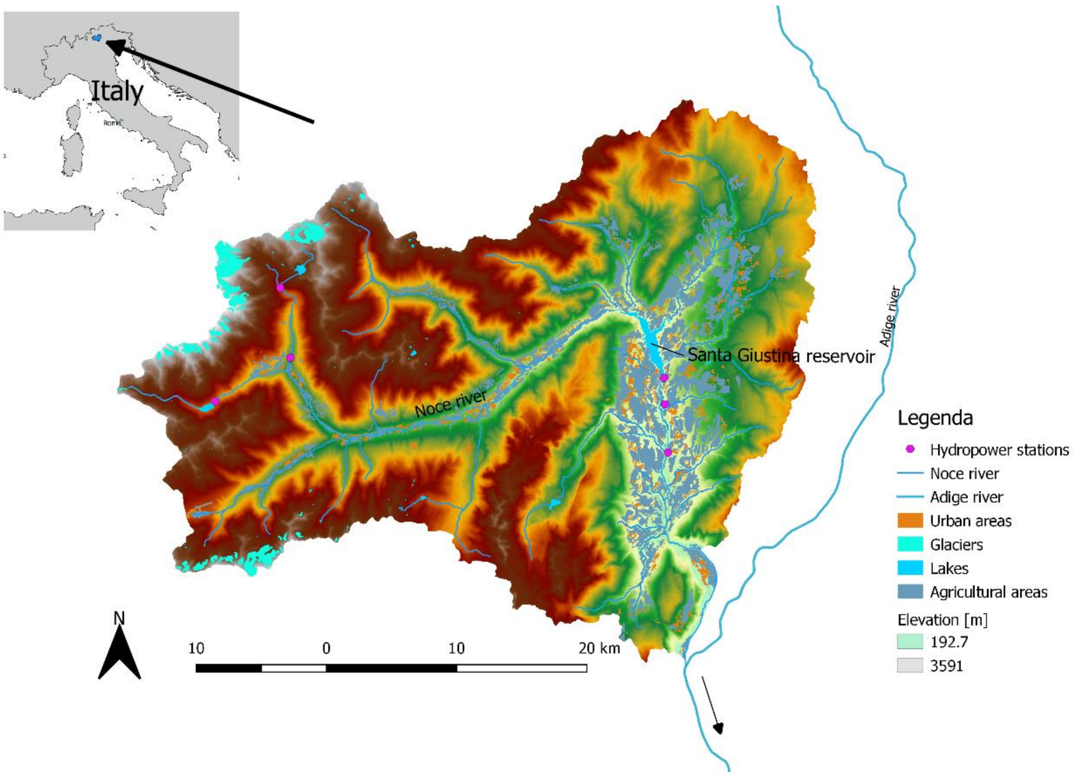

Figure 2- Map of the Noce river basin

Although water has always been considered abundant in the region and in the Alps in general, recent events of water scarcity in 2017 and 2015 raised concerns about water quantity and quality with consequences on the overall catchment (Laaha *et al.*, 2017; Chiogna *et al.*, 2018; Hanel *et al.*, 2018).

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 the 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 requiring a large amount of water to satisfy their need. However, tensions for water allocation have recently arisen asking for a fair use of the resource among the different actors. In particular, associations and civil society groups (e.g. local association for the Noce river safeguard: https://nocecomitato.wordpress.com/) were established showing at provincial level their concerns about ecological impacts of further rivers 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; Zebich *et al.*, 2018).

In the heart of the Noce river basin, the Santa Giustina (hereafter 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), but also regulating the water flow for downstream users and providing water for agricultural irrigation. Moreover, the local water use plan (Provincia Autonoma di Trento, 2006) established a monthly minimum ecological flow threshold ranging from 2.625 to 3.675 cubic meters per second to sustain the fluvial ecosystems, raising concerns among the different stakeholders on the possible economic impacts of such unused water releases.

Within this context, better understanding of the complex variables 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 and anthropogenic factors. Such information could then inform water dam 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).

3. Material and methods

3.1. Integrated risk modelling

Considering features and vulnerabilities of the case study area, we developed a system dynamics model integrating multiple sources of data (e.g. real observations, modelled values and climate projections) and connecting climate change effects with dam reservoir operations. By doing so, it was possible to explore the use of SDM together with statistical assessments of variables interactions considering resulting effects of climate change, water streamflow changes and their effects on water stored in S.Giustina, and used for hydropower production.

The framework in Figure 2 summarises the different models components, converging into the system dynamics modelling for the assessment of the S.Giustina reservoir operations and possible critical states. The climate projections box provides information on the models used at global level then downscaled to regional level, and bias corrected with local weather stations to better simulate climate local conditions. The regional climate model COSMO-CLM (i.e. Climate Limited-area Modelling) was considered in this study for its spatial resolution of 0.0715° × 0.0715° (≈ 8km×8km) allowing to look into climate impacts at local level (Rockel and Geyer, 2008). Such model information was developed by the CLM community and provided by Euro-Mediterranean Centre on Climate Change (CMCC) for the application to the Noce catchment (Bucchignani *et al.*, 2016). Temperature and precipitation information were then used as an input to the already existing physically-based model "GeoTransf" together with other topographical information so to replicate streamflow conditions of the Noce river within the OrientGate project (Box 2 in Figure 3). GeoTransf was already calibrated and validated on past water flow data in the case study area considering a baseline time range from 1980 to 2010 (Bellin *et al.*, 2016; Majone *et al.*, 2016). This model provides a description of the hydrological dynamics within the Noce alpine river catchment, assessing possible variations in water contributions coming from climate change effects in terms of temperature, soil moisture, glaciers, snow and rainfall.

Moreover, GeoTransf was applied with future COSMO-CLM future 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 4.5 and 8.5 (Bucchignani *et al.*, 2016). These already available applications of GeoTransf were then used as input data to the stochastic system dynamics model to focus on S.Giustina reservoir functioning operations and simulate future conditions accounting for both climate change impacts and human management.

Baseline simulation period was bound to the actual available data. In the case of climate data coming from COSMO-CLM, precipitation and temperature information was available from 1975 to 2005. This data was used to look into the Noce catchment climatology and to compare the baseline with future conditions of precipitation and temperature for the two future RCP scenarios (Table 3). While for water flows data to and from the reservoir and the water volume stored, baseline period goes from 1999 to 2004 and from 2009 to 2017.

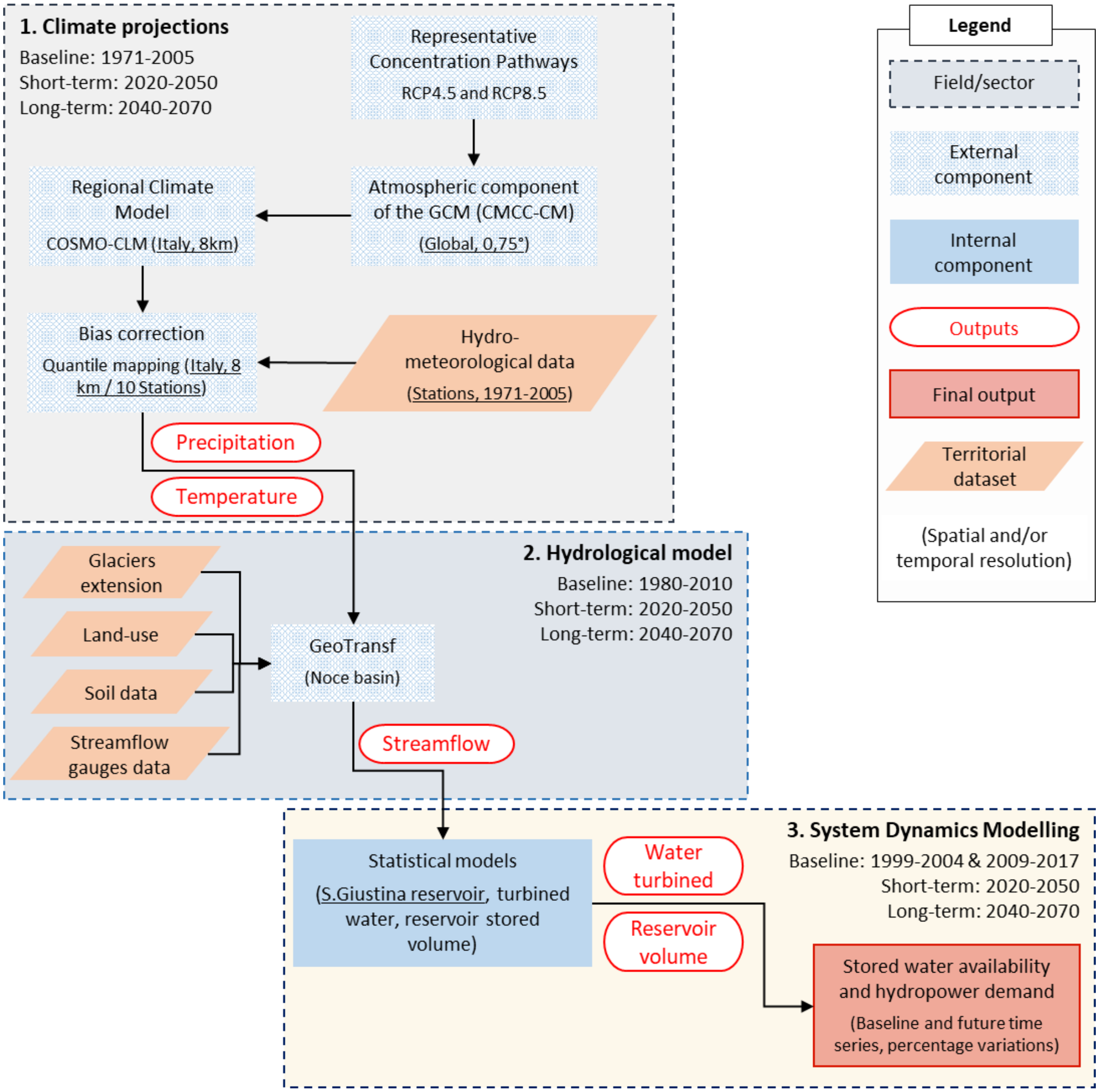

Figure 3 – Integrated modelling approach to quantify the impacts of climate change on water streamflow, water stored and turbined for hydropower production. Sources: adapted from Ronco et al., 2017; Vuong et al., 2018

As part of this study, we introduced the modelling set up and the SDM application aiming to estimate water availability variations being affected by both future climate change scenarios and water demand from the S.Giustina dam reservoir operations. The SDM approach was here implemented for integrated risk modelling of variables dynamic interactions related to one reservoir and one sectorial water demand, allowing further developments according to its modular approach.

3.2. System Dynamics modelling set up

3.2.1. Causal loop and input data

A first system conceptualization aims to identify the variables and their interactions involved within the description of the S.Giustina dam management and climate effects on water availability.

According to the most recent terminology developed by IPCC, 2014a within the 5th Assessment Report, a causal loop diagram was developed in STELLA to graphically support the comprehension of risk variables and their interactions for risk assessment of critical states for the S.Giustina water reservoir operations (Figure 4). 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. Others elements related to socio-economic vulnerability and the inclusion of other sectors characterizing the total water demand in different parts of the catchment will be included in a further SDM application.

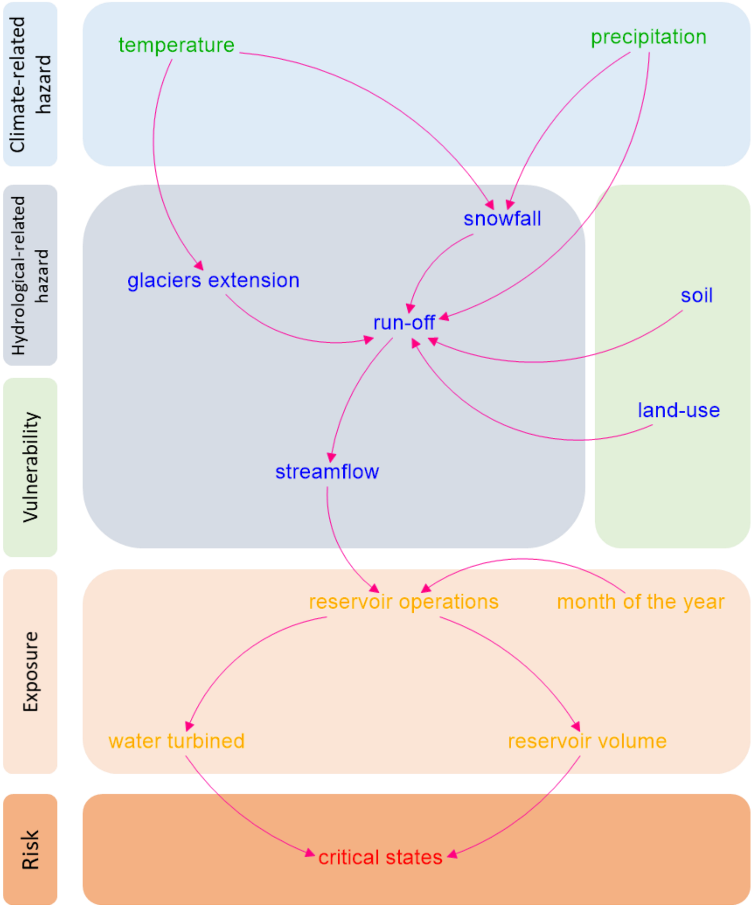

Figure 4 – Conceptual causal loop model used to describe the risk variables and their interactions leading to critical states of S.Giustina reservoir operations. Green variables comes from COSMO-CLM model, blue variables represent some of the GeoTransf hydrological model components. Yellow variables are those included in the SDM model converging into the final assessment of critical states.

The current SDM was built from GeoTransf outputs aiming to subsequently integrate human dynamics in a probabilistic manner, assessing the management of the reservoir and its future vulnerability to changing environmental conditions (Figure 4).

The SDM reservoir model covers two variables exposed to critical conditions: one focusing on the water volume stored within the reservoir and the other representing the water outflow diverted to the turbines for hydropower production.

Data availability was constrained by the time range of volume observations. The dataset used to represent each parameter of the SDM is summarised in Table 1. Due to the sensitivity of such data used for licensing water withdrawals, the analysis could only focus on 14 years of volume measurements.

Table 2 - Details of parameter values used in the S.Giustina reservoir SDM

Data type	Data type	Time range	Data source/reference
Water inflows [m^3/s]	Continuous daily data	1981-2010	Province of Trento – Agency for water resource and energy
Reservoir water outflow for hydropower use [m^3/s]		1981-2017	
Reservoir volume [Mm^3]	Continuous daily data	1999-2004 2009-2017	
Future projections of temperature [k]	Continuous daily data	2021-2050 2041-2070	Euro-Mediterranean Center on Climate Change
Future projections of precipitation [mm]	Continuous daily data		

3.2.2. Variables interaction analysis

In both modules, a linear mixed effects model was selected among other regression techniques (i.e. generalized additive models and support vector regression were tested) because of its ability to account for monthly variation (i.e. month effect) and its lower proneness to overfit the calibration data (i.e. compared to flexible non-linear models). The linear mixed effects model was calibrated and validated for 168 months (i.e. data available for two consecutive periods for a total of 14 years: from 1999 to 2004 and from 2009 to 2016). A monthly temporal step was chosen to better describe the intra-seasonal dynamics of water availability, which can be useful in case of water demand assessments, and for long-term dynamics representation for climate impact assessment. The model was then tested on the basis of multiple temporally independent test observations and finally applied to predict future conditions on the basis of climate scenario data.

Reservoir volume

The simulation of reservoir water volumes and outflow for hydropower production was developed combining the Stella software with statistical analysis using R. We used the *lme4* package in R (Bates *et al.*, 2015) to perform a linear mixed effect analysis of the relationship between water volumes stored in the reservoir (i.e. V) and water flow into the reservoir (i.e. Q_{in}) (*Equation 1*):

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

where, as fixed effect, we considered the water inflowing to the reservoir component (i.e. Q_{in}), hence accounting for the linear relation with the water volume stored. As random effect, we selected the month of the year factor (i.e. month) for its grouping effect on the recurrent water volume variations at 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 models and analysis aiming to explore the reservoir volume vulnerability to future changing conditions.

Hydropower

The second module of the SDM simulates the turbined outflows from the S.Giustina reservoir for hydropower production. Similarly to equation 1, we selected and performed a linear mixed effect analysis considering the relation between the water diverted to the turbines and the water inflow to the reservoir (Equation 2).

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

The water diverted to the turbines was linearly correlated with the water inflowing the reservoir (i.e. Q_{in}) and the month of the year, considered as a grouping factor, influencing the amount of water diverted to the turbines.

3.2.3. Model calibration and validation

The SDM model was calibrated and validated over 168 months of available data for the baseline period: a total of 14 years from 1999 to 2004 and from 2009 to 2017. Although this amount of data was limited, 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 the root mean square error (RMSE) metric. 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 calibrated using a subset of the original data that relates to the first 130 months of available data. Equations 1 and 2 are then tested using both training data (i.e. fitting performance) and the data set that relates to the remaining (not yet) considered months (i.e. predictive performance). The following 37 repetitions are based on the identical procedure, but on increasingly larger training data sets (i.e. consecutively adding 1 month within the forward time-window approach). 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, as often applied in the field of machine learning, consists in the possibility to exploit all the available data for the generation of the final prediction model.

3.2.4. Future projections

Once the models were calibrated and validated on past observations, future conditions of water inflow to the reservoir coming from the GeoTransf application were used to simulate future volumes stored in the S.Giustina reservoir. GeoTransf simulations considered unchanged maximum water withdrawals in the Noce catchment in the future and integrated downscaled COSMO-CLM climate scenarios (Bellin *et al.*, 2016; Bucchignani *et al.*, 2016). Such climate projections have already been demonstrated to well represent climate forcing variables (i.e. precipitation and temperature) over complex Alpine regions (Montesarchio *et al.*, 2013). For this reason, they were included in the GeoTransf hydrological application, which were made available from partners involved in the Orientgate project (http://www.orientgateproject.org).

Two Representative Concentration Pathways (RCPs) were selected according to the IPCC AR5 to simulate both the Paris Agreement emission stabilization scenario (RCP 4.5) and a business as usual emission scenario (RCP8.5) (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 finally the S.Giustina dam reservoir and its management.

Moreover, this study considered the number of times volume projections in the future overcome the 30th and 80th quantile thresholds corresponding to low and high level 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 (Yilmaz, Gupta and Wagener, 2008; Majone *et al.*, 2016).

For this case, a Monte Carlo approach was implemented by randomly sampling from the simulated future water volume predictions and replicating possible reservoir critical state conditions more than 10.000 times per each future climate scenario. 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 each scenario, so to directly compared such future values with the 14 years of the baseline. By doing so, it was possible to work on a wider range of possible predicted volume values and statistically inspect critical states in the future looking at the differences with respect to the baseline.

4. Results

4.1. Baseline period

The linear mixed-effect model was used to replicate past observations of water volumes stored in the S.Giustina reservoir (Figure 4). The model was calibrated and validated using a forward time-window approach (described in Section 4.4) resulting in a R^2= 0.71 and an estimate of the mean Root Mean Square Error (RMSE) equal to 13.5. Figure 4 shows the results, where stored water volume can fluctuate between 0 (i.e. no usable volume) when the hydropower production is interrupted, and a maximum level of 151.20 Mm3, or up to 159.30 Mm3 in case of flood prevention downstream the reservoir. In those cases of simulations projecting values of water stored greater than the maximum allowed, simulation values were set at such a maximum value.

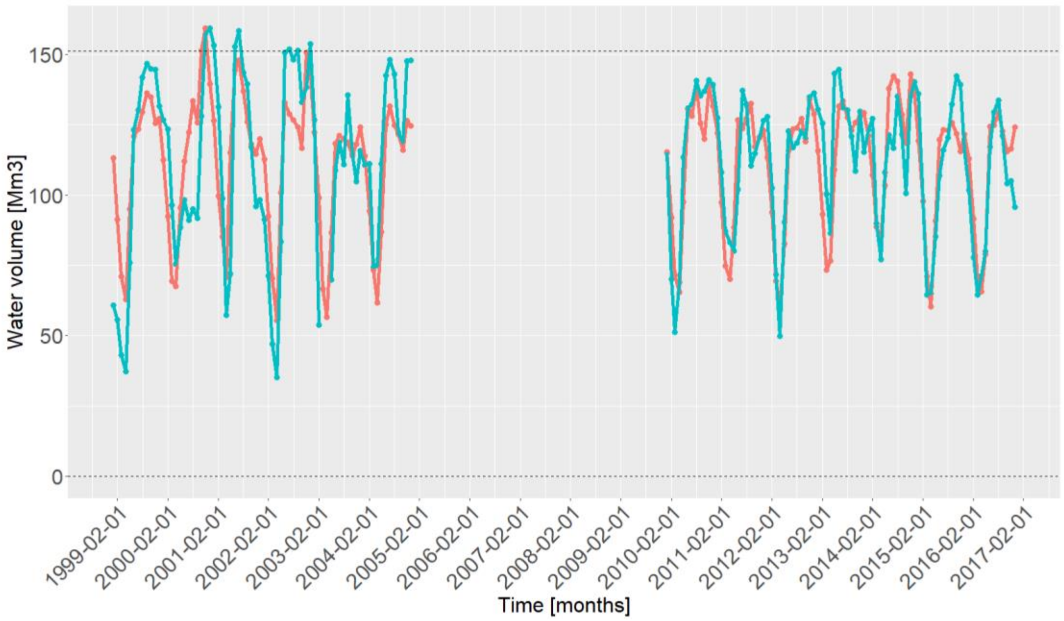

Figure 5 – S.Giustina time-series of water volume. Measured (blue line) and modelled (red line) water stored in S.Giustina from 1999 to 2017. R^2= 0.71, mean RMSE= 13.5

The same procedure was undertaken for simulating water flows diverted to the turbines (Figure 6). In this case, the maximum discharge of water flow to the turbines is 176 Mm^3 $month^{-1}$ for 31 days of full operations due to penstocks size. Equation 2 was applied so to estimate the water diverted from the reservoir to the turbines for hydropower production. In both cases, the water inflowing to the S.Giustina reservoir and modelled using the GeoTransf hydrological model played a key role influencing the operations related to the flow diverted to the turbines and hence the water stored.

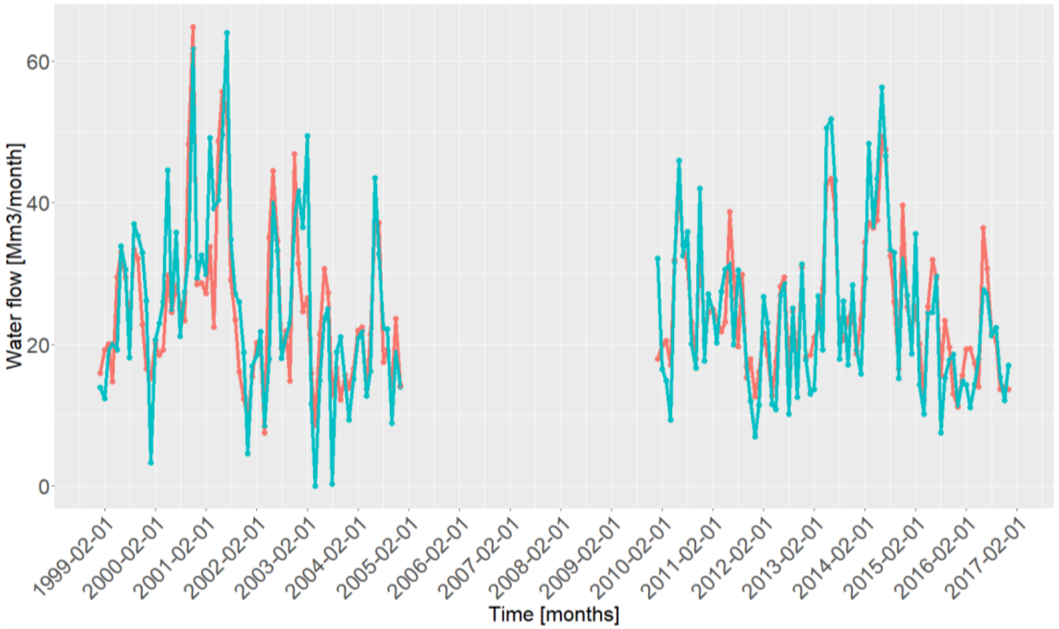

Figure 6 – S.Giustina time-series of water diverted to the turbines. Measured (blue line) and modelled (red line) water outflowing from the S.Giustina dam reservoir from 1999 to 2017. R^2= 0.79, RMSE= 4.7

4.2. Future projections

Future GeoTransf model results forced by the COSMO-CLM climate projections depict a situation of generalized decreases in precipitation and water inflowing to the reservoir (Table 3). However, such decreases differentiate for the two considered climate change scenarios. The short-term RCP4.5 scenario shows a substantial decrease of precipitation compared to the baseline and to the RCP8.5 scenario, which projects a slight increase of precipitation until 2050. However, such little increase seems not to have substantial consequences on the water flowing into the reservoir and consequently on the volume of water stored.

Table 3 – Average values of temperature and precipitation (COSMO-CLM projections), water inflow to the S.Giustina reservoir, volume stored and water turbined (SDM simulations), and their percentage differences compared to baseline values.
********Baseline period for climate data goes from 1975 to 2005, while for water inflow and volume stored spans over 14 years from 1999 to 2004 and from 2008 to 2017.*

	Baseline*	**RCP4.5**				**RCP8.5**			
		2021-2050		**2041-2070**		**2021-2050**		**2041-2070**	
	Value	Value	Δ	Value	Δ	Value	Δ	Value	Δ
Temperature [°C]	5,06	6,46	+0,5%	7,5	+0,9%	6,63	+0,5%	8,1	+1,1%
Precipitation [mm/year]	1495,1	1433,55	-4,1%	1391,5	-6,9%	1516,3	+1,5%	1430,7	-4,3%
Water inflow to S.Giustina [Mm3/month]	27.4	21.8	-20.4%	22.1	-19.3%	25.0	-8.8%	21.4	-21.9%
Volume stored [Mm3]	111.6	107	-4,1%	107	-4,1%	110	-1,4%	106	-5.0%
Water turbined [Mm3/month]	24.8	20.4	-17.7%	20.7	-16.5%	22.9	-7.6%	20.1	-19.0%

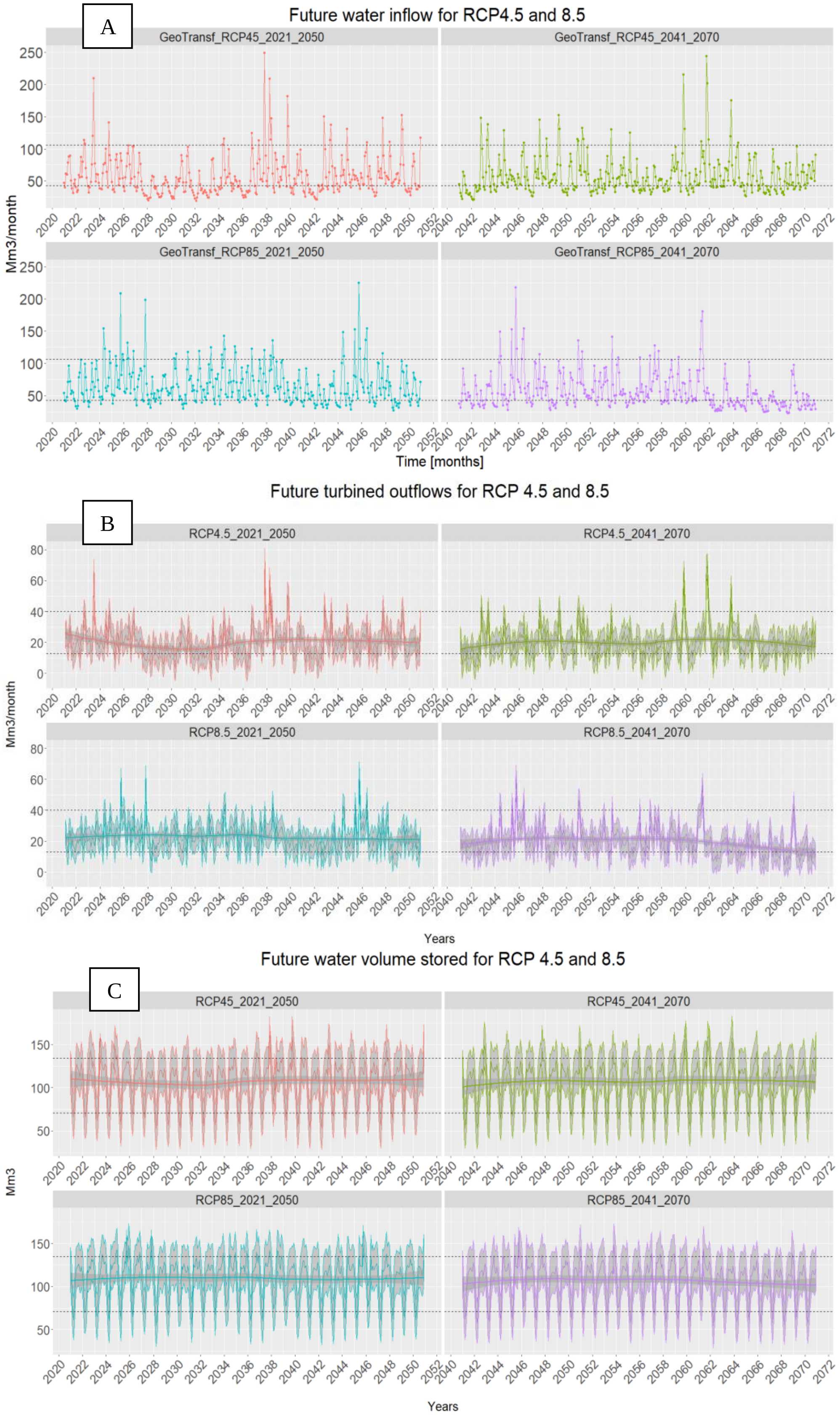

Figure 7 – Plots in A show future projections of simulated water inflow to the S.Giustina reservoir. Plots in B show simulated future water diverted to the turbines and plots in C simulated future water volume stored in the S.Giustina reservoir. Dotted lines indicate baseline 30 and 80 % quantiles. Grey shaded represents the confidence interval for the simulated outflows and water volumes.

On a long-term perspective, the trend of precipitation is negative reaching a 6.9% reduction for RCP4.5 and causing a reduction of 19.3% in river flow and of 4.1 % in volume stored compared to the baseline. The RCP8.5 scenario predicts a reduction of 4.3% in precipitation, but a higher decrease in water inflow to the reservoir of 21.9% and water stored of -5%. This is likely due to an increase of mean temperatures in the long-term scenarios (+1.1%) causing higher evaporation and evapotranspiration and hence reducing the flow of water to the reservoir and the volume stored.

Results from the SDM simulation at monthly temporal resolution are reported both in Figure 7 and then averaged over 30 years and compared to the baseline (i.e. percentage change; Figure 8). On the one hand, all the climate scenarios show agreement on the generalized decrease of volume for the spring and summer time going from April to September down to a minimum of -15.3% for RCP4.5 for the short-term case. Scenarios also agree on the negative trend in November where RCP8.5 in the long-term scenario reaches a minimum of -6.1% of volume difference. Moreover, agreement is shown on the increase of volume stored for January up to +2.7%. On the other hand, scenarios show cases of disagreement for February, March, October and December.

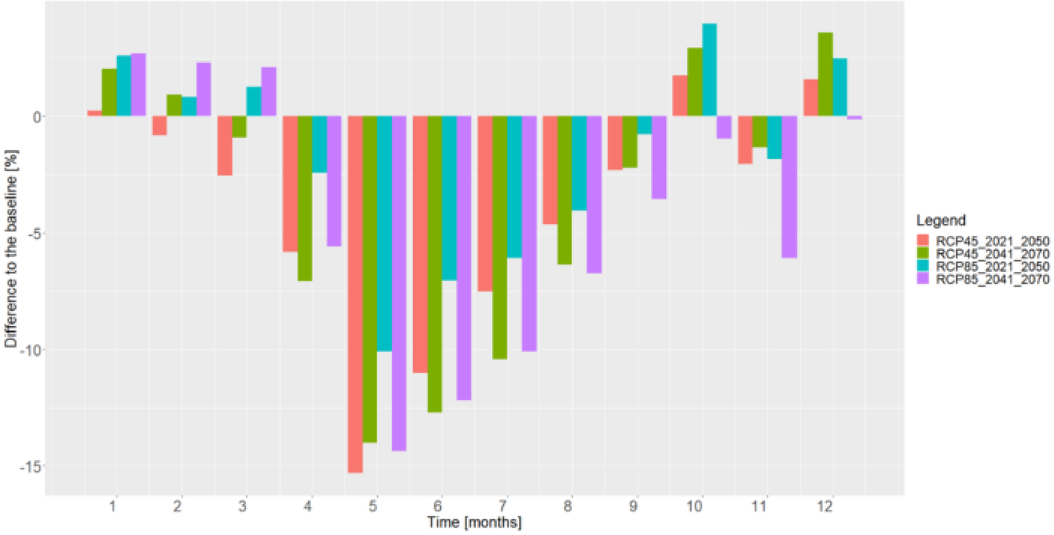

Figure 8 – Percentage change of volume [%] comparing the 4 climate scenarios to the baseline at monthly level

Such disagreement provides important information on the timing of reservoir management improvements. In particular, short-term RCP4.5 depicts a condition of continuous negative volume trends througout the year with positive, albeit minor, volume increases during October and December (+1.8% and +1.6%). Long-term RCP4.5 extend the positive months to January and February (+2% and +1%). Short-term RCP8.5 shows the most favourable conditions of water volumes, depicting positive differences in January (+2.6%) , February (+0.9%), March (+1.3), October (+4.0%) and December (+2.5%). While the long-term RCP8.5 envisages the first three months of the year only having positive values (+2.6%, +2.3%, +2.1%) and the rest of the year with negative values down to -14.3% in May.

Moreover, potentially critical states of stored reservoir water volumes (both high and low) were explored to further understand how climate change may impact on long-term reservoir operation and resilience (thresholds identified in section 3.2.4). For this reason, the number of events lower than the 30th and greater than the 80th quantiles were calculated on future predictions considering a moving time-window of 14 years and comparing such values to the 14 years of the baseline (Figure 8). In this case, boxplots of the 30th quantile threshold show an increasing number of low-volume events for RCP4.5, passing from 53 events for the baseline to 61 (i.e. +15.1%) for the short-term and 65 (i.e. +22.6%) for the long-term. RCP8.5 shows a potential decrease in the short-term to 52 events (-1.9%), but higher values in the long-term (i.e. average of 64 events, +20.8%) though having a wider interquantile range.

A better defined situation is represented in case of events greater than the 80th quantile. All scenarios show a decrease in the number of high volume events compared to the 49 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 (i.e. -6.1% for the short-term and -12.2% for the long-term average values). RCP8.5 depicts a less defined condition of high volumes, reaching the minimum number of high volume events (i.e. 39 events, -20.4%) in the short-term scenario, but also showing a strong decrease in the long-term scenario reaching 44 events (-10.2%). Overall, all future scenarios predict conditions of reduced high volume events being their 75% percentile lower than the baseline value and hence confirming the trend consistency.

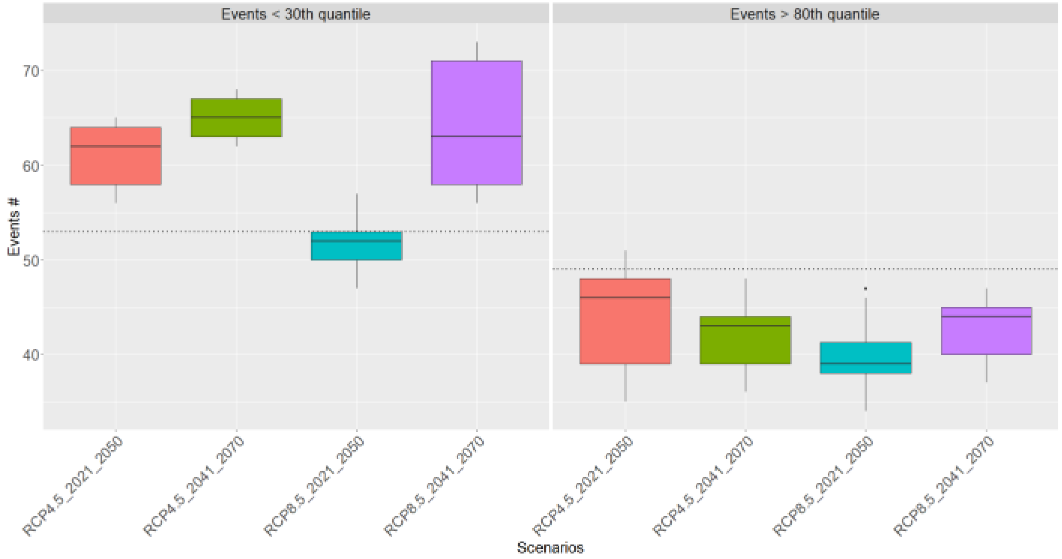

Figure 9 - Number of events lower than the 30th and greater than the 80th baseline quantile for future scenarios of water volume in the S.Giustina reservoir using a Monte Carlo approach. The dotted line shows the number of events for the baseline.

Finally, future conditions of water flow diverted to the turbines show similar trends of monthly decrease (Figure 9). Consistent with Figure 9, the water flow diverted to the turbines at monthly resolution and averaged over 30 years of simulations were compared to the baseline. The water flow diverted have the highest percentage changes during spring and summer with differences up to -5.2% for the RCP4.5 long-term scenario. Scenarios show agreement on a reduction of water flow during November reaching a minimum of -2.6% of volume difference for RCP8.5 long-term scenario.

In all the other months of the year, scenarios depict varying conditions of water flow. In particular, RCP4.5 depicts conditions of negative differences to the baseline for almost every month of the year, with exceptions during October (+0.4%) and December (+0.2%). Increased number of positive differences are predicted for long-term RCP4.5 during January (+0.6%) and February (+0.3%). Also for water flows diverted, short-term RCP8.5 shows larger positive differences during January (+0.7%), February (+0.4%), March (+0.4%), October (+1.3%) and December (+0.7%). However, long-term RCP8.5 projects negative trend for most of the year reaching a minimum difference of -5.2% during June and only showing positive values for January (+0.7%), February (+0.9%) and March (+0.7%).

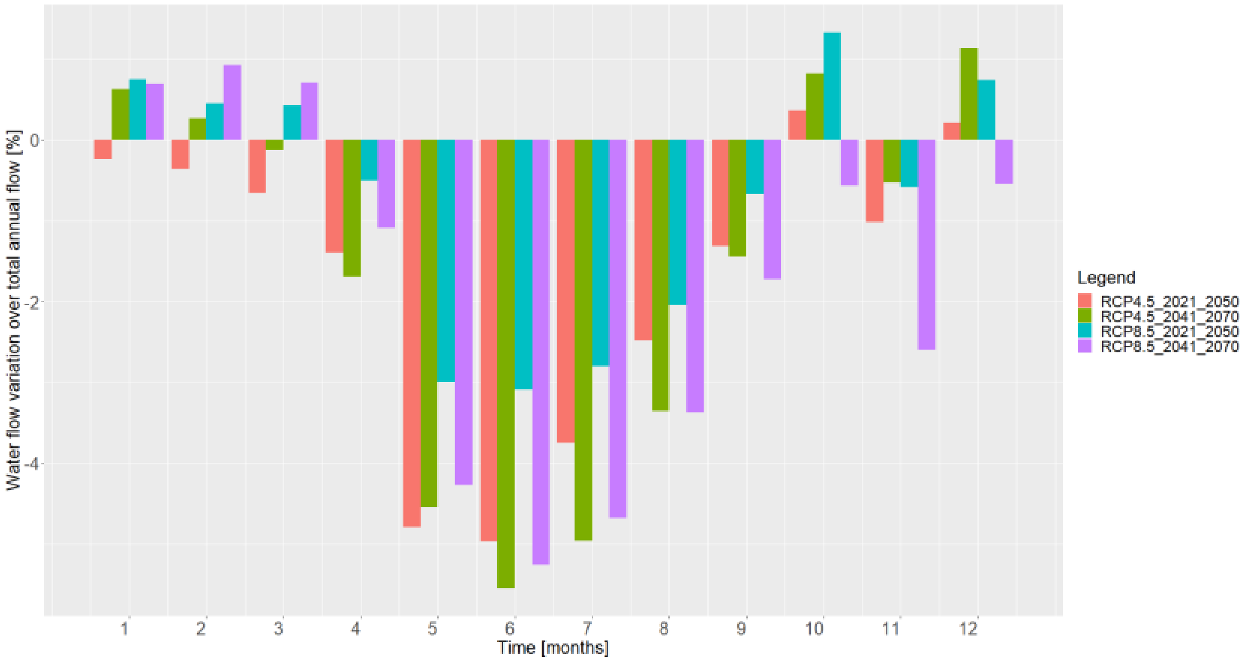

Figure 10 - Percentage of monthly water flow diverted to the turbines over the total annual water flow [%], comparison of the 4 climate scenarios to the baseline at monthly level

5. Discussion

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 is strategic for hydropower regulation and hydrologically disconnecting upstream with downstream river flow.

The application of an integrated risk modelling approach including climate change models, hydrological models and a stochastic assessments of variables interactions proved to be a quick and effective method to characterize the S.Giustina reservoir volume and flows management looking at their critical future conditions due to climate change effects. Such a method supports the identification of variables affecting dam operations and a quantitative evaluation of their interactions going beyond traditional deterministic hydrological assessments and paving the way for a more integrated assessment.

Results described in section 4 show how precipitation patterns change for the COSMO-CLM scenarios, influence the amount of water flowing to the reservoir and its future conditions, even in the RCP4.5 scenario (i.e. case of implementation of the Paris Agreement emission reductions objectives). On one side, results during months of highest reduction of volume and water flow to the turbines (i.e. from April to September) provide useful information on possible consequences coming from the combination of business as usual water withdrawals upstream the reservoir and climate change effects (i.e. -15.3% of volume reduction, +22.6% in the number of events with low stored volume, -20.4% in the number of high volume events and -5.2% of water diverted to the turbines). In particular, 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 years 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 quality supply downstream the reservoir.

On the other side, looking at those months of positive variations of volume and turbined water flow (i.e. autumn and winter months, November excluded) provides insights on the need to implement precautionary water conservation practices upstream, to reduce the number and intensity of water withdrawals. Moreover, there is a need to plan adaptation strategies to improve the management of the S.Giustina reservoir according to the timing of positive water volume changes aiming to prepare to increasing (spring and summer) conditions of negative variations. These results are in line with other findings in the Alps showing the need of an earlier reservoir water accumulation during winter to prevent downstream conditions of water issues during summer time (Hendrickx and Sauquet, 2013; Brunner *et al.*, 2019).

Such negative variations are confirmed by the increasing number of future water scarcity conditions of high and low volumes stored, especially in a long-term perspective. At the same time, high volume events are decreasing in number, confirming previous results of generalized negative trend of water stored. Results 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 flow. Moreover, the Monte Carlo results in Figure 8 provide additional information on the substantial reduction of high-volume states in S.Giustina for all future climate scenarios.

In general, the results hint at exacerbated risks to reservoir operation especially in terms of low flows in the summer threatening water supply security, hydropower production, and ecosystem services in the valley. Results presented here should be considered in future plans to change S.Giustina management practices in order to mitigate the impacts of climate change on reservoir operation. The findings presented here are in line with studies from similar regions (Hendrickx and Sauquet, 2013; Biemans *et al.*, 2019), further reinforcing the vulnerability of Alpine ‘water tower’ regions to supply water, power and ecosystem services to an increasing water demand.

Limitations of the study

This study is mostly driven by the GeoTransf applications considering the COSMO-CLM climate projections. However, several assumptions were involved hence introducing some limitations.

Accounting for the GeoTransf application means relying on a very accurate water evaluation within the catchment, but also considering only one climate model (i.e. COSMO-CLM) for future projections. Such climate model has been proved to well represent conditions in mountain regions (Montesarchio *et al.*, 2013) and differently from other climate models depict generalized conditions of decreased precipitation over the catchment (Table2) and hence providing more conservative information on possible impacts on streamflow and volume management.

Moreover, although local events of intense rainstorms and flash floods may occur, the study here presented considered precipitation, water flow and volume trends over a 30 years period and hence focusing on their long-term positive and negative variations.

The results coming from the GeoTransf application assumed a conservative condition of upstream water use set at the maximum licensed withdrawals values. This information was kept unchanged also for future scenarios, although possible variations in the future (e.g. from agricultural and touristic uses) may affect river water flows.

As reported in section 3.2.3, the available data on the reservoir volume was limited, hence affecting the model predicting performance. However, due to such condition, 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 proved to be 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, we assumed the existence of the same statistical relations in case of future conditions. Nevertheless, such constrain is justified by the high uncertainty associated to future changes in production patterns affected by societal conditions (e.g. energy price fluctuations) (Gaudard *et al.*, 2014; Ranzani *et al.*, 2018). Moreover, few variables were considered within the models and although some other variables play important roles within the management of the reservoir at different temporal resolution (e.g. hourly energy market price), in our monthly simulations it proved to be the best model possible.

6. Conclusions

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.

This is the first step of a more comprehensive multi-risk assessment of water scarcity in order to give policy-makers a better idea on the overall system behaviour and to identify climate adaptation strategies to gain systemic leverage effects. Due to its modular approach, future model improvements include the integration of other components for the development of different scenarios of both water demand and availability variations to support decision-makers in a more resilient management of water resources. By doing so it will be possible to ensure a sustainable long-term water management limiting climate change impacts on those economic activities relying on a high water availability.

These objectives are in line with the European Water Framework Directive on sustainable water management (European Parliament & Council, 2000), climate change adaptation (Zambrano Leal, 2012; European Commission, 2013), and in terms of adaptation to future climate change impacts in the Alps (Alpine convention, 2013).

Moreover, such a stochastic SDM is applicable to other cases at interregional / transnational scale to evaluate possible water management effects going beyond national boundaries hence enhancing the existing cooperation structures within and outside Europe in line with the objective of the Action group 8 of the European Strategy for the Alpine region (EUSALP).

In conclusion, the stochastic SDM approach was able to represent the effect of climate change and reservoir operations demonstrating the suitability of this method to extend deterministic applications commonly applied in the SDM community, accounting for a wider range of uncertainty.

Improvements and model extensions include the need to better characterize the influence of climate change and upstream human withdrawals on the reduction of water availability flowing to the reservoir, inspecting the relations between upstream socio-economic activities and downstream consequences. Finally, extending reservoir operations to future environmental and human conditions allows to better understand criticalities connected to unsustainable water demands and anticipate critical conditions, to inform dam managers and local authorities on the best climate change adaptation strategies to implement.

References

Alpine convention, 2013. Guidelines for Climate Change Adaptation at the local level in the Alps.

Baldassarre, G. Di, Viglione, A., Carr, G., Kuil, L., Yan, K., Brandimarte, L., Bloschl, G., 2015. Debates—Perspectives on socio-hydrology: Capturing feedbacks between physical and social processes. Water Resour. Res. 51, 4770–4781. https://doi.org/10.1002/2014WR016416.Received

Barnett, T.P., Adam, J.C., Lettenmaier, D.P., 2005. Potential impacts of a warming climate on water availability in snow-dominated regions. Nature 438, 303–309. https://doi.org/10.1038/nature04141

Bates, D., Mächler, M., Bolker, B.M., Walker, S.C., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Softw. 67. https://doi.org/10.18637/jss.v067.i01

Bellin, A., Majone, B., Cainelli, O., Alberici, D., Villa, F., 2016. A continuous coupled hydrological and water resources management model. Environ. Model. Softw. 75, 176–192. https://doi.org/10.1016/j.envsoft.2015.10.013

Beniston, M., Stoffel, M., 2014. Assessing the impacts of climatic change on mountain water resources. Sci. Total Environ. 493, 1129–1137. https://doi.org/10.1016/j.scitotenv.2013.11.122

Biemans, H., Siderius, C., Lutz, A.F., Nepal, S., Ahmad, B., Hassan, T., von Bloh, W., Wijngaard, R.R., Wester, P., Shrestha, A.B., Immerzeel, W.W., 2019. Importance of snow and glacier meltwater for agriculture on the Indo-Gangetic Plain. Nat. Sustain. 2, 594–601. https://doi.org/10.1038/s41893-019-0305-3

Brunner, M.I., Björnsen Gurung, A., Zappa, M., Zekollari, H., Farinotti, D., Stähli, M., 2019. Present and future water scarcity in Switzerland: Potential for alleviation through reservoirs and lakes. Sci. Total Environ. 666, 1033–1047. https://doi.org/10.1016/j.scitotenv.2019.02.169

Bucchignani, E., Montesarchio, M., Zollo, A.L., Mercogliano, P., 2016. High-resolution climate simulations with COSMO-CLM over Italy: Performance evaluation and climate projections for the 21st century. Int. J. Climatol. 36, 735–756. https://doi.org/10.1002/joc.4379

Chiogna, G., Skrobanek, P., Sheikhy, T., Ludwig, R., Stumpp, C., 2018. Effects of the 2017 drought on isotopic and geochemical gradients in the Adige catchment , Italy. Sci. Total Environ. 645, 924–936. https://doi.org/10.1016/j.scitotenv.2018.07.176

Davies, E., Simonovic, S.P., 2011. Global water resources modeling with an integrated model of the social-economic-environmental system. Adv. Water Resour. 34, 684–700. https://doi.org/10.1016/j.advwatres.2011.02.010

Davies, E.G.R., Simonovic, S.P., 2008. An Integrated System Dynamics Model for Analyzing Behaviour of the Social-Economic-Climatic System: Model Description and Model Use Guide.

Duran-Encalada, J.A., Paucar-Caceres, A., Bandala, E.R., Wright, G.H., 2017. The impact of global climate change on water quantity and quality: A system dynamics approach to the US-Mexican transborder region. Eur. J. Oper. Res. 256, 567–581. https://doi.org/10.1016/j.ejor.2016.06.016

Etter, S., Addor, N., Huss, M., Finger, D., 2017. Climate change impacts on future snow, ice and rain runoff in a Swiss mountain catchment using multi-dataset calibration. J. Hydrol. Reg. Stud. 13, 222–239. https://doi.org/10.1016/j.ejrh.2017.08.005

European Commission, 2018a. Report on the implementation of the EU strategy on adaptation to climate change.

European Commission, 2018b. Evaluation of the EU Strategy on adaptation to climate change. Accompanying the document: Report on the implementation of the EU Strategy on adaptation to climate change. https://doi.org/10.1017/CBO9781107415324.004

European Parliament & Council, 2000. Directive 2000/60/EC of the European Parliament and of the Council. Off. J. Eur. Communities 21, 196. https://doi.org/10.1039/AP9842100196

Farinotti, D., Usselmann, S., Huss, M., Bauder, A., Funk, M., 2012. Runoff evolution in the Swiss Alps: Projections for selected high-alpine catchments based on ENSEMBLES scenarios. Hydrol. Process. 26, 1909–1924. https://doi.org/10.1002/hyp.8276

Forrester, J.W., 1971. World Dynamics. Wright-Allen Press 142.

Fuhrer, J., Smith, P., Gobiet, A., 2014. Implications of climate change scenarios for agriculture in alpine regions - A case study in the Swiss Rhone catchment. Sci. Total Environ. 493, 1232–1241. https://doi.org/10.1016/j.scitotenv.2013.06.038

Gaudard, L., Romerio, F., Dalla Valle, F., Gorret, R., Maran, S., Ravazzani, G., Stoffel, M., Volonterio, M., 2014. Climate change impacts on hydropower in the Swiss and Italian Alps. Sci. Total Environ. 493, 1211–1221. https://doi.org/10.1016/j.scitotenv.2013.10.012

Gohari, A., Mirchi, A., Madani, K., 2017. System Dynamics Evaluation of Climate Change Adaptation Strategies for Water Resources Management in Central Iran. Water Resour. Manag. 31, 1413–1434. https://doi.org/10.1007/s11269-017-1575-z

Hanel, M., Rakovec, O., Markonis, Y., Máca, P., Samaniego, L., Kyselý, J., Kumar, R., 2018. Revisiting the recent European droughts from a long-term perspective. Sci. Rep. 8, 1–11. https://doi.org/10.1038/s41598-018-27464-4

Hastie, T. et. all., 2009. Springer Series in Statistics The Elements of Statistical Learning. Math. Intell. 27, 83–85. https://doi.org/10.1007/b94608

Hendrickx, F., Sauquet, E., 2013. Impact of warming climate on water management for the Ariège River basin (France). Hydrol. Sci. J. 58, 976–993. https://doi.org/10.1080/02626667.2013.788790

Huss, M., Hock, R., 2018. Global-scale hydrological response to future glacier mass loss. Nat. Clim. Chang. 8, 135–140. https://doi.org/10.1038/s41558-017-0049-x

IPCC, 2018. Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,.

IPCC, 2014a. Climate Change 2014 Synthesis Report Summary Chapter for Policymakers. Ipcc 31. https://doi.org/10.1017/CBO9781107415324

IPCC, 2014b. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change., Headline statements from the Summary for Policymakers. https://doi.org/10.1017/CBO9781107415324

Kohavi, R., 1995. A study of cross-validation and bootstrap for accuracy estimation and model selection. Int. Jt. Conf. Aritificial Intell. 0–6.

Kohler, T., Wehrli, A., M., J., 2014. Mountains and Climate Change.

La Jeunesse, I., Cirelli, C., Aubin, D., Larrue, C., Sellami, H., Afifi, S., Bellin, A., Benabdallah, S., Bird, D.N., Deidda, R., Dettori, M., Engin, G., Herrmann, F., Ludwig, R., Mabrouk, B., Majone, B., Paniconi, C., Soddu, A., 2016. Is climate change a threat for water uses in the Mediterranean region? Results from a survey at local scale. Sci. Total Environ. 543, 981–996. https://doi.org/10.1016/j.scitotenv.2015.04.062

Laaha, G., Gauster, T., Tallaksen, L.M., Vidal, J.P., Stahl, K., Prudhomme, C., Heudorfer, B., 2017. The European 2015 drought from a groundwater perspective. Geophys. Res. Abstr. EGU Gen. Assem. 19, 2017–12781.

Majone, B., Villa, F., Deidda, R., Bellin, A., 2016. Impact of climate change and water use policies on hydropower potential in the south-eastern Alpine region. Sci. Total Environ. 543, 965–980. https://doi.org/10.1016/j.scitotenv.2015.05.009

Malard, J.J., Inam, A., Hassanzadeh, E., Adamowski, J., Tuy, H.A., Melgar-Quiñonez, H., 2017. Development of a software tool for rapid, reproducible, and stakeholder-friendly dynamic coupling of system dynamics and physically-based models. Environ. Model. Softw. 96, 410–420. https://doi.org/10.1016/j.envsoft.2017.06.053

Masia, S., Sušnik, J., Marras, S., Mereu, S., Spano, D., Trabucco, A., 2018. Assessment of Irrigated Agriculture Vulnerability under Climate Change in Southern Italy. Water 10, 209. https://doi.org/10.3390/w10020209

Meadows, D.H., Meadows, D.L., Randers, J., Behrens, W.W., 1972. The Limits to Growth. Universe Books, New York.

Mehran, A., AghaKouchak, A., Nakhjiri, N., Stewardson, M.J., Peel, M.C., Phillips, T.J., Wada, Y., Ravalico, J.K., 2017. Compounding Impacts of Human-Induced Water Stress and Climate Change on Water Availability. Sci. Rep. 7, 1–9. https://doi.org/10.1038/s41598-017-06765-0

Mereu, S., Sušnik, J., Trabucco, A., Daccache, A., Vamvakeridou-Lyroudia, L., Renoldi, S., Virdis, A., Savić, D., Assimacopoulos, D., 2016. Operational resilience of reservoirs to climate change, agricultural demand, and tourism: A case study from Sardinia. Sci. Total Environ. 543, 1028–1038. https://doi.org/10.1016/j.scitotenv.2015.04.066

Montesarchio, M., Manzi, M., Cattaneo, L., Mercogliano, P., 2013. Performance Evaluation of a Regional Simulation with COSMO-CLM in the Alpine Space. Ssrn. https://doi.org/10.2139/ssrn.2195316

Neuwirth, C., Hofer, B., Peck, A., 2015. Spatiotemporal processes and their implementation in Spatial System Dynamics models. J. Spat. Sci. 60, 277–288. https://doi.org/10.1080/14498596.2015.997316

Permanent Secretariat of the Alpine Convention, 2013. Report on the State of the Alps. Alpine Signals - Special Edition 2. Alp. Conv. 135.

PGUAP, Provincia Autonoma di Trento, 2006. PGUAP - Piano Generale di Utilizzazione delle Acque Pubbliche. Trento.

R Core Team, 2014. R: A Language and Environment for Statistical Computing.

Ranzani, A., Bonato, M., Patro, E.R., Gaudard, L., De Michele, C., 2018. Hydropower future: Between climate change, renewable deployment, carbon and fuel prices. Water (Switzerland) 10, 1–17. https://doi.org/10.3390/w10091197

Rockel, B., Geyer, B., 2008. The performance of the regional climate model CLM in different climate regions, based on the example of precipitation. Meteorol. Zeitschrift 17, 487–498. https://doi.org/10.1127/0941-2948/2008/0297

Ronco, P., Zennaro, F., Torresan, S., Critto, A., Santini, M., Trabucco, A., Zollo, A.L., Galluccio, G., Marcomini, A., 2017. A risk assessment framework for irrigated agriculture under climate change. Adv. Water Resour. 110, 562–578. https://doi.org/10.1016/j.advwatres.2017.08.003

Sahin, O., Mohamed, S., 2014. Coastal vulnerability to sea-level rise: A spatial-temporal assessment framework. Nat. Hazards 70, 395–414. https://doi.org/10.1007/s11069-013-0818-4

Simonovic, S.P., 2015. Systems approach to management of disasters: methods and applications. J. Integr. Disaster Risk Manag. 5, 70–83. https://doi.org/10.5595/idrim.2015.0099

Simonovic, S.P., 2001. Systems Approach to Management of Disasters.

Sivapalan, M., Savenije, H.H.G., Blöschl, G., 2012. Socio-hydrology: A new science of people and water. Hydrol. Process. 26, 1270–1276. https://doi.org/10.1002/hyp.8426

Stave, K., 2010. Participatory system dynamics modeling for sustainable environmental management: Observations from four cases. Sustainability 2, 2762–2784. https://doi.org/10.3390/su2092762

Sušnik, J., Chew, C., Domingo, X., Mereu, S., Trabucco, A., Evans, B., Vamvakeridou-Lyroudia, L., Savić, D.A., Laspidou, C., Brouwer, F., 2018. Multi-stakeholder development of a serious game to explore the water-energy-food-land-climate nexus: The SIM4NEXUS approach. Water (Switzerland) 10. https://doi.org/10.3390/w10020139

Sušnik, J., Vamvakeridou-Lyroudia, L.S., Savić, D.A., Kapelan, Z., 2013. Integrated modelling of a coupled water-agricultural system using system dynamics. J. Water Clim. Chang. 4, 209–231. https://doi.org/10.2166/wcc.2013.069

Tashman, L.J., 2000. Out-of Sample Tests of Forecasting Accuracy: A Tutorial and Review. Int. J. Forecast. 16, 437–450.

Terzi, S., Torresan, S., Schneiderbauer, S., Critto, A., Zebisch, M., Marcomini, A., 2019. Multi-risk assessment in mountain regions: A review of modelling approaches for climate change adaptation. J. Environ. Manage. 232, 759–771. https://doi.org/10.1016/j.jenvman.2018.11.100

United Nations, 2012. The Future We Want: Outcome document of the United Nations Conference on Sustainable Development.

Varma, S., Simon, R., 2006. Bias in error estimation when using cross-validation for model selection. BMC Bioinformatics 7, 1–8. https://doi.org/10.1186/1471-2105-7-91

Viviroli, D., Archer, D.R., Buytaert, W., Fowler, H.J., Greenwood, G.B., Hamlet, A.F., Huang, Y., Koboltschnig, G., Litaor, M.I., López-Moreno, J.I., Lorentz, S., Schädler, B., Schreier, H., Schwaiger, K., Vuille, M., Woods, R., 2011. Climate change and mountain water resources: Overview and recommendations for research, management and policy. Hydrol. Earth Syst. Sci. 15, 471–504. https://doi.org/10.5194/hess-15-471-2011

Viviroli, D., Dürr, H.H., Messerli, B., Meybeck, M., Weingartner, R., 2007. Mountains of the world, water towers for humanity: Typology, mapping, and global significance. Water Resour. Res. 43, 1–13. https://doi.org/10.1029/2006WR005653

Vuong, H., Sperotto, A., Torresan, S., Acua, V., Jorda-capdevila, D., Rianna, G., 2018. Coupling scenarios of climate and land – use change with assessments of potential ecosystem services at the river basin scale.

Wever, N., Comola, F., Bavay, M., Lehning, M., 2017. Simulating the influence of snow surface processes on soil moisture dynamics and streamflow generation in an alpine catchment. Hydrol. Earth Syst. Sci. 21, 4053–4071. https://doi.org/10.5194/hess-21-4053-2017

Xu, D., Song, A., Tong, H., Ren, H., Hu, Y., Shao, Q., 2016. A spatial system dynamic model for regional desertification simulation - A case study of Ordos, China. Environ. Model. Softw. 83, 179–192. https://doi.org/10.1016/j.envsoft.2016.05.017

Xu, J., Grumbine, R.E., Shrestha, A., Eriksson, M., Yang, X., Wang, Y., Wilkes, A., 2009. The melting Himalayas: Cascading effects of climate change on water, biodiversity, and livelihoods. Conserv. Biol. 23, 520–530. https://doi.org/10.1111/j.1523-1739.2009.01237.x

Yilmaz, K.K., Gupta, H. V., Wagener, T., 2008. A process-based diagnostic approach to model evaluation: Application to the NWS distributed hydrologic model. Water Resour. Res. 44, 1–18. https://doi.org/10.1029/2007WR006716

Zebisch, M., Vaccaro, R., Niedrist, G., Schneiderbauer, S., Streifeneder, T., Weiss, M., Troi, A., Renner, K., Pedoth, L., Baumgartner, B., V, B., 2018. Rapporto sul clima - Alto Adige 2018.

Paper3 – Integrated System Dynamics Modelling for a multi-risk assessment of water scarcity in the south-eastern Alps

Introduction

Mountain regions are facing multiple impacts due to climate change and anthropogenic activities. While shifts in precipitation and temperature are affecting the available water, current economic activities rely on high water demands (Milner et al., 2017; Rull, 2014). The Alps are among those areas where recent events of decreased water availability already triggered emerging water disputes and spread of impacts across multiple economic sectors, such as hydropower, agriculture and tourism (Alpine convention and Convention, 2009; Beniston and Stoffel, 2014; Hanel et al., 2018; Majone et al., 2016). Moreover, the already existing issues are likely to become even more relevant within future climate change and human development projections (Gobiet et al., 2014; Milano et al., 2015). Both reliance on abundant water availability and on the same resource make economic sectors (e.g. hydropower, agriculture and tourism) exposed to primary climate change effects in terms of water availability reduction and to secondary cascading effects due to competing water demands from multiple anthropogenic activities (Pescaroli et al., 2018; Steele et al., 2018). In particular, such water scarcity events arise when anthropogenic water demand is higher than the actual water availability triggering multi-risk conditions on all the sectors relying on the same resource (Mehran et al., 2017).

Moreover, multi-risk assessments involving potential cascading effects over time and accounting for interrelated effects are internationally recognized as an emerging issue to address (UNISDR, 2015).

Hence, there is an urgent need to unravel interplays and dependencies that can lead to cascading impacts across interdependent sectors so to make our water management systems more resilient (Harrison et al., 2016).

However, current assessments dealing with climate change usually account for a mono sectoral and single risk perspective and hence can potentially lead to misrepresentations of the actual systemic risk conditions (Terzi et al., 2019).

For these reasons, multi-risk assessments represent an innovative perspective to better understand and investigate multiple impacts across sectors within a system. Among different available methodologies, System Dynamics Modelling (SDM) represents an innovative tool to investigate the spreading of hazards consequences to environmental and anthropogenic elements at risk interacting with each other. SDM is implemented to conceptualize complex systems accounting for interactions among multiple physical, ecological and socio-economic variables, across different areas and scales, where one change in a sub-system can have an unexpected impact in the larger system. It usually encompasses positive and negative connections in a causal loop diagram (Di Baldassarre et al., 2018), and it is then translated into a quantitative assessment integrating systems variables changes in time and their flows causality (i.e. stock and flow diagram) (Visconti, 2018). Although this methodology was already applied to assess natural resources variations, few applications considered risk and impacts assessments in mountain regions from natural hazards (Terzi et al., 2019).

In this study, a SDM was implemented to investigate how climate- and human-induced changes in water availability and demand can lead to mismatch between them, and hence to possible impacts. The SDM was applied to the Noce catchment (Province of Trento, Italy) combining outputs from physically based models and probabilistic assessments towards the assessment of water availability and water demand to sustain strategic activities for the economy of the area.

The integrated SDM considered water demands from four water sectors relying on the same resource: i) water turbined by large dam reservoirs for hydropower production, ii) apple orchards cultivation, iii) domestic and seasonal tourism activities and iv) minimum ecological water flow conditions. The analysis was performed accounting for spatial variability of both water availability and demand within the whole catchment, looking at its characteristics in three lumped areas. This application represents an innovative improvement for SDM since it is usually applied with limited or no spatial variability assessments over aggregated areas.

The aim of this study is hence to explore potential unbalanced conditions of water availability and demand, assessing the potential cascading effects propagation from upstream to downstream parts of the Noce catchment. Such conditions represent common features of mountain regions making this approach transferable to other mountain areas of the world to represent their highlands and lowlands spatially connection and dependency on the same water resource.

In particular, section 1 describes the conceptualization of the SDM, from an integrated cascading risk framework to a diagram identifying the variables of our system, their causalities and the data available to describe them. Section 2 focuses on the set up of the system dynamics modelling describing in details the components involved in water availability and water demand assessments, both for the baseline and for future scenarios. Section 3 includes the results coming from the assessment of the SDM application for both the baseline and future projections. Finally, section 4 includes the discussions and conclusions of the assessment explaining the limitations of this study and possible ways for future improvements.

1. Cascading risk framework in the Noce catchment

1.1. Study area

This study scrutinised the Noce catchment (1367 km^2) located in the south-eastern side of the Italian Alps within the Trento province. The area is a typical alpine catchment characterized by glaciers and winter snow precipitation contributing to the Noce river discharge. The catchment is also characterized by several economic activities, such as hydropower production, agriculture and tourism, differently spread within its area. Spatial variability of the catchment exists both in terms of bio-physical conditions affecting runoff regimes and in terms of anthropogenic activities affecting for example land-use and population density conditions. For these reasons, three lumped regions, each having a homogeneous characteristic were identified within the Noce catchment (Figure 11**Error! Reference source not found.**). The upstream part (i.e. A polygon in Figure 11) refers to the "Val di Sole" area and is characterized by three dam reservoirs (i.e. Careser, Malga Mare and Pian Palù) mainly fed by glacio-nival streamflow and producing about 34% of the total annual hydro energy. Climatological and topographical conditions also affect the water demand due to limited number of inhabitants (20% of total catchment population) and agricultural extension (14% of total agricultural lands) compared to the other areas. Nevertheless, seasonal tourism activities represent an important source of income (52% tourism presences over the total catchment for 2017). The middle part of the catchment (i.e. B polygon in Figure 11) refers to the "Alta Val di Non", an area characterized by the main dam reservoir for water volume stored of the whole Trentino-Alto Adige region (i.e. S.Giustina) with a maximum storage capacity of 171 Mm3 providing 33% of the annual hydro energy of the whole catchment. Moreover, this area has limited number of inhabitants (21% of total catchment population), very extensive agricultural lands famous for their apples production (48% of the total agricultural extension) and limited tourist presences (8% over the total catchment for 2017). Finally, the lowest part of the catchment (i.e. C polygon in Figure 11) is the “Bassa Val di Non”, where the Mollaro reservoir is located producing about 33% of the total annual hydro energy. Moreover, 59 % of total catchment population is located in the lowest part of the catchment, which is also characterized by still intensive apple production (38% of the total agricultural extension) and with high touristic attractiveness (40% tourism presences over the total catchment for 2017).

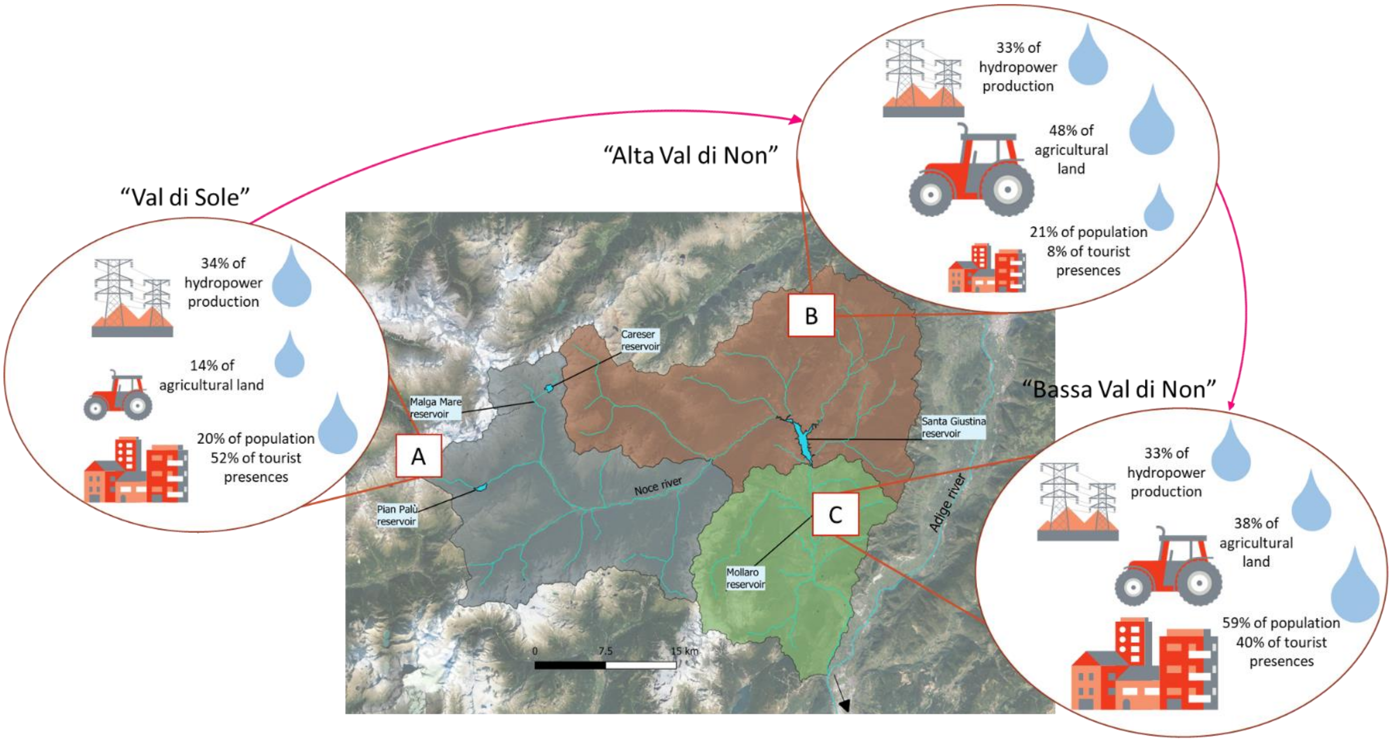

Figure 11 - Schematic representation of Noce catchment and its sub-division. We summarised each sub-catchment area characteristics and their downstream effect due to water availability and demand interactions. The Noce catchment is divided in three parts: the A grey polygon represents the “Val di Sole”, the B brown polygon the “Alta Val di Non” and C green polygon the “Bassa Val di Non”. Dam reservoirs positions and names within the three sub-catchment areas are reported in the figure

In addition, such subdivision allowed us to investigate possible consequences originating from the interactions among the three selected areas in terms of their water availability and demand ratio from upstream to downstream. Figure 11 reports the cascading effects propagation where upstream conditions variations affect downstream management of water.

1.2. Integrated framework

According to the characteristics of the Noce catchment and their spatial variations, we developed an integrated framework expanding the analysis performed in paper 2 on a larger scale. In this case, we considered potential impact relations leading to cascading effects among multiple sectors applying a water-food-energy Nexus perspective (Sušnik et al., 2012). Such application aimed to better describe all the components involved in climate change effects on water availability and demand from different sectors of the Noce catchment (Figure 12). Variables from the climate modelling to the hydrological components and to the SDM are then connected to each water demand sectors to explore possible unsustainable conditions between water availability and water demand.

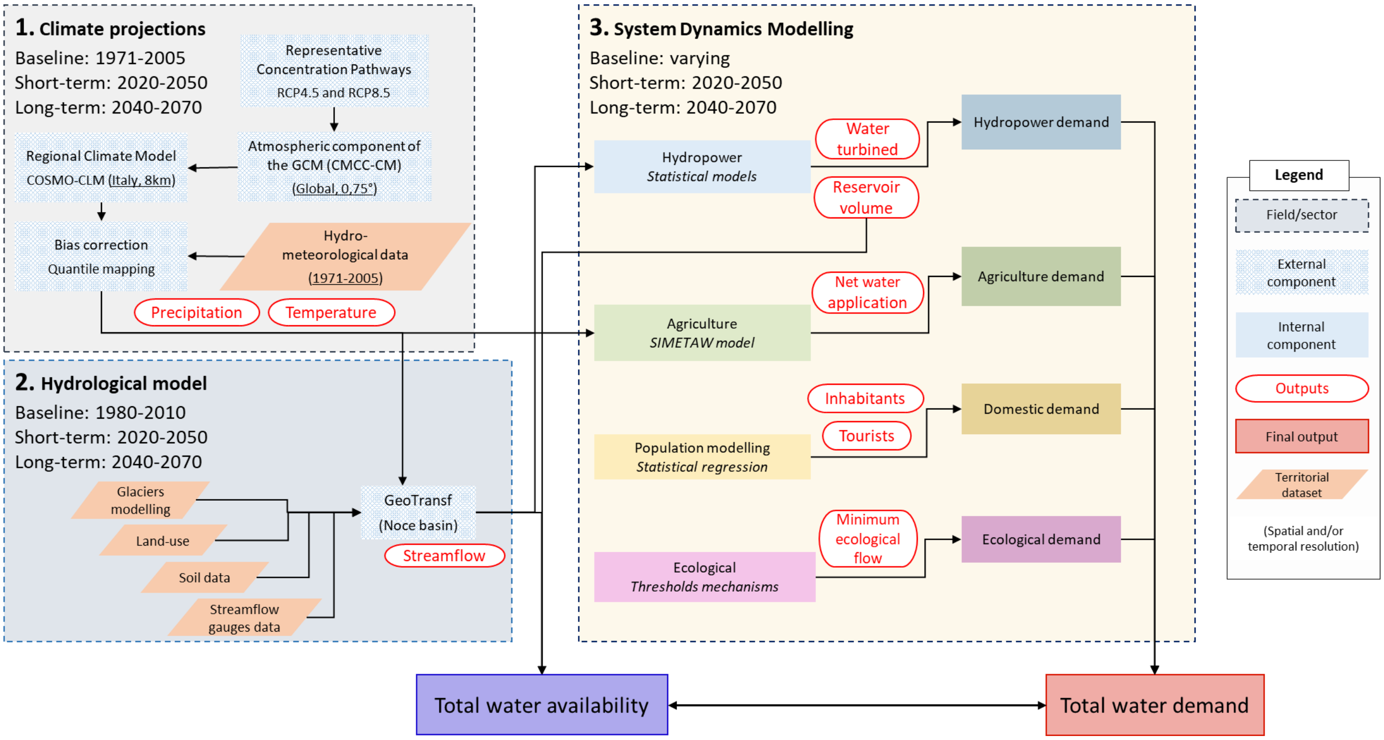

Figure 12 - Integrated framework bringing together different modelling approaches to quantify climate change effects on water availability and water demand from different sectors within the Noce catchment. Sources: Adapted from Vuong et al., 2018

1. Information on the climate models used at global level, then downscaled to COSMO-CLM regional level and bias corrected to climate local conditions were provided by the Euro-Mediterranean Centre on Climate Change (CMCC) for the application to the Noce catchment (Bucchignani et al., 2016). COSMO-CLM climate projections of temperature and precipitation from 2021 to 2070 for two Representative Concentration Pathways 4.5 and 8.5 were used as climatological input for the hydrological model "GeoTransf".
2. The "GeoTransf" hydrological model was developed, calibrated and validate in the Noce catchment by the University of Trento (Bellin et al., 2016). Results from the hydrological model provided information on the Noce river streamflow and contributed to the definition of the total water availability in different parts of the catchment.
3. A System dynamics modelling was then used to characterize water demands from the main water demand sectors within the Noce catchment integrating different modelling approaches. The representation of 5 dam reservoirs operations within the Noce catchment provided information on their water demand (i.e. water turbined) and the water availability as water accumulated in time (i.e. reservoir volume). Moreover, a soil and water balance model (i.e. SIMETAW) was directly integrated to describe the water demand for irrigation of apple orchards (i.e. net water application). Domestic water demand was described considering both inhabitants data and their future projections elaborated by the Province of Trento, and a statistical regression of tourist presences based on previous

observations. Finally, minimum ecological flow information were retrieved from the Provincial Plan for Public Water Use (PGUAP, 2006) and kept constant for future scenarios.

1.3. Causal loop and input data

Starting from the representation of system macro components and modelling approaches used in the integrated framework, we focused on a causal loop diagram to further conceptualize the specific variables involved and their interactions (Figure 13). The approach used here, started and further expanded the conceptualization and application of one single element exposed to water scarcity conditions previously explained in paper 2 to a wider geographical areas, integrating the interplay among sub-basins and considering different sectors and their water demand. In particular, components related to socio-economic vulnerability were included (e.g. population variation and crop type) considering multiple elements from different sectors exposed to water scarcity, relying on the same water resource. The system expansion encompassed the application of a similar logic to different parts of the catchment resulting in a spatially explicit assessment of unbalanced water conditions leading to multiple cross-sectoral impacts. The System Dynamics Model in this study is composed of modular parts describing the water availability coming from hydrological processes and water demand to sustain hydropower production, agriculture, domestic and the minimum ecological flow water needs.

This model was developed combining a first causal loop conceptualization using the Stella software (https://www.iseesystems.com/), which was then translated into a quantitative model assessing variables interactions and causality through statistical analysis using R Studio (R Core Development Team, 2013) and physically based models.

Figure 13 shows the main variables and their interactions considered in the conceptualization and then used for quantitative assessments. In particular, this study focused on the evaluation of total water demand and total water availability so to represent possible unbalance conditions potentially leading to multiple water scarcity impacts on different sectors. Total water demand is driven by the sum of hydropower, agricultural, domestic and ecological water demands. Both hydropower and ecological water demands are directly affected by streamflow quantity and hence by precipitation and temperature variations. Climate change also affects the evapotranspiration calculation leading to variation in the agricultural water demand. Finally, the water use % factor depicts unbalanced conditions between availability and demand variables leading to possible conditions of water scarcity. To do so, data from different sources were collected and used to characterize variables interactions within the causal loop. A summary of each variable name, type and source was reported in Table 4 together with a classification of the macro field (i.e. hydropower, agricultural, domestic, ecological and climate)

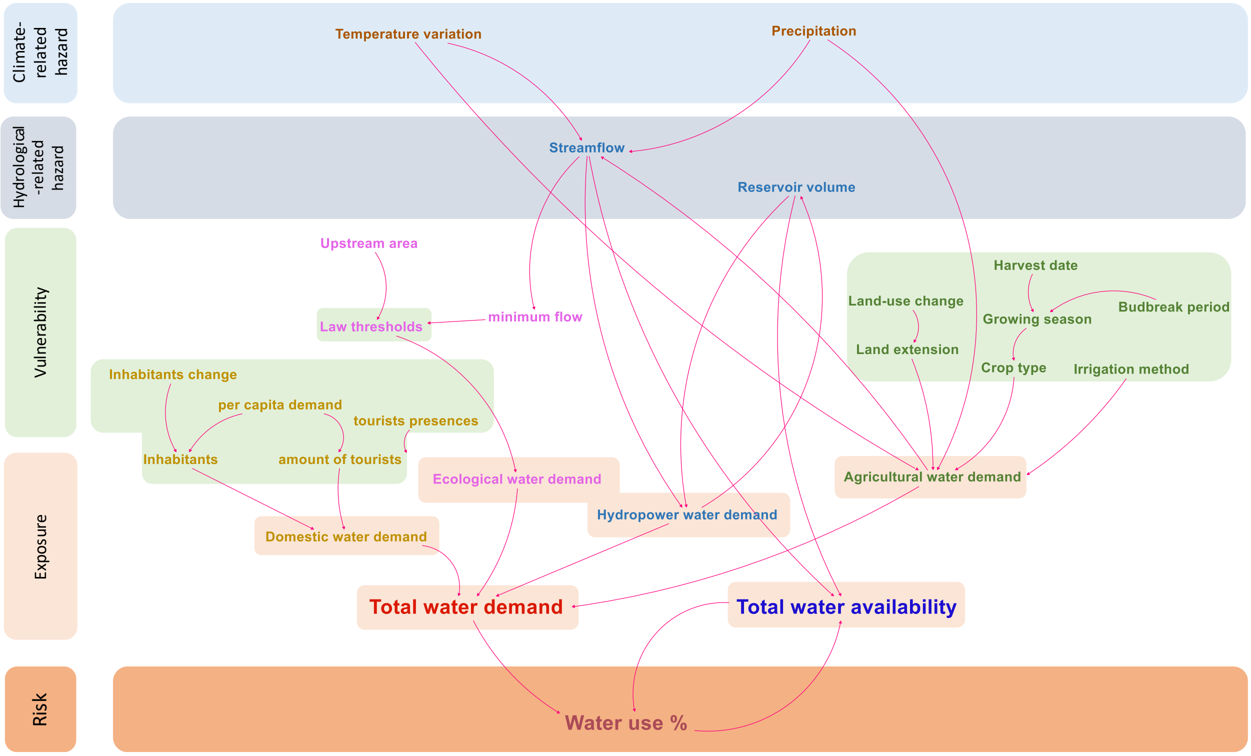

Figure 13 - Causal loop diagram for an integrated water scarcity risk assessments in the Noce catchment. Yellow variables are related to domestic water demand. Light blue variables are the hydrological variables related to the assessment of total water availability and affecting the hydropower water demand. Pink variables refers to ecological water demand, green variables are related to agricultural water demand, while variables in brown represent climate drivers.

.

Table 4 - Datasets used to characterize both sectoral water demand and water availability for the baseline and future projections

	Variables	Data type	Time range	Data source
Hydropower	Dam reservoirs minimum and maximum volume [Mm3]	Discrete data	varying per each dam	(Majone et al., 2016)
	Dam maximum turbined flow [m3/s]			
	Dams volume time series	Daily values		Province of Trento – Agency for water resource and energy
	Dams water flows (inflow, turbined and released)			
Agricultural	Agricultural land extension [ha]	Spatial vector data	2007	Open data Trentino
	Crop type [-]	Discrete data	-	
	Bud break date [day of the year]		-	(Eccel et al., 2000; Rea and Eccel, 2006; Zucaro et al., 2009)
	Irrigation method [-]		2018	Provincial federation of irrigation and territorial improvement consortia
	Harvest date [day of the year]		-	(Zucaro et al., 2009)
Domestic	Per capita water demand [m^3/person·day]	Discrete data	-	Technical report on the Noce river (Tovazzi, 2012)
	Inhabitants for the baseline [#]	Monthly values at municipal level	1985-2017	Province of Trento - Institute of Statistics
	Tourists presences (baseline) [#]		1985-2017	
	Future inhabitants [#]	5-years step projections at valley level	2020-2050 2040-2070	
Ecological	Minimum ecological flow conditions [m^3/s]	Discrete data	varying per each dam	Provincial Plan for Public Water Use (PGUAP, 2006)
	Minimum dam releases [m^3/s]	Discrete data at dams releases location		Province of Trento – Agency for water resource and energy
Climate	Daily maximum and minimum temperature [K]	Daily gridded values	1971-2005	Euro-Mediterranean centre on Climate Change
	Total precipitation amount [mm/day]			
	Relative humidity [%]			
	Average solar radiation [W/m^2]			
	Average thermal radiation [W/m^2]			
	Horizontal and vertical wind components [m/s]			

2. System Dynamics Modelling set up

The SDM is here described considering the modelling background leading to the assessment of water availability and water demand. For each component, we aimed at assessing the amount of water available, which was then related to each sub-catchment area. In case of water availability, natural streamflow and reservoir volume stored were considered and summed up per each month, while in case of water demand we accounted for the needs for hydropower production, agricultural irrigation, domestic demand and minimum ecological flow.

2.1. Water availability

Streamflow

The hydrological dynamics within the Noce catchment were already described by previous applications of the GeoTransf hydrological model created and applied by Bellin et al., 2016 and Majone et al., 2016. This model was already calibrated and validated on historical observations well representing the hydrological dynamics associated to glaciers and snow processes and their consequences in terms of rivers streamflow. GeoTransf application provided daily values of streamflow in different parts of the catchment considering a baseline from 1981 to 2010. This information was aggregated at a monthly temporal resolution due to its suitability to describe potential water scarcity issues accounting for seasonal variability (Brunner et al., 2019b).

Furthermore, GeoTransf was also applied to the Noce catchment within the OrientGate project simulating natural conditions of streamflow without human withdrawals. This particular application provided useful information on the actual effects of upstream water demand on the residual water availability downstream and hence the assessment of any related unbalanced water use conditions and cascading effects.

Reservoirs volume

Five dam reservoirs within the catchment were considered for the volume analysis (names and position reported in Figure 11). Historical values of water volume stored in reservoirs were made available by the Agency for water resource and energy (Table 4) for each reservoir. According to the availability of each reservoir historical data, different statistical models were selected, calibrated and validated to replicate past observations (Table 6). Due to the tight nature of reservoir stored water and water diverted for hydropower demand, further details on the statistical models used are provided in the following section.

2.2. Water demand

Total water demand accounted for four main user-sectors: i) hydropower ii) agriculture, iii) domestic and iv) ecological flow. These sectors were recognised as the most relevant for both their water demand and their strategic economic role in the Noce catchment (Table 5).

Water demand comprised both consumptive and non-consumptive water uses. On the one side, agriculture demand was considered as a consumptive user due to the high rate of spring and summer evapotranspiration and hence it was assumed not to be available for downstream users. On the other side, hydropower, domestic and ecological water demands were considered as non-consumptive, hence accounted within the total water demand of the area they belong to, but then released and made available again for downstream areas.

Table 5 – Licensed water withdrawals per sector (year 2017) and respective percentage. Large hydropower plants (average nominal capacity greater than 3MW) water withdrawals are excluded (Data source: Provincial Agency for Water and Energy).

Sector	**Licensed water withdrawals [m^3/s]**	**Percentage [%]**
Agriculture	148928.0	9.48
Other	2515.9	0.16
Domestic	67702.1	4.31
Hydropower	1323083.0	84.24
Industrial	8269.4	0.53
Snowmaking	4712.7	0.30
Fish farming	15307.6	0.98

The assessment of water demand in different sectors relied on outputs from physically-based models and statistical analysis of variables correlation and future projections.

Hydropower

Within the Noce catchment, we considered water stored in each dam reservoir and their hydropower water demand, neglecting small run-of-the-river hydropower plants. Hydropower management plays a dual role in terms of water demand diverted to the turbines and affecting the reservoir volume and hence total water availability.

Moreover, we assumed the total storage capacity of the existing reservoirs in each sub-catchment area of the Noce catchment as a single, virtual reservoir (Brunner et al., 2019a; Garrote et al., 2018). In particular, total hydropower water demand was computed for each single dam reservoir and then aggregated per sub-catchment area into an overall hydropower water demand.

In this case, water demand was considered as a non-consumptive use since all the water diverted to the turbines is then released into the natural river for downstream users.

GeoTransf streamflow simulations were used as input values through stochastic SDM assessments so to replicate trends of water stored in the main dam reservoirs and their water demand in terms of water turbined for hydropower production. Stochastic SDM models considered a linear mixed-effect model selected for its ability to represent both environmental dependencies affected by climate change (i.e. Q_{in}) and recurrent dam operations influenced by specific timing (i.e. day or month random effect variables). In those cases where simulation was first run on a daily level and then aggregated monthly, day of the week was found to have significant effects and was considered as an important proxy variable of energy market prices influencing the hydropower production.

In particular, since the Malga Mare reservoir directly receives the water turbined from the Careser dam we neglected Malga Mare water demand in terms of water turbined so not to double count the hydropower water demand within the Val di Sole considering the same water turbined twice by in series Careser and Malga Mare hydropower plants.

Table 6 - Summary of dam reservoir characteristics and model used to represent their turbined outflows and volume stored both for the baseline and for future projections. Not significant volume refers to those reservoirs where inflow is equal to turbined outflow due to their limited volume capacity.

Dam reservoir	Turbined outflow equation	R^2	Stored volume equation	R^2	Data time range
Careser	$Q_{turbined}(t) = f(Q_{in}(t\text{-}1), month)$	0.73	$V(t) = V(t\text{-}1)+Q_{in}(t\text{-}1)\text{-} Q_{turbined}(t\text{-}1)\text{-} Q_{iecological}(t\text{-}1))$	0.75	1990-2010
Pian palù	$Q_{turbined}(t) = f(Q_{in}(t\text{-}1), month)$	0.74	$V(t) = f(Q_{in}(t\text{-}1), month)$	0.66	2004-2013
S.Giustina	$Q_{turbined}(t) = f(Q_{in}(t\text{-}1), month)$	0.79	$V(t) = Q_{in}(t\text{-}1), month)$	0.71	1999-2004 2009-2017
Mollaro	$Q_{turbined}(t)=f(Q_{in}(t\text{-}1), weekday, month)$	0.99	Not significant volume	-	2000-2010

Moreover, Mollaro dam water turbined was evaluated considering daily values due to their better performance and then aggregated at monthly resolution for volume calculation. A summary of each dam reservoir equation on their water turbined and volume stored is reported in Table 3. Moreover, Mollaro reservoirs work as intermediate reservoirs all the water inflowing is then diverted to the turbines for hydropower production and hence the statistical models shown high performances. For this reason, their total capacity is very limited and not accounted within the total water availability calculation. Finally, S.Giustina dam reservoir operations and management was already investigated more in details in Paper 2 of this thesis.

Agricultural

Agriculture is the second sector for water demand within the Noce catchment (Table 5). Simulations aimed to represent monthly water demand for irrigation considering climate change effects in terms of temperature and precipitation variations.

In this case, agriculture was considered as a consumptive sector assuming water used for drip irrigation fully evaporates or evapotranspirates. This assumption was justified by conditions of full irrigation associated to drip irrigation methods leading to optimum soil water conditions (i.e. no water stress) and hence to maximum evapotranspiration rates (Testa et al., 2011).

In order to evaluate agricultural water demands, we considered the soil and water balance model SIMETAW_GIS for its previous applications, performance and ease of use (Mancosu et al., 2016; Masia et al., 2018). This physically based model evaluated the net water application calculating the potential evapotranspiration trough the Penman-Monteith equation (Testa et al., 2011). Climate variables were retrieved using COSMO-CLM data with a spatial resolution of 0.0715° × 0.0715° (≈ 8km×8km) as reported in Table 1. Moreover, climate variables time series were provided by CMCC having already applied a Quantile Mapping bias correction method on station points locations within the Orientgate project. Such application is commonly performed in order to correct usual mismatches between climate model representations and actual local measurements, especially for complex mountain orographic and climate conditions (Bucchignani et al., 2016; Maraun, 2016). Bias corrected values of temperature and precipitation were then spatially interpolated from station locations to grid maps having the same COSMO-CLM climate resolution. Such method was applied using the external drift kriging method through the *gstat* R package (Gräler et al., 2016; Hudson and Wackernagel, 1994). Altitude, aspect and slope were selected and used as the external drift variables for spatial interpolation. The other climate variables used within the Penman-Monteith equation (i.e. wind speed, relative humidity and solar radiation) were not bias corrected due to the lack of local measurements. Bias and non-bias corrected variables were then used as inputs to the Penman-Monteith equation so to better evaluate evapotranspiration conditions and hence net water applications within the Noce catchment.

Net water applications were then associated to each agricultural land polygon available from the Trentino Open Data portal (Table 4**Error! Reference source not found.**). In particular, we assumed a n apple orchards dominated cultivation due to the intensive monoculture apple production in the catchment (Marini et al., 2012; Tattoni et al., 2017) and a growing season range from 15th April to 1st October (Zucaro et al., 2009). Using this information, the total water demand for irrigation was computed at a monthly time step per each sub-catchment area.

Modelling baseline considered a time range 1971-2005, while results within the whole catchment span in a range of 714 - 3000 m3/ha per year and agree with provincial yearly range values of 1395 - 10050 m3/ha.

Domestic

Domestic water demands account for both permanent inhabitants living in the area and population variation due to seasonal tourism presences. In particular, tourism presences differentiate across the three sub-division areas due to their landscape characteristics and presence of accommodation facilities (e.g. presence of ski resorts), contributing to the total domestic water demand. Population water demand was characterized by 0.250 cubic meters per day per capita, since it is the standard value in provincial assessments (Tovazzi, 2012). Historical and future projections of inhabitants data were available from the Provincial Statistical department respectively at municipal or valley level (Table 4).

However, tourism data was only available for historical presences. For this reason, historical tourist presences from 1985 to 2017 were used as a dataset for a statistical model implementation. Tourism presences are particularly difficult to predict due to the high dependence on uncertain socio-economic conditions at national and international levels. However, we represented tourism presences for each sub-division through a mixed effect linear-regression model using the *lme4* package available in R (Bates et al., 2015). Such regression replicated past tourist presences as a function of “date” and accounting for each “month” of the year as a grouping factor, relevant to describe the seasonality patterns of tourism presences.

Ecological

Minimum ecological flow aims to preserve an optimal ecological status also during months of reduced streamflow availability. Recent events of water scarcity in 2017 and 2015 raised concerns not only on the amount of streamflow, but also on the ecological status related to the quality of water with consequences on the overall catchment (Chiogna et al., 2018; Hanel et al., 2018; Laaha et al., 2017). For these reasons, minimum ecological flows are regulated by Provincial law (Provincia Autonoma di Trento, 2006) introducing monthly thresholds for minimum streamflow discharge and releases from hydropower dam reservoirs.

2.3. Future projections

All future scenarios were based on the same temporal extension of medium-term (2020-2050) and long-term (2040-2070) time scenarios at a monthly time step for two representative concentration pathways (RCP) 4.5 and 8.5. Future climate COSMO-CLM (i.e. climate limited-area modelling) climate scenarios were developed by the CLM community and provided by the Euro-Mediterranean centre on Climate Change (CMCC)(Bucchignani et al., 2016). Due to their spatial resolution COSMO-CLM projections are considered as a suitable model for climate impacts assessments at local level (Rockel and Geyer, 2008).

Climate data were used as input for the hydrological model GeoTransf which outputs were used as information within the SDM (Figure 12)

Streamflow

GeoTransf was applied within the OrientGate project together with climatological data and providing information on the Noce river streamflow in different sections of the catchment in natural conditions (i.e. without human withdrawals).

Reservoirs volume

Future projections of reservoir volumes were simulated reproducing the statistical linear-mixed effect models retrieved using historical time series to include future GeoTransf streamflow values

Hydropower

Future conditions of water used for hydropower production were modelled by the statistical relations among predictors extracted from historical values. We considered no changes in the production patterns, hence assuming relation valid in the past will be valid in future too. This assumption is motivated by the high uncertainty associated to future changes in production patterns affected by societal conditions (e.g. energy price fluctuations) (Gaudard et al., 2014; Ranzani et al., 2018)

Agriculture

Water demand for irrigation was estimated considering potential evapotranspiration driven by future climate conditions of COSMO-CLM spatial data. Agricultural land extension, growing period, harvest date, crop type and irrigation method were assumed constant in time.

Domestic

Future projections of inhabitants were provided by the Provincial Statistical department based on past and current conditions of population age distribution. Population was projected to decrease in all sub-catchment areas affecting the overall domestic water demand.

Future tourist presences were projected using a linear-mixed effect model regression. Future water demand for this sector considered the same amount of capita water demand as assumed for inhabitants.

Ecological

Future conditions of minimum ecological flow are assumed to remain constant as in the baseline for all the future scenarios.

2.4. Cascading effects

The final evaluation of possible cascading effects on water availability and its use from upstream to downstream it was conceptualize in Figure 13 and then translated into a stock and flow model in Figure 14. The final aim of this assessment was to apply the SDM model to each sub-catchment area subtracting the agricultural demand from the water availability for downstream uses.

The easiness of creating a stock and flow model using the Stella software allowed to bring together many components from different analysis into one single model keeping a wider perspective on the whole system.

Figure 14 shows a consecutive application of the stock and flow model to each area according to its features of water availability and demand. Agricultural water demand is the only component which was subtracted from the water streamflow component going into the following downstream area.

First, the stock and flow approach can be applied to polygon A (1) to assess total water availability and demand within its borders. Second, streamflow to polygon B would be reduced by the amount of water demanded for agricultural purposes (2). Third, the approach is repeated to polygon B assessing total water availability and demand (3). Fourth, streamflow to polygon C is decrease by the amount of agricultural water demanded in polygon B (4), and finally the stock and flow approach is applied to polygon C (5).

The process is repeated for each area assessing any water scarcity issues arising with concurrent conditions of high water demand and decrease in streamflow.

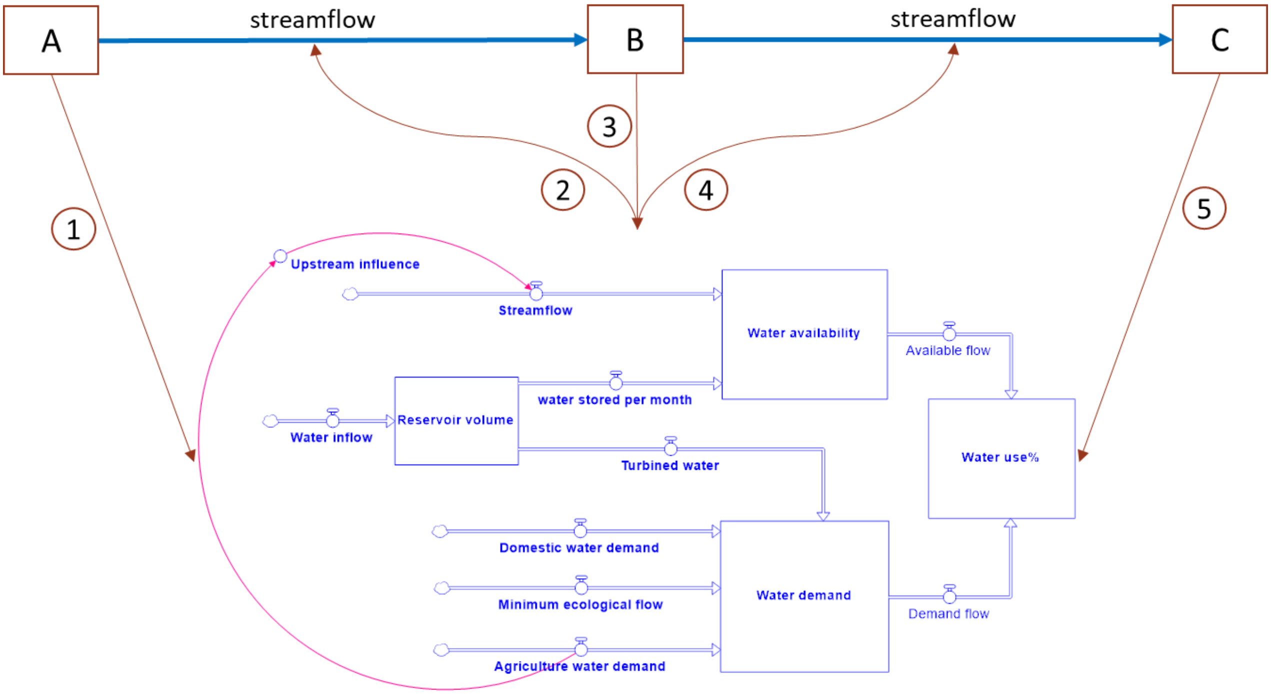

Figure 14 - Stock and flow diagram applied to each sub-catchment area to characterize water availability and demand, and its effect on downstream streamflow.

For each application of the stock and flow approach to each sub-catchment area conditions of water scarcity can be assessed looking at water use as a ratio between water availability (i.e. sum of monthly water stored in reservoirs and streamflow conditions) over water demand (i.e. sum of water for monthly hydropower production, agricultural irrigation, domestic uses and ecological flow). Future monthly values of water use can detect conditions of possible water mismatch with consequences on the selected sub-catchment area and to those downstream. For these cases, water use index can have values greater than 1 showing no water scarcity issues in the area, equal to 1 when water availability and demand has the same value, or lower than 1 when water demand is higher than availability.

3. Results

Preliminary results are here presented considering the Val di Sole (A polygon) and Alta val di Non (B polygon) only. Next development will consider the assessments of the Bassa val di Non area.

3.1. Baseline

Results are divided according to each macro-area (polygons A and B in Figure 1) reporting the contributions from the selected sectors.

A Polygon – "Val di Sole":

Careser and Pian Palù are the main dam reservoirs in the Val di Sole with a storage capacity of 15.2 and 15.3 Mm3. Statistical models for the baseline simulations show to grasp monthly trends replicating average volume observations (Table 6). However, they also show limitations in representing particular variations in terms of sudden operational modifications related to human decision-making especially in the case of water turbined for the Careser dam reservoir.

Figure 15 -. Careser and Pian Palù dam reservoir volume stored and water turbined for their baseline periods (x scales are different)

B Polygon – "Alta val di Non":

The S.Giustina dam reservoir has a maximum net available volume of 152.6 Mm3 and is the only reservoir located within the Alta val di Non area. Results from the statistical modelling provided sufficient accuracy to replicate past observations especially of the overall trend (R^2= 0.71 and mean Root Mean Square Error of 13.5).

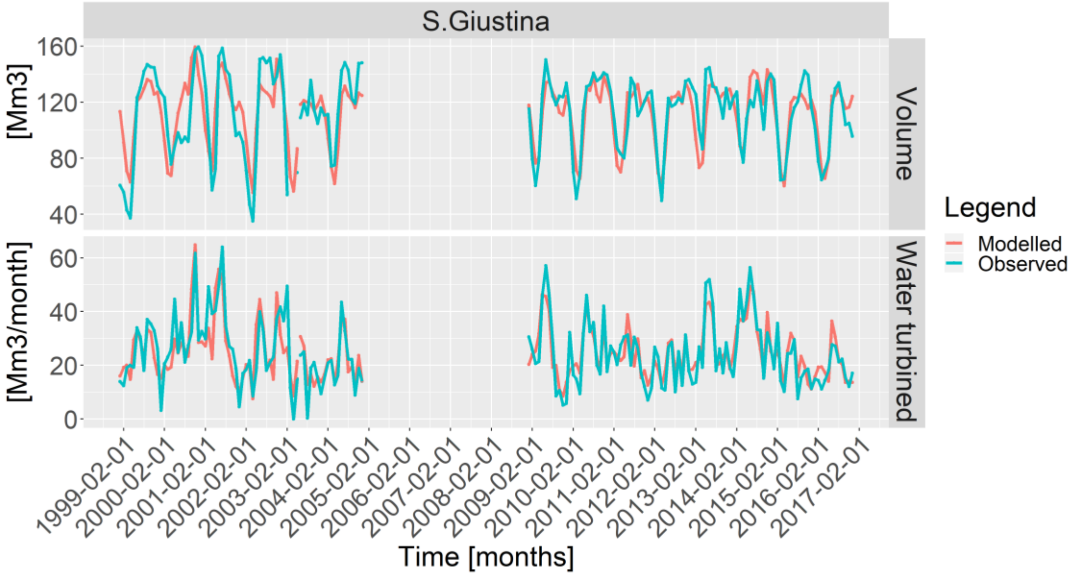

Figure 16 - Baseline reservoir volume and water turbined simulations for S.Giustina. Red line represents real observations and light blue represents simulated values.

Agriculture

Agricultural baseline for water demand was selected implementing SIMETAW in a time range from 1975 to 2005 and at a monthly time step. Results were multiplied by the extension of agricultural land hence providing information on the total net water application used to irrigate. Moreover, baseline results show a clear difference between the three selected areas due to differences in agricultural land extensions. In particular, Alta val di Non shows the highest extensions of agricultural land (5068 ha) compared to Bassa val di Non (4698 ha) and val di Sole (1434 ha).

Results were compared with provincial agricultural reports analysing the amount of water needed in past observations per hectare to sustain the apple production. SIMETAW outputs fitted the provincial ranges hence confirming the accuracy of SIMETAW water demand assessment.

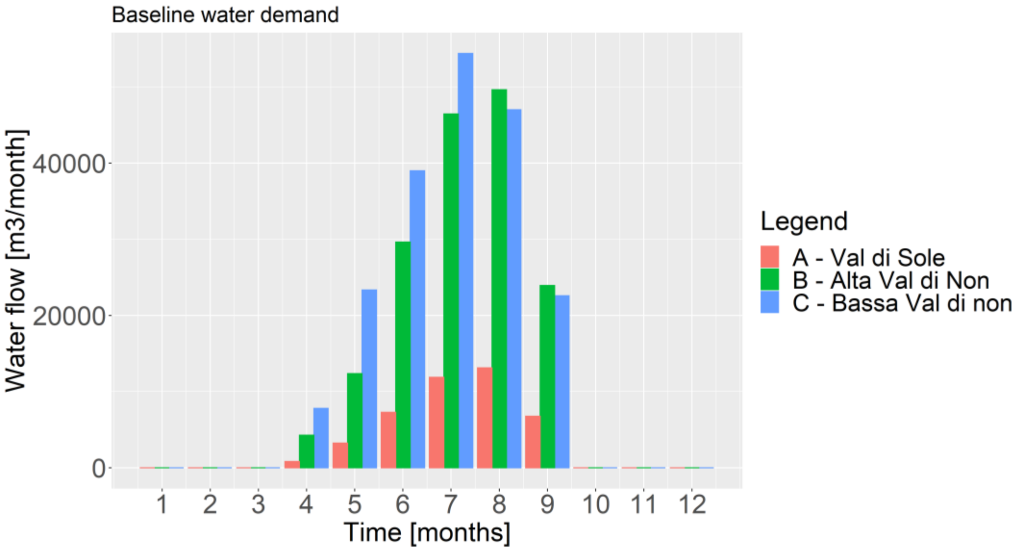

Figure 17 - Water demand for the baseline (1975-2005) for polygons A (“Val di Sole”) represented in red, B (“Alta Val di Non”) in green and C (“Bassa Val di Non”) in blue.

Domestic

A, B and C Polygons - "Val di Sole", "Alta val di Non" and "Bassa val di Non"

Tourist presences were analysed considering the available data spanning from 1985 to 2017 from the Province of Trento (Table 4). Figure 18 reports the baseline period and the differences among two sub-catchment areas in terms of tourist presences. Past observations were replicated through a linear-mixed effect model able to simulate seasonality conditions. Although such model simplified the possible variations in presences number, it replicated the overall linearly growing trend and the monthly differences, especially for maximum values.

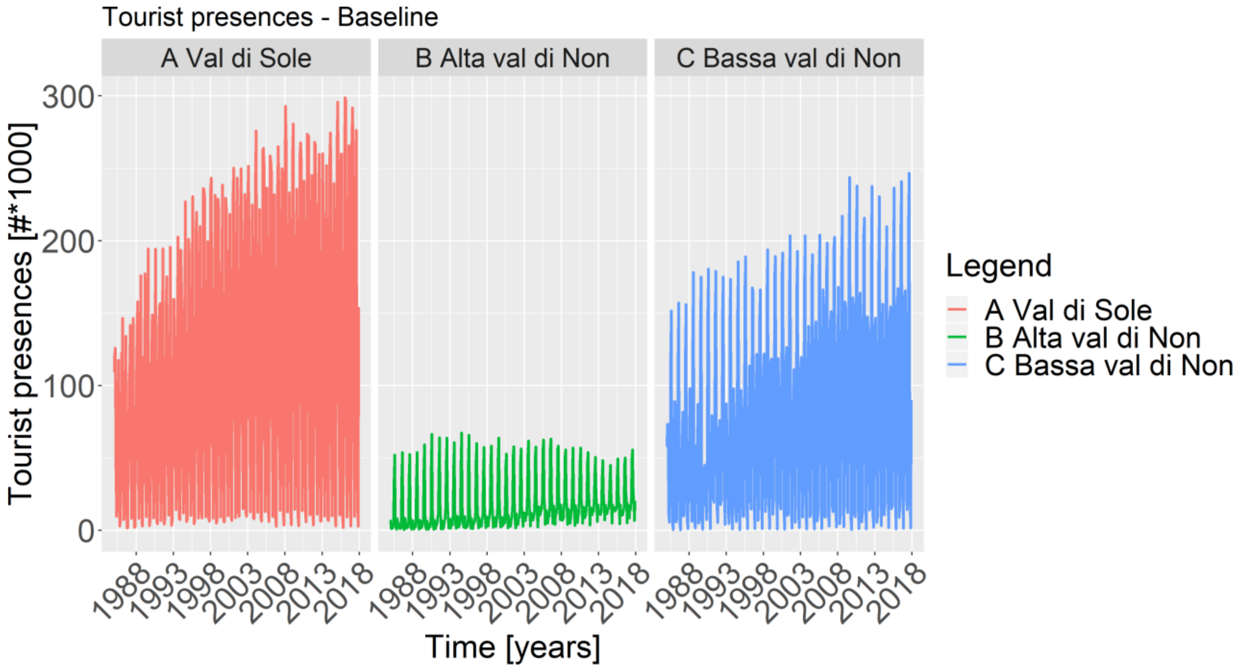

Figure 18 - Number of tourist presences per selected area from 1985 to 2017 at a monthly time step

For the Val di Sole conditions of water demand for the tourist sector during the baseline period spans from a minimum of 11783 m^3 per month to a maximum of 2242103 m^3 per month, for the Alta val di Non spans from 2963 to 505920 m^3 per month, while for the Bassa val di Non spans from 975 to 1851848 m^3 per month.

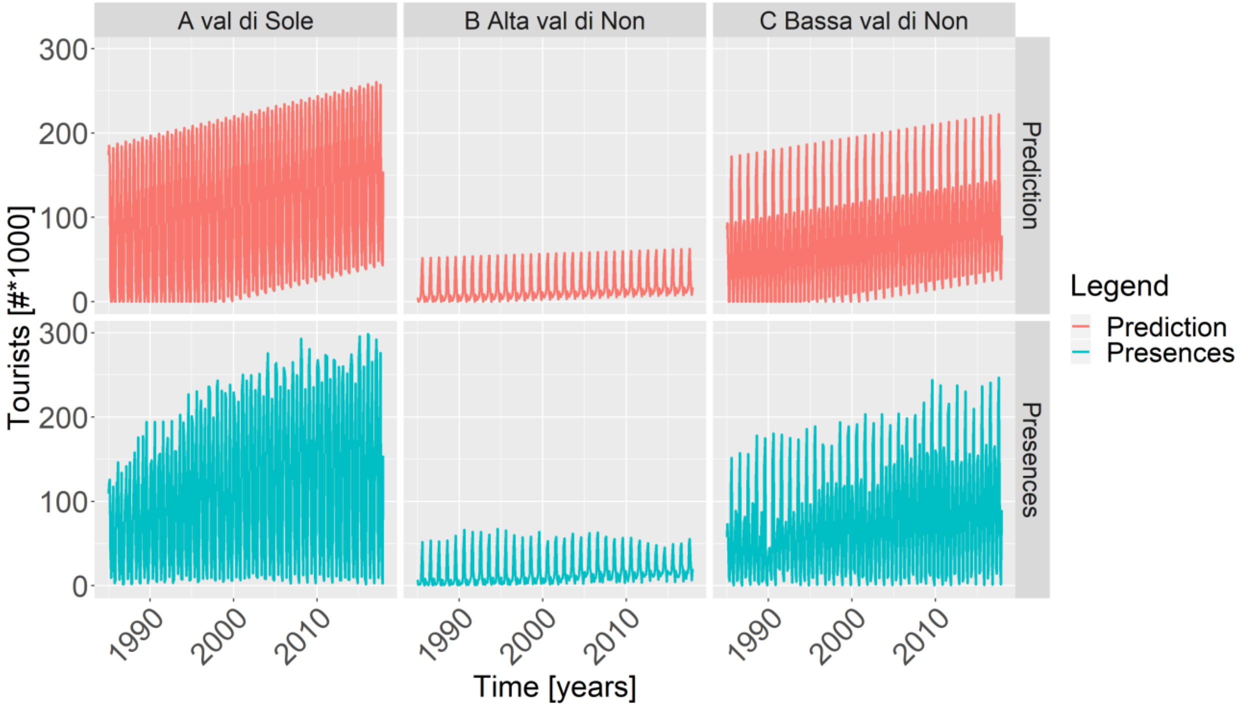

Figure 19 - Modelled (red line) and observed (light blue line) number of tourist in the baseline. Prediction performance is evaluated by mean RMSE using a moving window approach (further explanation in section 3.2.3 of paper 2): Val di Sole = 39961; Alta val di Non = 5443; Bassa val di Non= 22868

Ecological

Minimum ecological values were set at the values established by Provincial laws and were kept constant for future scenarios too. Minimum ecological flow values are set for each dam reservoir release as well according to the upstream area and for each month of release (Table 7).

Table 7 - Minimum ecological flow values for each dam reservoir releases. Values are available per each month

Dam reservoir	Minimum ecological flow value
Careser	0.081 m3/s
Pian Palù	from 0.179 to 0.277 m3/s

3.2. Future projections

Future water availability

Streamflow: A Polygon – "Val di Sole"

Streamflow for the head part of the catchment shows a glacial behaviour, with only one clear yearly peak for the baseline period. However, future climate change projections are shifting towards a more nivo-glacial behaviour characterized by a second lower peak during autumn time. Maximum peak for the baseline is lowered from 82.7 to 57.7 Mm3/month for the long-term scenario of RCP4.5 and expected to anticipate by one month from July to June for short-term scenarios, and to more than one month for long-term scenarios (i.e. anticipation of snow and glaciers melting periods).

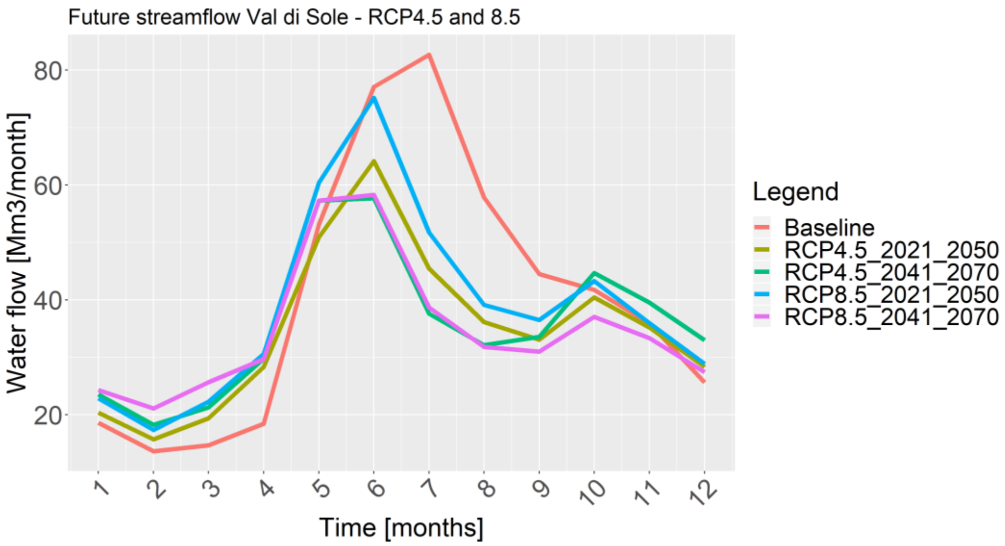

Figure 20 - Monthly average over 30 years of simulation for the Noce streamflow at the end of the Val di Sole for RCP4.5 and 8.5, short and long-term scenarios.

B Polygon – "Alta val di Non"

The Alta val di Non already shows a nivo-glacial behaviour for the baseline, which is going to persist for future climate conditions. However, future scenarios of streamflow show a significant reduction of the maximum yearly peak with a greater difference from 117.57 down to 87.80 Mm3/month for the RCP4.5 long-term scenario. Moreover, long-term scenarios for both RCPs show an anticipation of the maximum discharge peak of one month.

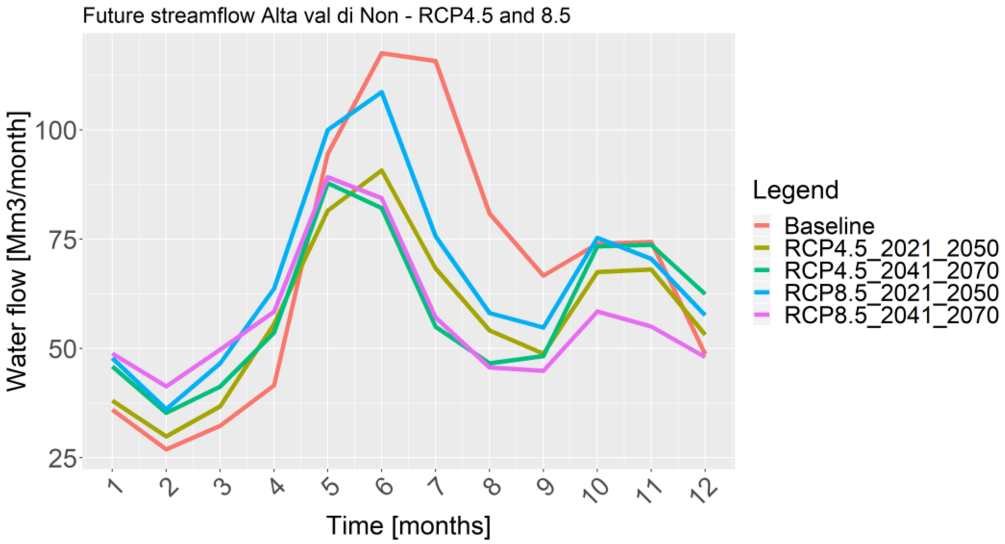

Figure 21 - Monthly average over 30 years of simulation for the Noce streamflow at the end of the Alta val di Non for RCP4.5 and 8.5, short and long-term scenarios.

C Polygon – "Bassa val di Non"

The Bassa val di Non shows a river flow regime having nivo and glacial contributions peaks. The baseline scenario also shows a third peak during September due to the regulation of the S.Giustina reservoir greatly affecting downstream flows. Future scenarios depict a generalized trend of peak flow reduction and anticipation for RCP4.5 during the 2021-2050 time range. RCP4.5 for the 2041-2070 period is the only case with an increase of maximum flow peaks during spring and autumn time. Maximum reduction of streamflow is expected for RCP8.5 during 2041-2070 time range, shifting from -8.35% in December to -28.9% in August, but an increase of streamflow up to +29.4% in March.

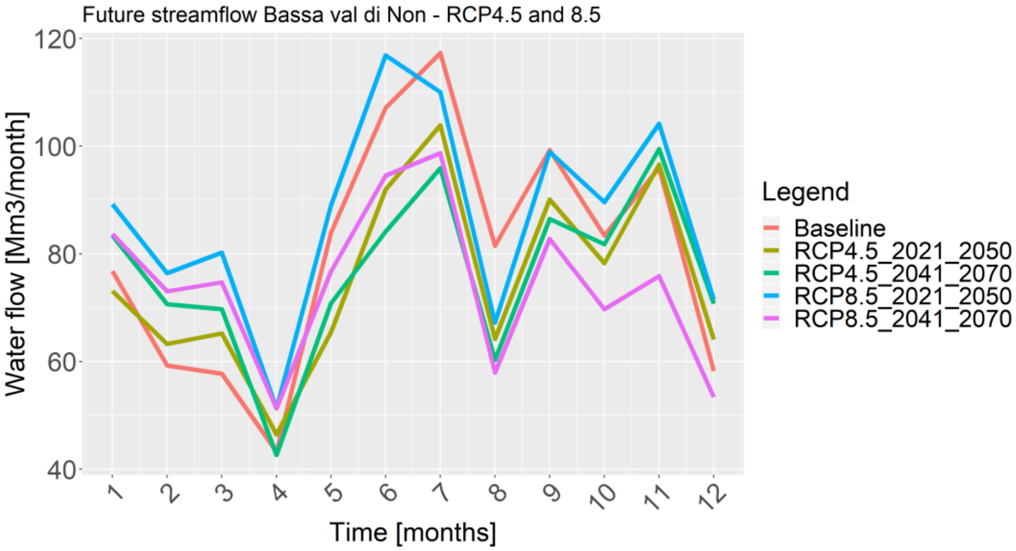

Figure 22 - Monthly average over 30 years of simulation for the Noce streamflow at the end of the Bassa val di Non for RCP4.5 and 8.5, short and long-term scenarios.

Reservoir and water turbined simulations show different trends according to each dam reservoir and scenario.

Reservoirs and hydropower: A Polygon – "Val di Sole":

The Careser dam reservoir is highly affected by the upstream glaciers dynamics feeding it. Figure 23 shows such dynamic in terms of recurrent empty volumes during winter months. In RCP4.5 short- and long-term scenarios the volume dynamics are not suffering high variations, while in the long-term RCP8.5 there is a clear decreasing trend of the volume stored.

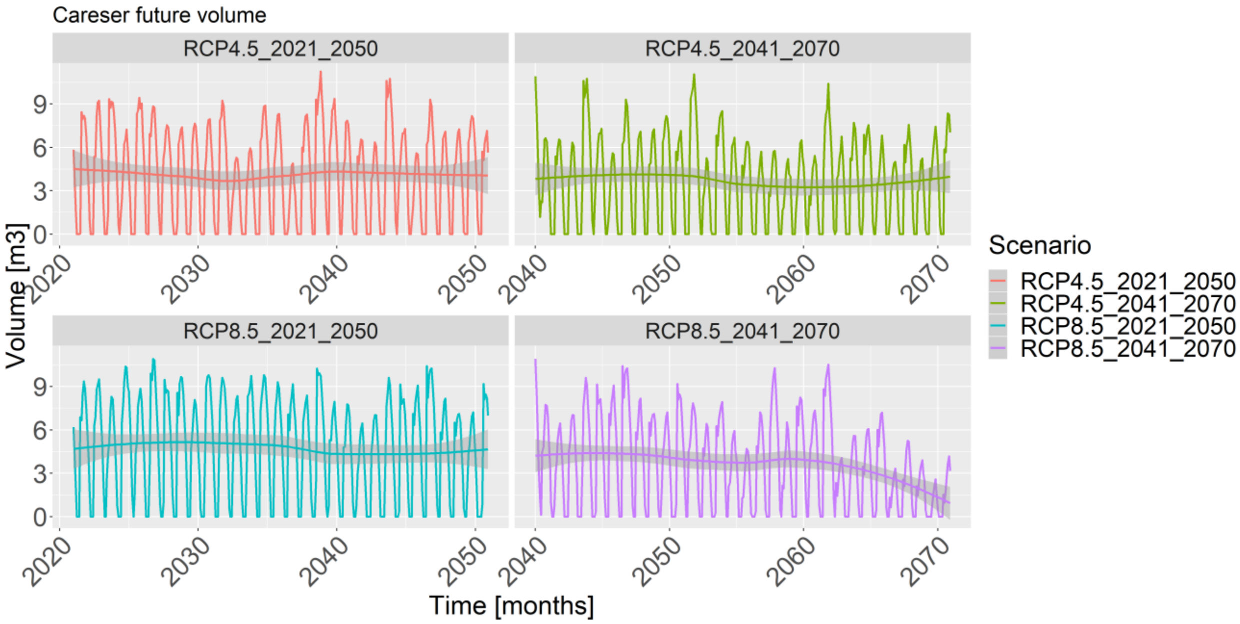

Figure 23 - Careser reservoir stored volume for future scenarios of climate change

Such conditions of reduced stored volume seems to have little consequences on the amount of water turbined in Figure 24.

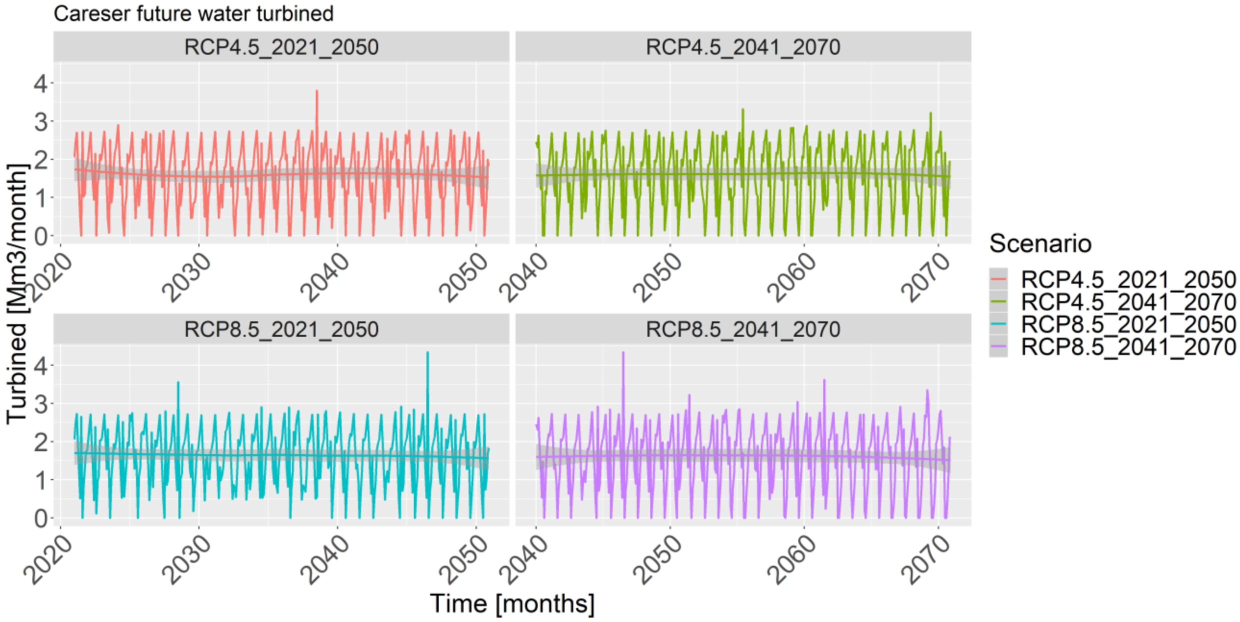

Figure 24 – Careser water turbined for future scenarios of climate change and streamflow

While different conditions are expected for the Pian Palù future water turbined in Figure 25. Similarly to the trend of future Careser volume, the Pian Palù water turbined is severely affected in the worst case scenario, with a decrease in the number of maximum values especially in the last 10 years of simulation.

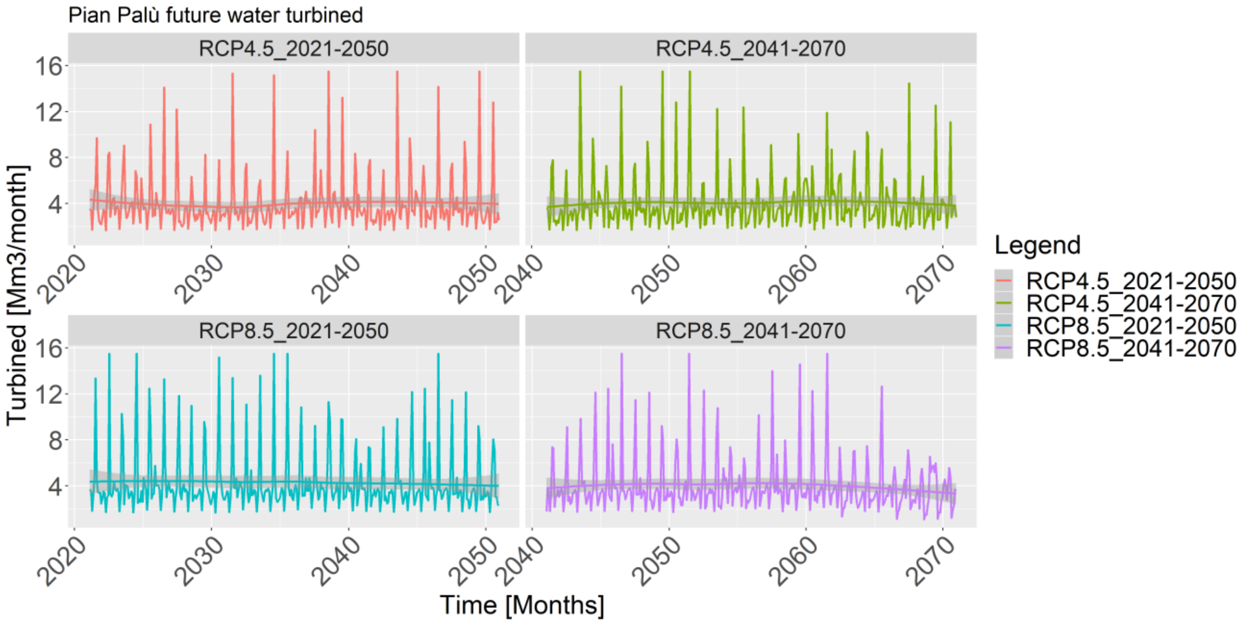

Figure 25 – Pian Palù water turbined for future climate change scenarios

B Polygon – "Alta val di Non":

Results for the S.Giustina reservoir were already assessed more in details in paper 2. Results showed a decreasing trend in the number of maximum volume stored for all scenarios. At the same time, the number of minimum values of water stored is increasing.

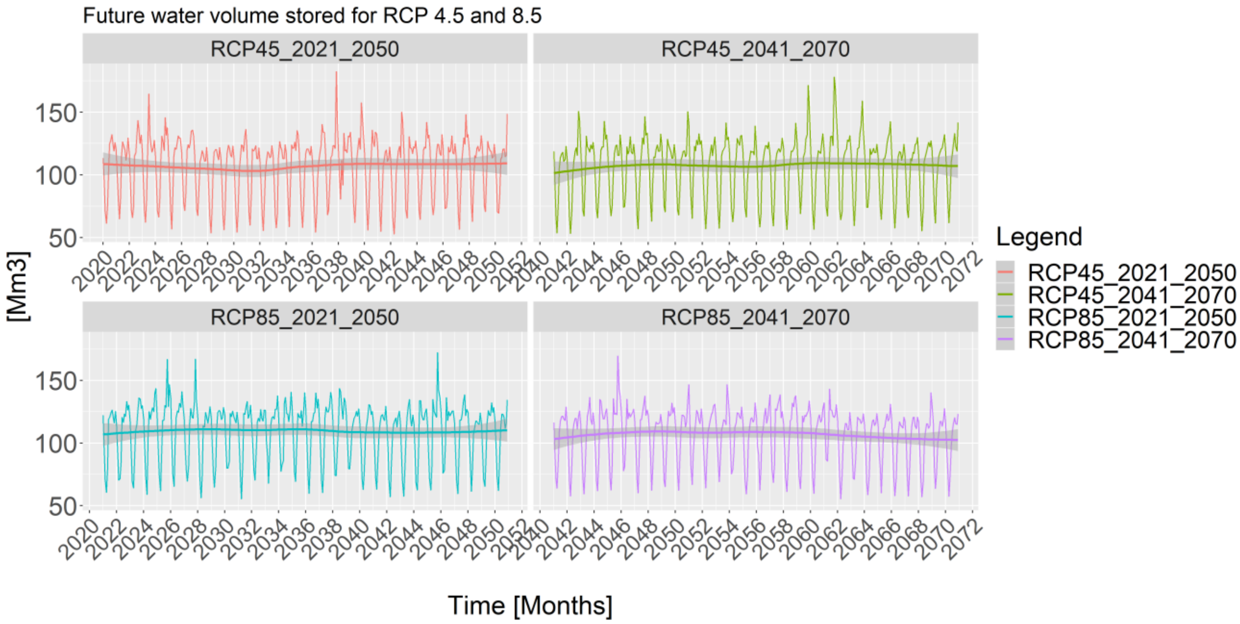

Figure 26 - S.Giustina volume for future scenarios of climate change and streamflow

Consequences of reduced streamflow are more evident in case of water turbined. Limited variations are expected for the RCP4.5 both short and long-term, while RCP8.5 shows a decreasing trend especially in the long-term (Figure 27).

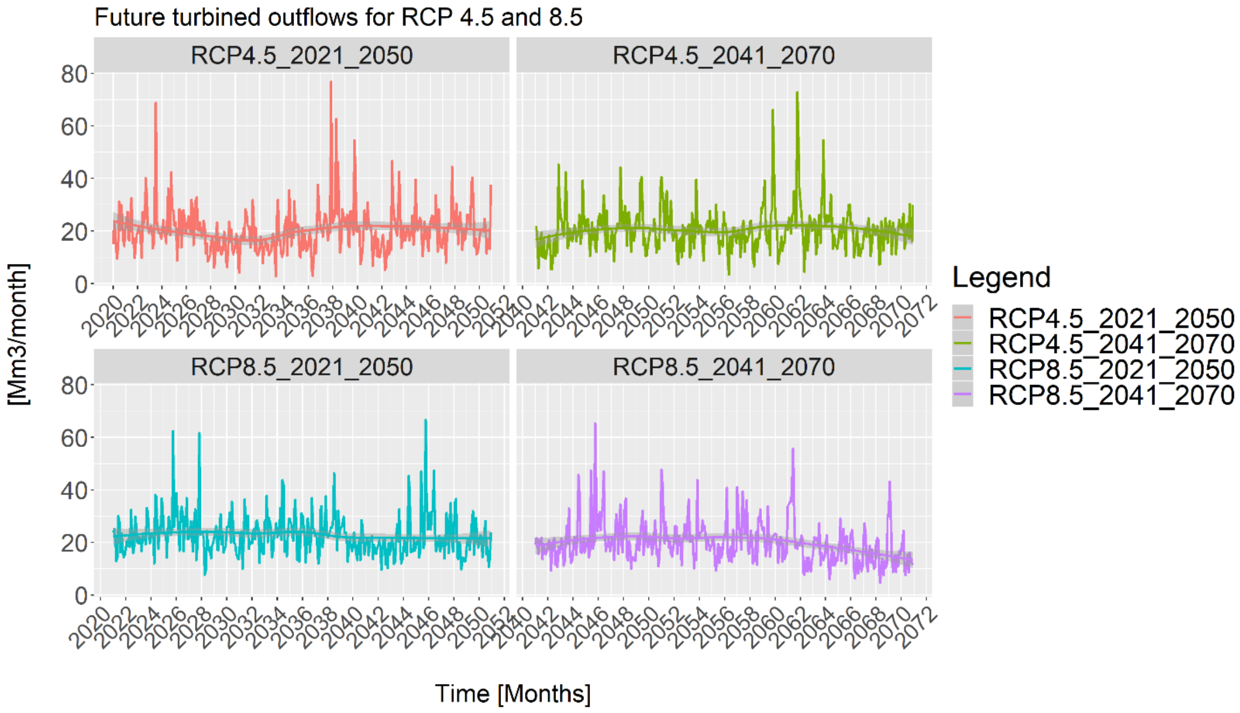

Figure 27 – S.Giustina water turbined for future climate change scenarios

C Polygon – "Bassa val di Non"

The Mollaro reservoir operates only diverting water already turbined from S.Giustina to another penstock, hence all water incoming to the Mollaro reservoir is turbined and released downstream. Such reason, justify the high model performance replicating past water turbined observations.

Future water demand

Agriculture

A, B and C Polygons - "Val di Sole", "Alta val di Non" and "Bassa val di Non"

Preliminary results of monthly averaged water demand for both RCP 4.5 and 8.5 short term and long-term scenarios show a substantial increase for apple cultivation with respect to the baseline. Anticipation of water demand is higher for long-term scenarios for all the three areas.

Val di Sole shows increase both for RCP4.5 and 8.5, the latter having lower maximum values but a generalized larger increase over all the considered growing period. In the short term, RCP4.5 increase ranges from 8% in June to 31.8% increase in April, while in the long-term scenario from 11% in September to 36.9% in May. RCP8.5 shows short-term values increase ranging from 7% in September to 16% in July, and long-term increases from 17% in September to 36% in July.

Alta val di Non also shows a lower increase of water demand compared to the Val di Sole. In particular, Alta val di Non includes an agricultural land extension 3.5 times larger than Val di Sole and still values increase ranges for RCP4.5 short-term from 0.5% in June to 7% in July; for RCP4.5 long-term from 6% April to 17% July; RCP8.5 short-term 0.5% in June to 7% in July, and finally RCP8.5 long-term from 16% in May to 28% July.

For Bassa val di Non the increases are the highest most likely due to the larger extension in agricultural land and a lowest altitude locations, meaning a higher increase of temperature values in future. Such conditions leads to increases of RCP4.5 short-term from 65% April to 86% July; RCP4.5 long-term from 63% in April to 103% in July; RCP8.5 short-term from 55% in April to 80% in June, and finally RCP8.5 long-term ranging from 78% in April and 106% in July.

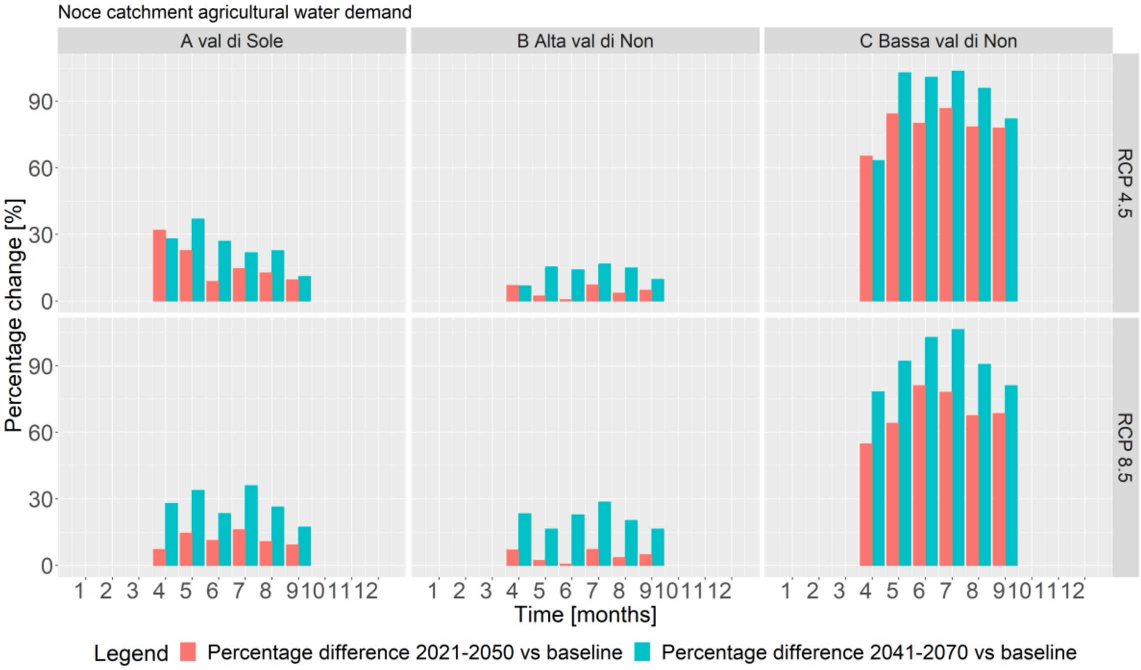

Figure 28 – Percentage changes of agricultural water demand (already accounting for agricultural land extension): in red percentage differences between the 2021-2050 scenario and baseline, in light blue differences between the 2041-2070 scenario and baseline.

Domestic

Future inhabitants projections depict a decrease of population living in all the valley of the Noce river from 54692 in 2020 to 43156 in 2070. This is likely due to a combination of low birth rates and an already existing and persistent trend of rural population move towards urban centre that is common across all mountain areas in Europe (Lasanta et al., 2017; van den Belt et al., 2010).

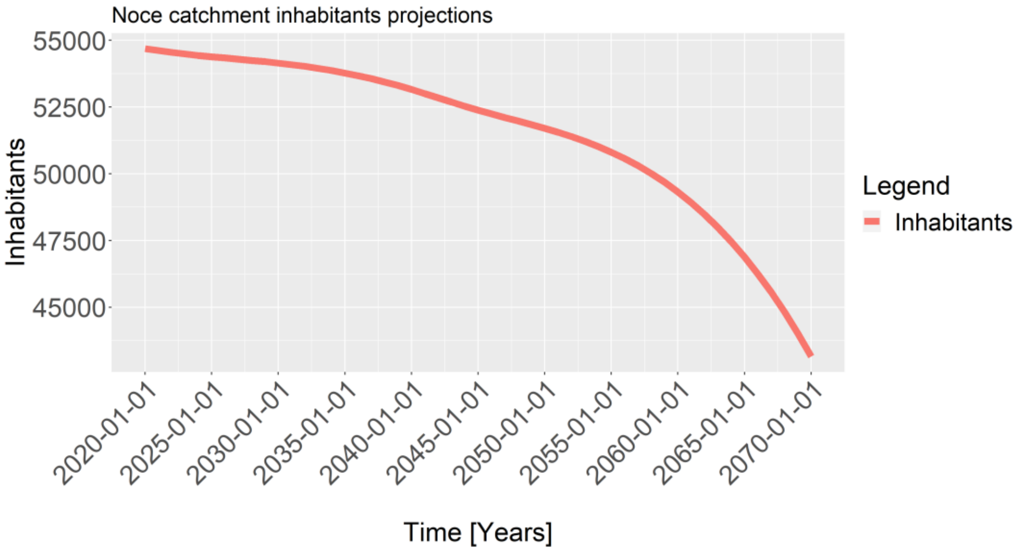

Figure 29 –Future inhabitants' projections of inhabitants for the whole Noce catchment

In case of future tourist presences scenarios, the Val di Sole area (A) is projected to reach and going beyond 350000 presences for the long-term scenario, doubling values from 1985. Maximum values of presences are projected to occur during winter months of January, February and March, and summer season (i.e. in particular July and August) corresponding to the peaks of seasonal outdoor activities and leading to a maximum water demand of 96000 m^3 per month for the long-term scenario. Similarly the projections for the Alta val di Non (B) depict maximum values during the summer period from July to September and leading to maximum of water demand of 20000 m^3 per month in a long-term perspective.

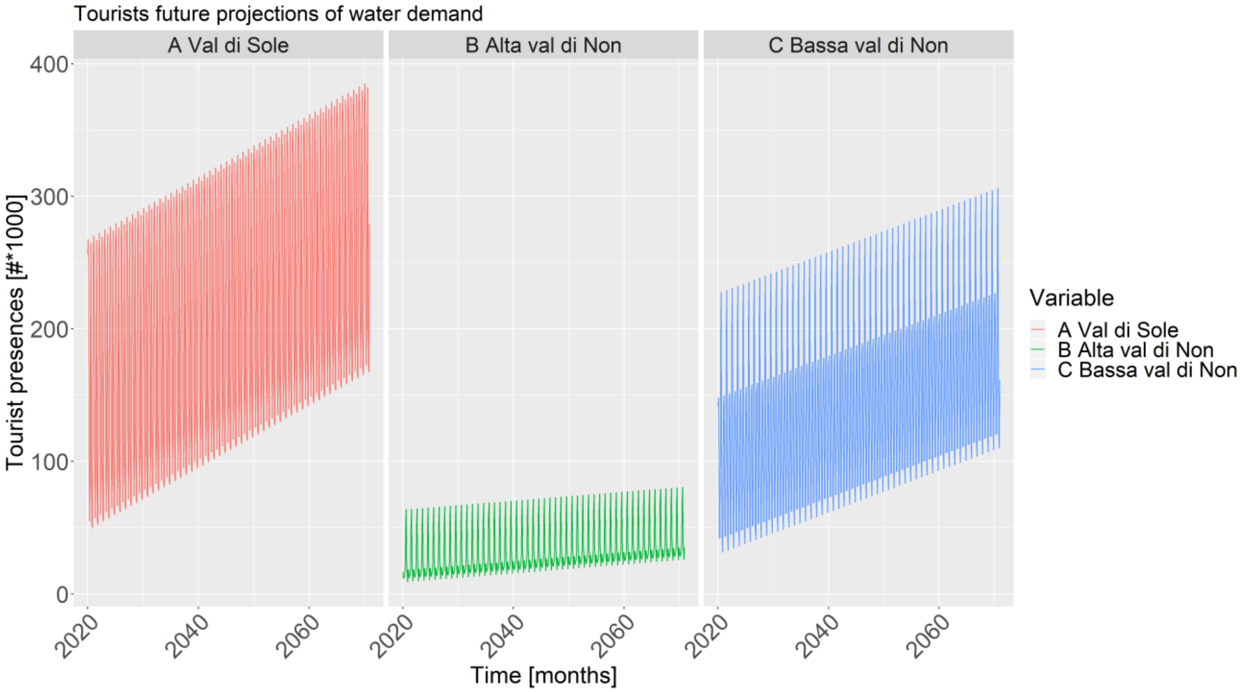

Figure 30 –Future scenarios of tourist presences for Val di Sole (A) and Alta val di Non (B) using a liner-mixed effect model

Ecological

Minimum ecological flow kept constant according to the Provincial regulation (Provincia Autonoma di Trento, 2006). Future scenarios not considered any modifications in the minimum flow to sustain ecological systems.

4. Discussion and conclusion

This study provides insights on the Noce river mountain catchment and the assessment of climate change and anthropogenic effects on water availability and demand. In particular, it widen traditional single-risk perspectives adopting a SDM to include multiple and cross-sectoral components involved in water scarcity issues. This application encompassed bio-physical and socio-economic factors related to multi-risk processes. In particular, SDM was applied to multiple areas where economic sectors share and depend on the same water resource and are exposed to potential cross-sectoral and cascading effects caused by upstream withdrawals. The aim of the integrated multi-risk assessment was to investigate possible conditions of unbalanced water use at different locations. By doing so, we explored potential impacts of water scarcity propagation from upstream to downstream exacerbated by climate change and increasing water demand for anthropogenic activities.

Preliminary results showed climate change influences decreasing river streamflow in the Val di Sole and Alta val di Non characterized by an anticipation of the monthly averaged maximum peak of discharge of one month. This result has consequence on the amount of water turbined, especially for the Pian Palù and downstream to S.Giustina dam reservoirs. While for the baseline scenario streamflow peaks timing (i.e. May, June, July, August) mostly overlaps with months of maximum water demand for agriculture and tourism (i.e. June, July, August and September), for future scenario a streamflow peak anticipation can lead to consequences for the availability of water for all the sectors at the same time. This is particularly significant for long-term RCP8.5 scenario where the agricultural water demand is increasing up to 60% for the Val di Sole case and to 90% for the Alta Val di Non during the worst scenario. Moreover, tourism is projected to linearly increase in time leading to a significant water demand increase in a long-term scenario. Nevertheless, inhabitants scenarios depict conditions of decreased population living in the valley, hence compensating the increasing water demand from the other sectors. This is of particular importance as the number of population living in the Noce catchment increases from upstream to downstream although the current and future depopulation trend could compensate conditions of increased water demand from agriculture and tourism downstream the catchment.

Possible adaptation strategies for the Noce catchment should involve coordinated actions among all sectors. An increase of water stored in reservoirs (either with new reservoirs or improving the already existing ones) can provide water during those months of peak demand. Moreover, an earlier filling of reservoirs in winter and autumn are also identified as a beneficial strategy to support months of higher demand (Hendrickx and Sauquet, 2013; Brunner *et al.*, 2019).

Strategies for the tourism sector could aim to spread possible unsustainable water demand during periods of relatively mild pressure. This would be possible attracting tourists during those months when presences are at the lowest as opposite to high peak seasons (Becken, 2014; Bonzanigo et al., 2016; Debarbieux et al., 2014; Gössling et al., 2012; Meyer-Cech and Pröbstl, 2006; Permanent Secretariat of the Alpine Convention, 2015; Scott et al., 2019).

For the agricultural sector, a transition from apple orchards dominated cultivations into more diverse and less water demanding crop types should be considered to mitigate potential economic losses in case of water scarcity affecting the whole apple production sector.

Finally, spring and summer months are the most exposed to water use critical states, where emergency strategies need to be implemented in order to limit water demand and possible impacts on multiple sectors. Strategies identification and adoption should be conducted together with various local actors (e.g. hydropower companies, agricultural associations and local municipalities) to minimize the spread of unexpected consequences that can have high impacts on multiple sectors. A participatory approach could be set up engaging local stakeholder to present and discuss the results from this analysis, fostering the discussion on possible trade-off solutions.

Limitations of the study

The objectives of this study were achieved implementing some assumptions in order to model and represent a complex reality related to water management in the Noce catchment. Here we summarised the most relevant assumptions according to the field of application.

From a climate modelling perspective, we considered COSMO-CLM climate model only. This was due to the already existing application of GeoTransf coupled with COSMO-CLM climate models to represent future streamflow conditions from the OrientGate project. Although current approaches consider ensemble means of multiple climate models, our approach considered a conservative perspective associated with COSMO-CLM precipitation prediction reduction.

Within the assessment of unbalance water availability and demand conditions, we considered water demand instead of water consumption. This was due to the lack of past data on actual water consumption for different sectors (e.g. agriculture and domestic) evaluating the real consumption of water. For this reason, we adopted a more conservative and applicable perspective accounting for the theoretical water demand per each sector.

For the assessment of hydropower demand, the numerous small run-of-the-river power plants in the Noce river were excluded. The aim was to account for the main water users understanding their water demands. This is particularly relevant since implementing adaptation strategies on high demanding sectors means having the greatest benefits in terms of sustainable water management. In the case of in-series hydropower water diversions, we considered only the hydropower plant having a higher demand. This was assumed not to double account for multiple in-series uses of water leading to a very high (greater than 100%) ratio between water used and water available.

In case of water demand from agriculture, we considered future agricultural land extension and growing period being the same as in the baseline. These assumptions were justified by the lack of information on agricultural future scenarios, but we are aware their characterization represent a future improvement to this study so to better describe the impacts of temperature increase on agricultural areas and growing period.

Moreover, the crop type within SIMETAW simulations considered apple orchards only. This assumption is supported by literature data on the very intensive apple production characterizing the Noce river area (Marini et al., 2012; Tattoni et al., 2017). Moreover, the assumption of apple orchards dominated cultivations contributes to a more conservative description of agricultural water demand.

In case of domestic water demand, tourist presences for future scenarios was explained extending its growing trend to the future without considering a maximum carrying capacity. Although defining a maximum carrying capacity can lead to more realistic results, it is also a threshold difficult to define and in this case was not considered so to depict conservative conditions for a higher tourist water demand.

Moreover, the spatial assessment performed with SDM allowed to aggregate results over a certain area, but also reducing landscape heterogeneity. Such approach was considered due to the need of bringing together many dataset and modelling outputs into one map, hence relying on a computational efficient approach to represent the general system conditions.

Overall, this study showed the complexity arising when bio-physical and socio-economic factors are interacting together within a multi-risk framework. The adoption of an integrated perspective is fundamental to address complex multi-risk issues in a comprehensive way. Within this context, System Dynamics Modelling represents a valuable support to bring together contributions from deterministic and stochastic assessments in a wider perspective. Although in this way uncertainties associated to different modelling approaches can increase, this application represents an initial step to investigate unknown consequences from future scenarios of climate change across different water demanding sectors. A systemic perspective is particular important and needed to better understand possible unexpected consequences on the whole system and finally find leverage strategies to trigger maximum climate adaptation benefit.

References

Alpine convention, Convention, A., 2009. Report on the State of the Alps Alpine Signals - Special Edition 2, Water and water management issues. Permanent secretariat of the Alpine Convention, Innsbruck.

Bates, D., Mächler, M., Bolker, B.M., Walker, S.C., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Softw. 67. https://doi.org/10.18637/jss.v067.i01

Becken, S., 2014. Water equity - Contrasting tourism water use with that of the local community. Water Resour. Ind. 7–8, 9–22. https://doi.org/10.1016/j.wri.2014.09.002

Bellin, A., Majone, B., Cainelli, O., Alberici, D., Villa, F., 2016. A continuous coupled hydrological and water resources management model. Environ. Model. Softw. 75, 176–192. https://doi.org/10.1016/j.envsoft.2015.10.013

Beniston, M., Stoffel, M., 2014. Assessing the impacts of climatic change on mountain water resources. Sci. Total Environ. 493, 1129–1137. https://doi.org/10.1016/j.scitotenv.2013.11.122

Bonzanigo, L., Giupponi, C., Balbi, S., 2016. Sustainable tourism planning and climate change adaptation in the Alps: a case study of winter tourism in mountain communities in the Dolomites. J. Sustain. Tour. 24, 637–652. https://doi.org/10.1080/09669582.2015.1122013

Brunner, M.I., Björnsen Gurung, A., Zappa, M., Zekollari, H., Farinotti, D., Stähli, M., 2019a. Present and future water scarcity in Switzerland: Potential for alleviation through reservoirs and lakes. Sci. Total Environ. 666, 1033–1047. https://doi.org/10.1016/j.scitotenv.2019.02.169

Brunner, M.I., Zappa, M., Stähli, M., 2019b. Scale matters: Effects of temporal and spatial data resolution on water scarcity assessments. Adv. Water Resour. 123, 134–144. https://doi.org/10.1016/j.advwatres.2018.11.013

Bucchignani, E., Montesarchio, M., Zollo, A.L., Mercogliano, P., 2016. High-resolution climate simulations with COSMO-CLM over Italy: Performance evaluation and climate projections for the 21st century. Int. J. Climatol. 36, 735–756. https://doi.org/10.1002/joc.4379

Chiogna, G., Skrobanek, P., Narany, T.S., Ludwig, R., Stumpp, C., 2018. Effects of the 2017 drought on isotopic and geochemical gradients in the Adige catchment, Italy. Sci. Total Environ. 645, 924–936. https://doi.org/10.1016/j.scitotenv.2018.07.176

Debarbieux, B., Varacca, M.O., Rudaz, G., Maselli, D., Kohler, T., Jurek, M., 2014. Tourism in mountain regions. Hopes, fears and realities. Sustainable mountain development series. Department of Geography and Environment, University of Geneva, Geneva.

Di Baldassarre, G., Wanders, N., AghaKouchak, A., Kuil, L., Rangecroft, S., Veldkamp, T.I.E., Garcia, M., van Oel, P.R., Breinl, K., Van Loon, A.., 2018. Water shortages worsened by reservoir effects. Nat. Sustain. 1, 617–622. https://doi.org/10.1038/s41893-018-0159-0

Eccel, E., Toller, G., Dalsant, C., Agrario, I., Michele, S., 2000. L'epoca di fioritura in specie arboree in un contesto di variabilità climatica: il caso del melo 46–55.

Garrote, L., Iglesias, A., Granados, A., 2018. Country-level assessment of future risk of water scarcity in Europe. Proc. Int. Assoc. Hydrol. Sci. 379, 455–462. https://doi.org/10.5194/piahs-379-455-2018

Gaudard, L., Romerio, F., Dalla Valle, F., Gorret, R., Maran, S., Ravazzani, G., Stoffel, M., Volonterio, M., 2014. Climate change impacts on hydropower in the Swiss and Italian Alps. Sci. Total Environ. 493, 1211–1221. https://doi.org/10.1016/j.scitotenv.2013.10.012

Gobiet, A., Kotlarski, S., Beniston, M., Heinrich, G., Rajczak, J., Stoffel, M., 2014. 21st century climate change in the European Alps-A review. Sci. Total Environ. 493, 1138–1151. https://doi.org/10.1016/j.scitotenv.2013.07.050

Gössling, S., Peeters, P., Hall, C.M., Ceron, J.P., Dubois, G., Lehmann, L.V., Scott, D., 2012. Tourism and water use: Supply, demand, and security. An international review. Tour. Manag. 33, 1–15. https://doi.org/10.1016/j.tourman.2011.03.015

Gräler, B., Pebesma, E., Heuvelink, G., 2016. Spatio-temporal interpolation using gstat. R J. 8, 204–218. https://doi.org/10.32614/rj-2016-014

Hanel, M., Rakovec, O., Markonis, Y., Máca, P., Samaniego, L., Kyselý, J., Kumar, R., 2018. Revisiting the recent European droughts from a long-term perspective. Sci. Rep. 8, 1–11. https://doi.org/10.1038/s41598-018-27464-4

Harrison, P.A., Dunford, R.W., Holman, I.P., Rounsevell, M.D.A., 2016. Climate change impact modelling needs to include cross-sectoral interactions. Nat. Clim. Chang. 6, 885–890. https://doi.org/10.1038/nclimate3039

Hudson, G., Wackernagel, H., 1994. Mapping Temperature Using Kriging With External Drift - Theory and an Example From Scotland. Int. J. Climatol. 14, 77–91. https://doi.org/10.1002/joc.3370140107

Laaha, G., Gauster, T., Tallaksen, L.M., Vidal, J.P., Stahl, K., Prudhomme, C., Heudorfer, B., Vlnas, R., Ionita, M., Van Lanen, H.A.J., Adler, M.J., Caillouet, L., Delus, C., Fendekova, M., Gailliez, S., Hannaford, J., Kingston, D., Van Loon, A.F., Mediero, L., Osuch, M., Romanowicz, R., Sauquet, E., Stagge, J.H., Wong, W.K., 2017. The European 2015 drought from a hydrological perspective. Hydrol. Earth Syst. Sci. 21, 3001–3024. https://doi.org/10.5194/hess-21-3001-2017

Lasanta, T., Arnáez, J., Pascual, N., Ruiz-Flaño, P., Errea, M.P., Lana-Renault, N., 2017. Space–time process and drivers of land abandonment in Europe. Catena 149, 810–823. https://doi.org/10.1016/j.catena.2016.02.024

Majone, B., Villa, F., Deidda, R., Bellin, A., 2016. Impact of climate change and water use policies on hydropower potential in the south-eastern Alpine region. Sci. Total Environ. 543, 965–980. https://doi.org/10.1016/j.scitotenv.2015.05.009

Mancosu, N., Spano, D., Orang, M., Sarreshteh, S., Snyder, R.L., 2016. SIMETAW# - A model for agricultural water demand planning. Water Resour. Manag. 30, 541–557. https://doi.org/10.1007/s11269-015-1176-7

Maraun, D., 2016. Bias Correcting Climate Change Simulations - a Critical Review. Curr. Clim. Chang. Reports 2, 211–220. https://doi.org/10.1007/s40641-016-0050-x

Marini, L., Quaranta, M., Fontana, P., Biesmeijer, J.C., Bommarco, R., 2012. Landscape context and elevation affect pollinator communities in intensive apple orchards. Basic Appl. Ecol. 13, 681–689. https://doi.org/10.1016/j.baae.2012.09.003

Masia, S., Sušnik, J., Marras, S., Mereu, S., Spano, D., Trabucco, A., 2018. Assessment of Irrigated Agriculture Vulnerability under Climate Change in Southern Italy. Water 10, 209. https://doi.org/10.3390/w10020209

Mehran, A., AghaKouchak, A., Nakhjiri, N., Stewardson, M.J., Peel, M.C., Phillips, T.J., Wada, Y., Ravalico, J.K., 2017. Compounding Impacts of Human-Induced Water Stress and Climate Change on Water Availability. Sci. Rep. 7, 1–9. https://doi.org/10.1038/s41598-017-06765-0

Meyer-Cech, K., Pröbstl, U., 2006. Sustainable tourism in mountainous regions, in: Schmitz, M.F., Diaz, P. (Eds.), WIT Transactions on Ecology and the Environment. WIT Press, pp. 239–249. https://doi.org/10.2495/ST060221

Milano, M., Reynard, E., Köplin, N., Weingartner, R., 2015. Climatic and anthropogenic changes in Western Switzerland: Impacts on water stress. Sci. Total Environ. 536, 12–24. https://doi.org/10.1016/j.scitotenv.2015.07.049

Milner, A.M., Khamis, K., Battin, T.J., Brittain, J.E., Barrand, N.E., Füreder, L., Cauvy-Fraunié, S., Gíslason, G.M., Jacobsen, D., Hannah, D.M., Hodson, A.J., Hood, E., Lencioni, V., Ólafsson, J.S., Robinson, C.T., Tranter, M., Brown, L.E., 2017. Glacier shrinkage driving global changes in downstream systems. Proc. Natl. Acad. Sci. 201619807. https://doi.org/10.1073/pnas.1619807114

Permanent Secretariat of the Alpine Convention, 2015. DEMOGRAPHIC CHANGES IN THE ALPS. Report on the State of the Alps – Alpine Signals – Special Edition 5. Innsbruck; Bolzano; = Bozen.

Pescaroli, G., Nones, M., Galbusera, L., Alexander, D., 2018. Understanding and mitigating cascading crises in the global interconnected system. Int. J. Disaster Risk Reduct. 30, 159–163. https://doi.org/10.1016/j.ijdrr.2018.07.004

PGUAP, 2006. PGUAP - Piano Generale di Utilizzazione delle Acque Pubbliche. Trento.

Provincia Autonoma di Trento, 2006. PGUAP - Piano Generale di Utilizzazione delle Acque Pubbliche. Trento.

R Core Development Team, 2013. A language and environment for statistical computing.

Ranzani, A., Bonato, M., Patro, E.R., Gaudard, L., De Michele, C., 2018. Hydropower future: Between climate change, renewable deployment, carbon and fuel prices. Water (Switzerland) 10, 1–17. https://doi.org/10.3390/w10091197

Rea, R., Eccel, E., 2006. Phenological models for blooming of apple in a mountainous region. Int. J. Biometeorol. 51, 1–16. https://doi.org/10.1007/s00484-006-0043-x

Rockel, B., Geyer, B., 2008. The performance of the regional climate model CLM in different climate regions, based on the example of precipitation. Meteorol. Zeitschrift 17, 487–498. https://doi.org/10.1127/0941-2948/2008/0297

Rull, V., 2014. Biodiversity, mountains and climate change, Collectanea Botanica. https://doi.org/10.3989/collectbot.2013.v33.006

Scott, D., Hall, C.M., Gössling, S., 2019. Global tourism vulnerability to climate change. Ann. Tour. Res. 77, 49–61. https://doi.org/10.1016/j.annals.2019.05.007

Steele, C., Reyes, J., Elias, E., Aney, S., Rango, A., 2018. Cascading impacts of climate change on southwestern US cropland agriculture. Clim. Change 148, 437–450. https://doi.org/10.1007/s10584-018-2220-4

Sušnik, J., Vamvakeridou-Lyroudia, L.S., Savić, D.A., Kapelan, Z., 2012. Integrated System Dynamics Modelling for water scarcity assessment: Case study of the Kairouan region. Sci. Total Environ. 440, 290–306. https://doi.org/10.1016/j.scitotenv.2012.05.085

Tattoni, C., Ianni, E., Geneletti, D., Zatelli, P., Ciolli, M., 2017. Landscape changes, traditional ecological knowledge and future scenarios in the Alps: A holistic ecological approach. Sci. Total Environ. 579, 27–36. https://doi.org/10.1016/j.scitotenv.2016.11.075

Terzi, S., Torresan, S., Schneiderbauer, S., Critto, A., Zebisch, M., Marcomini, A., 2019. Multi-risk assessment in mountain regions: A review of modelling approaches for climate change adaptation. J. Environ. Manage. 232, 759–771. https://doi.org/10.1016/j.jenvman.2018.11.100

Testa, G., Gresta, F., Cosentino, S.L., 2011. Dry matter and qualitative characteristics of alfalfa as affected by harvest times and soil water content. Eur. J. Agron. 34, 144–152. https://doi.org/10.1016/j.eja.2010.12.001

Tovazzi, M., 2012. Relazione tecnica : il bacino del Noce.

UNISDR, 2015. Sendai Framework for Disaster Risk Reduction 2015 - 2030.

van den Belt, M., Forgie, V., Bremer, S., Mcdonald, G., Montes de Oca, O., Joy, M., 2010. Modelling tools for integrated , adaptive management : a case study of New Zealand Regional Authorities 1–20.

Visconti, G., 2018. Modeling the environment, Second edi. ed, Springer Climate. Washington, DC : Island Press. https://doi.org/10.1007/978-3-319-65669-4_3

Zucaro, R., Cesaro, Luca, 2009. Rapporto Sullo Stato Dell’Irrigazione in Trentino-Alto Adige.

Discussions and conclusions

This thesis focused on multi-risk assessments considering future climate change projections in mountain regions. The initial literature review on multi-risk applications was based on the current gap of an internationally recognised multi-risk definition. Different modelling approaches were reviewed looking at their advantages and limitations in addressing distinctive features of multi-risk assessments with a specific focus on mountain regions.

As a result, System Dynamics Modelling was identified and selected as a suitable methodology to investigate variables interactions and feedback loops characteristics of multi-risk conditions. In particular, the SDM approach is used to conceptually and quantitatively describe bio-physical and socio-economic variables interacting in time and allowing to adopt a cross-sectoral perspective for a systemic representation of their dynamics.

Such methodology was implemented aiming to depict varying conditions of water availability and demand on strategic economic sectors of the Noce river catchment in the Italian Alps.

Within this context, SDM was first applied to the case of the S.Giustina dam reservoir in the Noce river catchment (Italy) integrating statistical assessments of variables interactions to describe the dam functioning in terms of water turbined and volume stored and looking at future climate change scenarios.

This application provided information on the risk conditions associated to future critical states of the S.Giustina dam reservoir and the impact on the water stored and turbined water used for hydropower production. Moreover, it provided information on the temporal dynamics of the critical states, highlighting the need of seasonal dam operations in order to prevent possible water scarcity issues arising during spring and summer: months of maximum water demand. The results from this application represent an important foundation to inform local decision-makers and dam managers on the need to prepare to future reduced conditions of water volume and streamflow. In particular, actions should be taken acting in cooperation with the territorial local actors for trade-off solutions in agreement with the international objectives coming from the European Water Directive to make our water management resilient to climate change effects (European Parliament & Council, 2000).

The third paper widen the previous risk assessment application integrating a larger set of bio-physical and socio-economic factors defining water demand from hydropower, agriculture, domestic and ecological need. Water availability was described considering streamflow values and the amount of water stored in multiple reservoirs within the Noce catchment. This application overcome usual spatial limitations associated with SDM studies considering three sub-catchment areas and evaluating their water use defined as the ratio between water availability and demand from multiple sectors. By doing so, it was possible to look at potential unbalanced conditions of water use that can propagate downstream the catchment.

Overall, SDM fosters a system thinking perspective, helping modellers and decision-makers to better understand the variables involved in risk processes analysing their dynamic connections and feedback loops. Although previous SDM applications mainly relied on deterministic explanations of variables interactions, SDM applications integrating both deterministic and stochastic models represent a valuable improvement to address uncertainties associated with risk assessments. Spatial assessments represent another limitation of SDM applications. However, in this thesis a spatial lumped subdivision was considered accounting for spatial heterogeneity within the Noce catchment.

The SDM approach implemented in this thesis connected for the first time the main water demanding sectors within the Noce catchment providing insights on possible cascading effects. Such methodological application could be extended to include other areas (e.g. Adige river) and working at intra-regional level where recent water scarcity and drought events are becoming more relevant and impacting current human activities and ecosystems (Chiogna et al.2018; Hanel et al.2018). Moreover, SDM can encompass participatory approaches to identify suitable adaptation strategy together with relevant local stakeholder. In particular, social-related qualitative variables involved in water management could be integrated within the SDM. Such application can provide innovative insights on the way to couple quantitative and qualitative information to tackle climate-related water scarcity.

Supplementary Material

Table 1- Analysis of multi-risk and climate change assessment applications with the 5 selected methodologies

Bayesian networks	**References**	**Management issue**	**Hazards**	**Hazards interactions**	**Exposed types**	**Cross-sectoral assessment**	**Climate change scenarios**	**Spatial scale**	**Temporal dynamic**	**Stakeholder involvement**	**Software used**	**Case study**
1.	(Liu, Siu and Mitchell, 2016b)	Loss evaluation from multiple interacting hazards	Typhoons	Hazards in series affecting the same area	Economic assets through GDP data on county basis	Economic and social vulnerability-related indicators	None	Region extension	None	Not involved	ArcGis	Northeast Zhejiang, Yangtze River Delta (China)
2.	(Balbi *et al.*, 2016)	Early warning system assessment for urban flood	Flood	None	People	None	None	Local extension (78 km2)	None	Questionnaires to a panel of experts	GeNIe and QGIS integrated through k.LAB platform	Zurich city (Switzerland)
3.	(van Verseveld *et al.*, 2015)	Hurricane damages prediction	Hurricanes	Simultaneous effects of one hurricane hazard	Buildings	None	None	Local extension (16 km^2)	None	Not involved	XBeach model, Netica model for the Bayesian network	Rockaway Peninsula, New York City (USA)
4.	(Molina *et al.*, 2013)	Impact of climate change on groundwater resource	Rainfall reduction	None	Groundwater level, economic profits	None	A1B and A2 IPCC scenarios	Municipality extension (690 km^2)	Time steps of 5 years length for the 30 years period (2070-2100)	None	Hugin	Serral-Salinas aquifer, Murcia province (Spain)
5.	(Song *et al.*, 2012)	Analysis of earthquake-induced landslide-causing factors	Earthquake-induced landslides	Hazards in series affecting the same area	None	None	None	Province extension (1914 km^2)	None	Expert evaluation for landslide-causing factors classification	Bayes Net Toolbox for MATLAB, ArcGis and Erdas Imagine	Beichuan, Mianyang Municipality, Sichuan, (China)
6.	(Grêt-Regamey and Straub, 2006)	Avalanche risk in Davos city	Avalanche	None	People, vehicles, buildings	Physical and economic impacts on exposed	None	Municipality extension (254 km^2)	None	None	Hugin and ArcGis	Davos city (Switzerland)

Agent-based model	**References**	**Management issue**	**Hazards**	**Hazards interactions**	**Exposed types**	**Cross-sectoral assessment**	**Climate change scenarios**	**Spatial scale**	**Temporal dynamic**	**Stakeholder involvement**	**Software used**	**Case study**
1.	(Eid *et al.*, 2017)	Disaster recovery under decision-making	Hurricane	None	Resident, insurance companies and government	Economic (income, equity, occupation) Social (ethnicity, adaptive capacity)	None	Not specified (Hancock, Harrison, and Jackson Mississippi counties)	Six months' time-steps for 2007-2012 period	None	Hazus-mh and GeoMason	Katrina Hurricane on Mississippi coastal counties Hancock, Harrison, and Jackson(USA)
2.	(Mashhadi Ali, Shafiee and Berglund, 2017)	Water supply-demand dynamics	Drought	None	Household	Physical (hydrologic) Social (agents behaviour)	Flows, precipitation, and evapotranspiration factors decrease in increments of 10% till the value of 10% of the initial conditions	Municipality extension (370 km^2)	The model runs on a monthly time step for 50 years (1983-2032)	Surveys for agents data collection	Mason	Raleigh, North Carolina (USA)
3.	(Becu *et al.*, 2016)	Foster social learning about coastal risk prevention measures	Coastal flood	None	People	Physical (hydrodynamic) Socio-economic (taxes budget and population)	None	Not specified (~80 km^2)	Simulations over 14 years of time	Role game mechanism during 2 workshops	Gama 1.6 Lisflood-fp	Oléron Island (France)
4.	(Haer *et al.*, 2016)	Incorporates human decision making in flood risk analysis	Flood	None	Buildings	Economic (expected annual damages)	Sea-level rise of 10.5 mm/year from the Ensemble of CIMP5 Earth System Models for 2.6, 4.5, 6.0 and 8.5 RCP scenarios	Local extension (0.5 km^2)	Monthly time-steps over a period of 100 years	None	Netlogo	Heijplaat in Rotterdam (Netherlands)
5.	(Girard *et al.*, 2015)	Changes in temperature and water availability due to climate change	Water scarcity	None	Salamanders	Physical (hydrodynamic) Ecological (move of salamanders)	A1B and A2 IPCC scenarios	Simulation on 50x50 m grid per each water spring	30 years of simulation for the 2041–2070 period	None	HydroGeoSphere	Covey Hill, Montreal (Canada)
6.	(Acosta *et al.*, 2014)	Land-use change due to manager's decisions, climate and economic changes	Food yields scarcity	None	Crops, farmers, semi-natural ecosystem	Economic (accounting for global economic changes) Ecological (loss of ecosystems/landscape)	A1fi IPCC scenarios	Local extension (44 km^2)	Simulations consider land-use dynamic up to 2050	Semi-structured, social survey for agents attributes collection	Netlogo	Amendoeira da Serra (Portugal)
7.	(Balbi *et al.*, 2013)	Climate change influence on winter tourism industry	Snow cover reduction due to global warming	None	Local economy relying on winter tourists	Economic (future development) Social (tourists behaviour)	A1B and B1 IPCC scenarios	Municipality extension (220km^2)	None	Field surveys for tourist profiles characterization	AuronzoWinSim1.0; Netlogo	Auronzo di Cadore (Italy)
8.	(Dawson, Peppe and Wang, 2011)	Flood vulnerability and effectiveness of different flood management strategies	Storm surge	Concurrent storm, failed defence and evacuation	People	Physical (hydrodynamic) Socio-economic (human behaviour)	None	Local extension (10 km^2)	Each simulation represents 3.25h of event time	None	Netlogo	City of Towny (Wales)

System dynamic models	**References**	**Management issue**	**Hazards**	**Hazards interactions**	**Exposed types**	**Cross-sectoral assessment**	**Climate change scenarios**	**Spatial scale**	**Temporal dynamic**	**Stakeholder involvement**	**Software used**	**Case study**
1.	(Duran-Encalada *et al.*, 2017)	Quality/quantity water variation due to climate change	Water scarcity	None	Industry, agriculture and household	Social (education, health, housing) Economic (households, agriculture, industry)	AB1 and A2 IPCC scenarios	Municipality extension	70 years, from 2010 to 2080	None	I-think 10.0.2	Nuevo Laredo and Reynosa (Mexico)
2.	(Mereu *et al.*, 2016)	Water reservoirs resilience assessment	Water scarcity	None	Hydropower, agriculture and domestic water supply	Physical (water quantity) Socio-economic (tourism development and water demand)	Ensemble of CIMP5 Earth System Models for 4.5 and 8.5 RCP scenarios	Local extension	Monthly time step over 4 years of simulation	None	Stella	Pedra e' Othoni reservoir, Sardinia (Italy)
3.	(Armenia *et al.*, 2014)	Decision-makers support for mitigation of critical events effects	Floods	None	Critical infrastructure (transportation, energy production and telecommunications) and people and authorities behaviours	None	None	Municipal extension	Minute temporal resolution over 3 days of simulation	None	Stella	Central-east Europe 2002, United Kingdom 2007
4.	(Sahin and Mohamed, 2014)	Spatio-temporal representation of coastal hazards for future adaptation	Sea level rise	None	Population and land area	None	3 future scenarios of sea-level rise (0.5, 1.0, 1.5 cm/year)	Municipal neighbourhood	10 year resolution over a period of 100 years (2010-2110)	None	Vensim	Gold Coast City, Queensland, (AUS)
5.	(Hartt, 2011)	Evaluate storm impacts through a spatio-temporal approach	Storm surge	None	Residential, commercial, heritage properties and municipal infrastructures	Environmental, Economic Social and Cultural	None	Municipality extension	6 scenarios considering from 1.5 to 7 days of simulations	None	Stella and ArcGis	Charlottetown (Canada)
6.	(Simonovic and Ahmad, 2005)	Decision-making evacuation process during a flood event	Flood	None	People (52 families for 200 individuals)	Social (previous flood experience, awareness of risk, behaviour of others)	None	Extension not explicitly mentioned, despite the model used GIS data	Total horizon of the simulation is 96 h	Field survey with families evacuated during the 1997 flood	Stella	Red river, Manitoba (Canada)
7.	(Li and Simonovic, 2002)	Snow melting contribution to flood events	Flood	None	None	None	None	Regional extension	One year of streamflow simulation on a daily basis	None	Stella	Assiniboine River and Red river, Manitoba (Canada)

Event and fault trees	**References**	**Management issue**	**Hazards**	**Hazards interactions**	**Exposed types**	**Cross-sectoral assessment**	**Climate change scenarios**	**Spatial scale**	**Temporal dynamic**	**Stakeholder involvement**	**Software used**	**Case study**
1.	(Sandri *et al.*, 2014)	Assess volcano multi-hazard probabilities	Volcanic phenomena: lahars, pyroclastic density currents, tephra fall and ballistic ejecta	None	None	None	None	Simulations varying according to the hazard: spatial grid with a finer 1×1-km, and a coarser 5×5-km spacing up to 90km from the volcano	No dynamics represented. probabilistic assessments refer to one year time window	None	Eject!	El Misti Volcano, Arequipa (Peru)
2.	(Rosqvist *et al.*, 2013)	Flood protection of critical infrastructure	Flood	None	Infrastructures, residential buildings	Economic (emergency response, production loss, repair)	A1B IPCC scenario on Finland (Perrels *et al.*, 2010)	Four areas considered : from 1, 10, 100 and 1000 km^2	Simulations look to future climate 2020-2050 floods	Three workshop during one year with flood experts and sector managers	ThinkTank group decision support	Kokemäki river city of Pori (Finland)
3.	(Marzocchi *et al.*, 2012)	Risk amplification due to hazard interactions	Volcanic, earthquake, floods, landslide and industrial	Simultaneous	People	None	None	Casalnuovo municipality (~8 km^2)	No dynamics represented. probabilistic assessments refer to one year time window	None	None	Casalnuovo municipality, (Italy)
4.	(Lacasse *et al.*, 2008)	Assessment of rock fall inducing tsunami	Rock-fall and tsunami	Cascade	None	None	None	Local extension (~1 km)	None	Three day meeting with scientist and stakeholders	None	Aknes slope (Norway)
5.	(Neri *et al.*, 2008)	Risk assessment of volcanic hazard	Volcanic eruption	None	Buildings	None	None	Assessment ranging from 4 to 13,3 radius km from the crater	Up to 1000 days of simulated eruption	Questionnaires to implement a performance-based expert scoring scheme	Excalibr/excalibur and Gis	Vesuvius volcano (Italy)
6.	(Peila and Guardini, 2008)	Protect roads subjected to rock-falls	Rock-fall	None	Roads	None	None	Length of the slope of 400 m	None	None	None	Theoretical application
7.	(Frieser, 2004)	Evacuation decision-making during flood	Flood	None	People	Economic (evacuation and indirect costs)	None	Nijmegen municipality	4 simulations considering evacuation prediction lead time up to 4 days	None	None	Nijmegen region (Netherlands)

Hybrid models	References	Models combined	Management issue	Hazards	Hazards interactions	Exposed types	Cross-sectoral assessment	Climate change scenarios	Spatial scale	Temporal dynamic	Stakeholder involvement	Software used	Case study
1.	(Bertone, Oz Sahin, *et al.*, 2016)	System dynamic model and bayesian network	Water resource management under great uncertainty due to climatic and non-climatic factors	Drought, flood, bushfire and contamination from extreme human actions	None	Water quality	Socio-economic (agricultural practices, reservoir maintenance)	Two scenarios: (i) temperature increase by 3°C, 10% increase of summer evapotranspiration, 10 % increase summer wind peaks; (ii)) temperature increase by 6°C, 20% decrease rainfall, 20% increase of summer and spring evapotranspiration, 30 % increase summer wind peaks;	Metropolitan extension	Daily temporal resolution over a period of 25 years	Two participatory workshops	Netica, Vensim	Sydney Area (Australia)
2.	(Phan, Sahin and Smart, 2016)	System dynamic model and bayesian network	Vulnerability of coastal water supply and demand system to climatic and non-climatic drivers	Sea level rise-salinity intrusion	None	Agriculture, industries and residential	Socio-economic (GDP, investments, water demand)	None	Not specified	Not specified	Workshop with experts for conceptual model development	None	Da Do Basin in Hai Phong City (Vietnam)
3.	(Wang *et al.*, 2016)	System dynamic model and bayesian network	Water quality outlets management strategies	Water quality deterioration	None	Water flow	None	None	269.157 km of total length of the river and tributaries	Three years of observations: 2010-2012	None	Anylogic 7 Netica	The Second Songhua River, Jilin (China)
4.	(Pope and Gimblett, 2015)	Bayesian network and agent-based model	Groundwater resource management	Drought	None	Herd, riparian vegetation and ecosystem services	Economic (ranchers) Ecosystem (change of vegetation)	Two scenarios: a period of average rainfall and a period of below average rainfall (first quartile of the long-term rainfall dataset)	21 km stretch along the river	Temporal resolution of 6 months, over a period of 6 years	Stakeholders workshops to build the Bayesian network and collect data	GeNie, Netlogo, ArcGis	Rio Sonora (Mexico)
5.	(Martin and Schlüter, 2015)	System dynamic and agent-based model	Restoration of a turbid lake	Sewage water pollution	None	Ecosystem (lake algae and fishes)	Social (environmental laws, population willingness) Ecological (lake ecosystem)	None	Not specified	Lake dynamics at daily scale and decision process at annual scale for three time spans (10, 20 and 40)	Surveys for willingness decisions	Matlab, Netlogo	Archetypical case: restoration of a turbid lake
6.	(Kocabas and Dragicevic, 2013)	Bayesian network and agent-based model	Land-use change in urban area under the influence of human behaviour	Population increase	None	None	Socio-economic (household and firms decision making)	None	Municipality extension (~300 km^2)	Temporal resolution of 5 years over a period of 20 years (2001-2021)	None	Matlab and ArcGis	City of Surrey, British Columbia, (Canada)

List of relevant contributions

Peer reviewed journals

2019	**Terzi**, S., Torresan, S., Schneiderbauer, S., Critto, A., Zebisch, M., Marcomini, A., 2019. Multi-risk assessment in mountain regions: A review of modelling approaches for climate change adaptation. J. Environ. Manage. 232, 759–771. https://doi.org/10.1016/j.jenvman.2018.11.100
2018	Pesce, M., **Terzi**, S., Issa, R., Al-jawasreh, M., Bommarito, C., Calgaro, L., Fogarin, S., Russo, E., Marcomini, A., Linkov, I., 2018. Selecting sustainable alternatives for cruise ships in Venice using multi-criteria decision analysis. Sci. Total Environ. 642, 668–678. https://doi.org/10.1016/j.scitotenv.2018.05.372

Conference session organization

2019 European Geosciences Union, Vienna (AT)	Co-authored the recently accepted "Multi-hazards" sub-division proposal Organizing and convening the PICO session titled: "*Multi-hazards: Innovative approaches for disaster risk reduction and climate change adaptation*"- General Assembly 2019
2018 European Geosciences Union, Vienna (AT)	Organizing and co-convening the PICO session titled: "*Single and multi-hazard risk assessment and mitigation in developing countries: Challenges and opportunities for innovation*" - General Assembly 2018

Extended abstracts of international conferences

2019	
Inquimus workshop, Bonn (DE)	**Terzi** S., Susnik J., Masia S., Schneiderbauer S., Torresan S., Critto A. *"System Dynamics Modelling for multi-risk assessments of water scarcity in the south-eastern Italian Alps"* (poster)
Italian Society for Climate Science, Trento (IT)	**Terzi** S., Susnik J., Masia S., Schneiderbauer S., Torresan S., Critto A. *"An integrated System Dynamics Model for multi-risk assessment for water scarcity in the Noce river catchment (Province of Trento, Italy)"* (poster and travel grant winner)
International Mountain Conference, Innsbruck (AT)	**Terzi** S., Susnik J., Masia S., Schneiderbauer S., Torresan S., Critto A. *"Integrated System Dynamics Modelling for a multi-risk assessment of water scarcity in the south-eastern Alps"* (poster)
European Geosciences Union, Vienna (AT)	**Terzi** S., Susnik J., Schneiderbauer S., Torresan S., Critto A.

	"System Dynamics Model for mountain water management and climate change adaptation in the south-eastern Alps" (poster)
International workshop on modelling risk and resilience in human and natural systems, Bern (CH)	**Terzi S.**, Schneiderbauer S., Torresan S., Zebisch M., Critto A. *"Impact Chains and System Dynamics Modelling for multi-risk assessments and climate change adaptation"* (poster)
The Fourth Northern European Conference on Emergency and Disaster Studies, Uppsala (SE)	**Terzi S.**, Sušnik J., Masia S., Schneiderbauer S., Torresan S., Critto A. *"Multi-Risk Assessments of Water Scarcity in the Alps: a System Dynamics Model for Climate Change Adaptation"* (oral presentation)
International Mountain Conference, Innsbruck (AT)	**Terzi** S., Sušnik J., Masia S., Schneiderbauer S., Torresan S., Critto A. *"Integrated System Dynamics Modelling for a multi-risk assessment of water scarcity in the south-eastern Alps"* (poster)

2018

Inquimus, Venice (IT)	**Terzi**, Susnik, Torresan, Schneiderbauer, Critto, Marcomini *"Multi-risk assessment on mountain water resource: a System Dynamics Model for climate change adaptation in the south-eastern Alps"* (poster)
Natural Hazards and Risks in a Changing World, Potsdam (DE)	**Terzi**, Torresan, Schneiderbauer, Critto, Zebisch, Marcomini *"System Dynamics Modelling for mountain water management and climate change adaptation"* (poster)
Italian Society for Climate Science, Venice (IT)	**Terzi**, Torresan, Schneiderbauer, Critto, Zebisch, Marcomini "*Climate change impact assessment on mountain water resources: a System Dynamics approach supporting multi-risk management and adaptation planning*" (poster)
European Geosciences Union, Vienna (AT)	1) **Terzi**, Torresan, Schneiderbauer, Critto, Zebisch, Marcomini *"Climate change impacts on water management in mountain regions: a complex system framework"* (poster presentation) 2) Schneiderbauer, Zebisch, Renner, **Terzi**, Kofler *"Multi-hazard and multi-risk in mountains - applying the IPCC-AR5 concept in practice"* (PICO presentation)

2017

European Geosciences Union, Vienna (AT)	**Terzi**, **Torresan**, Schneiderbauer, Critto, Zebisch, Marcomini *"A comparative review of multi-risk modelling methodologies for climate change adaptation in mountain regions"* (poster presentation)

European Climate Change Adaptation conference, Glasgow (UK)	**Terzi**, **Torresan**, Schneiderbauer, Critto, Zebisch, Marcomini *“Multi-risk analysis in mountain regions: a review of models, methodologies and future perspectives for climate change adaptation”* (poster)
Inquimus, Salzburg (AT)	**Terzi**, **Torresan**, Schneiderbauer, Critto, Zebisch, Marcomini *“Reviewing five modelling techniques for multi-risk assessments and climate change adaptation in mountain regions”* (poster)

Acknowledgments

I would like to thank who believed in what I did and achieved in this three years journey, especially during those moments when thoughts and perspective seemed to be dark. I learned difficult times are opportunity not to be missed and I tried my best to fully live them during the three years of the PhD path.

I thank Eurac Research for having given me the opportunity to pursue my Doctoral studies collaborating with the Ca' Foscari University of Venice and the Risk Assessment and Adaptation Strategies Division of CMCC. In particular, I thank Prof. Andrea Critto who supervised and pushed me during my PhD. I also thank my co-tutors, Dr. Silvia Torresan and Dr. Stefan Schneiderbauer for being always available and patient and for sharing their experiences and knowledge.

I also would like to thank Dr. Janez Susnik who gave me the chance to spend my period abroad at the IHE Institute for Water Education in Delft giving me valuable suggestions and Dr. Sara Masia for her positive attitude during the time in Delft.

I thank all the new friends I met during my amazing time in Delft (Maurizio, Irene, Janis, Juan Carlos, Francesco, Alessandro, Claudia, Yared, Shanoor, Thaine, Nelier and all the others).

I thank all my friends and colleagues from the offices in Venice Vuong, Anna, Elisa, Marco and all the others I met during quick meetings and lunch breaks in Venice.

I also would like to thank friends and colleagues from Eurac in Bolzano. Kathrin for sharing the office with me and being always sunny, Mattia R for the breaks and the R-hints, Stegi for sharing his knowledge in statistics at C10, Christian, Abraham, Ruth, Paola and all the others for the good time in the office and outside enjoying the nice Bolzano. People from UniBZ for sharing great times and worries about the PhD: Anuschka, Chris, Michele, Laura, Anna (and Rocco!) Coco and Maura.

A very special thank to Luigi, my PhD (and life :P) buddy. Sharing our PhD adventures has been like reading a book and I hope to keep on reading amazing stories!

I thank Alessandro who taught me more than a PhD can teach: making me understand myself better and to live fully, especially appreciating difficult times, full of life!

A special thank to all my family and my brother Daniele always being supportive and believing in what I decided to undertake.

Finally, I thank all the people who were next to me during the last three years especially from a human point of view.