

Politecnico di Torino

Master Thesis

Title: Evaluation of Regional Glacier Changes Using Machine Learning and AI, Case Study: Alpine North-West of Italy

Supervisor: Professor Paolo Dabove

Advisor: Dr Milad Bagheri

Student: Aram Abdollahi

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Abstract

Alpine glaciers have lost a significant share of their volume and have retreated during the last decades. They have a strong impact on their downstream water availability and hydrology Thus, predicting the future of mountain glaciers under different scenarios is of significant importance, but very challenging, because their response to climate change is influenced by a non-linear intersection between climate forcing, topography, elevation, and glacier geometry. In this thesis, a regional, data-driven workflow is developed to evaluate the future of glaciers in the north-west of the Alps, targeting their mass balance and volume.

The study used glacier outlines and attributes from the RGI/GLIMS inventory. The 100 largest glaciers, which represent approximately 89.9% of the total glacierized area within the study region, were filtered. Ensuring a representative yet computationally feasible sample. A historical dataset covering 2001 to 2025 was constructed by combining glacier attributes, ERA5 summer temperature and winter precipitation, and annual glacier mass-balance records, and then, five predictive models were compared, including Multiple Linear Regression, Gradient Boosted Trees, Random Forest, Multi-Layer Perceptron Neural Network, and a sequence-based LSTM. Model performances were evaluated by splitting the data temporally, from 2001 to 2020 for the training phase, and 2021 to 2025 for the validation phase.

The MLP Neural Network achieved the best validation performance, with an R^2 of 0.334 and an RMSE of 0.742 m w.e. Although the validation period included unusually extreme glacier-loss years, particularly 2022 and 2023, the MLP showed the strongest generalization among the tested models. Sensitivity analyses confirmed that these extreme years substantially increased model error, while an extended 1951–2025 modelling experiment showed that longer temporal records improved MLP performance but did not improve the LSTM models.

The final MLP was applied to future climate projections from NEX-GDDP-CMIP6 under SSP2-4.5 and SSP5-8.5 for 2026–2100. Future mass-balance predictions were then converted into glacier volume using dynamic volume-area scaling. Results indicate increasingly negative glacier mass balance throughout the century, with the strongest losses under SSP5-8.5. The remaining volume of 100 selected glaciers by 2100 was only 2.62% of the 2001 total volume under SSP2-4.5 and 1.32% under SSP5-8.5.

Ultimately, the results show that the regional workflow based on machine learning and volume area scaling can provide a practical approach to evaluate the future of glacier changes. In addition, they highlight the vulnerability of Alpine glaciers in the long-term and the stronger impact of the high emission scenario in comparison with the moderate one at the end of the century.

Keywords: glacier mass balance; machine learning; Alpine glaciers; climate change; glacier volume projection; volume-area scaling.

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1 Introduction and Literature Review

1.1 Research background and problem statement

One of the most visible and sensitive indicators of climate change is mountain glaciers. The retreat of these glaciers shows changes in temperature, precipitation, snow accumulation, and melt season conditions, which are subject to the changes in regional and global climate. Due to the increasing global warming the world has experienced over the last few decades, many glaciers have lost their mass globally, contributing to the sea level rise. These affect the regional glaciers and their downstream hydrological systems (Hugonnet et al., 2021; Zemp et al., 2019). Changes in the volume of mountain glaciers have direct and indirect consequences for downstream societies and the environment. The mountain glaciers in the European Alps have a significant role in Agriculture, water availability, seasonal runoff, and hydropower production in the downstream areas. Therefore, investigating and studying these glaciers is important because they have substantial influences on the regional environment and downstream hydrology. Additionally, their retreats are a strong signal of global warming.

Predicting glacier changes is very difficult because it is not just under the influence of temperature changes. Other parameters, such as glacier geometry, elevation, winter accumulation, summer melt, topographic exposure, and local climate changes, have a significant role in glacier annual mass balance changes. This makes the glaciers' evaluation a very complex and non-linear process. In many studies that have been conducted previously, it has been demonstrated that there is a strong link between glacier volume loss in the future and climate warming. With higher emission pathways under IPCC future scenarios, the glaciers will experience more volume loss(Rounce et al., 2023a). The main challenge here is that a reliable prediction of the mountain glaciers with global models and projections, especially over a short period of time, is not possible, since the mountain glaciers have shown different behavior over short distances.

During the last decades the glacier research and studies have experienced a substantial improvement. They shifted from a simple geometric estimation toward remote sensing, geodetic mass balance assessment, physics-based models, and, eventually, in recent years, machine learning approaches and AI-based models. This methodological improvement has led to a better prediction of glacier volume, reconstruction of the historical glacier changes, and projection of the future glacier evolution. In recent years, due to the global glacier models and geodetic dataset essential information on the large-scale ice loss is available, but for understanding the future of local or regional glacier behavior, especially in the European Alps where the annual mass balance changes are under the influence of many factors like topography, elevation, accumulation, and melt conditions, the large-scale global projection is still not sufficient.

In recent studies, it has been demonstrated that machine learning and deep learning approaches are very useful and effective in explaining the non-linear relationship between glacier mass balance and climate variables. For instance, Bolibar et al. (2022), in a study, have shown that a deep learning approach is more effective in capturing the non-linear glacier mass balance

sensitivity to air temperature and precipitation changes than just a simple linear or temperature index approaches. This is important for regional glacier modelling because future glacier response may depend not only on average warming trends, but also on extreme years and compound seasonal conditions. Therefore, data-driven approaches can complement physically based glacier models by offering flexible tools for regional-scale prediction.

In this thesis, we try to address this problem by developing a regional data-driven workflow for Alpine glacier mass-balance prediction and volume projection. The study combines glacier inventory attributes, ERA5-Land climate variables, reconstructed annual mass-balance data, future climate scenarios, machine-learning model comparison, and dynamic volume-area scaling. The main purpose is to evaluate whether a machine-learning approach can support regional-scale glacier projection by linking future climate forcing to annual mass balance and then converting predicted mass-balance change into glacier volume evolution.

1.2 Evolution of glacier monitoring and volume estimation

Predicting mountain glacier volume and mass balance changes has always been very challenging since direct in-situ observation has been very limited. In the many mountainous regions, access to the glaciers is so hard. Therefore, the number of long-term field measurements is small, and they are spatially uneven, mostly fixed on a small number of glaciers. Accordingly, for estimating glacier characteristics and climate sensitivity, regional glacier studies at the beginning stages were conducted based on geometric assumptions. These early approaches were important because they provided the first regional baselines for glacier volume and potential future loss, even though they were based on simplified representations of glacier geometry.

In this regard, Haeberli & Hoelzle (1995) conducted a study to estimate glacier characteristics and regional climate change effects in the European Alps. They used glacier inventory data such as area, surface slope, length, and elevation. They estimated the total Alpine glaciers volume at the mid-1970s of 130km^3. They also indicated that Alpine glaciers are highly sensitive to continuous negative mass balance circumstances. Their study was of significant importance since it proved that it is possible to estimate the regional glaciers' volume and their climate sensitivity using simple inventory data. However, it still emphasized the main restriction of early methods, which was inferring the glaciers' volume and future response based on static geometry relationships, instead of spatially continuous observations of glacier thickness, elevation change, or dynamic behavior.

The development of satellite remote sensing and digital elevation data marked an important methodological transition. Instead of estimating glacier change only from inventory geometry, researchers were increasingly able to observe changes in glacier area, surface elevation, velocity, and frontal position. (Kääb, 2005) showed that optical remote sensing and geographic information science could be used to monitor mountain glaciers and permafrost processes over large and remote regions. This was an important step because it reduced the dependence on isolated field observations and made it possible to analyze glacier change in a spatially distributed way. Remote sensing, therefore, provided a bridge between earlier static inventory-based methods and more dynamic forms of glacier monitoring.

The importance of geodetic methods became particularly clear in studies that used digital elevation model differencing to quantify glacier thinning and volume change. In a study, (Rivera & Casassa, 2004) analyzed ice elevation, areal, and frontal changes in glaciers of the Southern Patagonia icefield. They used a set of maps, digital elevation models, GPS measurements, and optical survey data. Their results showed strong thinning in glacier ablation areas and demonstrated that glacier volume loss cannot always be explained by surface melt alone. Dynamic processes, like frontal retreat, calving, and ice-flow-related changes, can strongly influence volume loss. However, their study was not conducted in Alpes; it is still important for this thesis because it shows why glacier change should be understood as a dynamic and non-linear process rather than only as a simple geometric reduction in area.

As glacier monitoring methods became more diverse, the need for standardized terminology also became more important. (Cogley et al., 2011), in a study, tried to solve this problem, and they published the Glossary of Glacier Mass Balance and Related Terms. In this glossary, they were able to clarify the differences between concepts like mass balance, volume change, geodetic balance, and glaciological balance, and they provided a standardized terminology for glacier studies. This standardization was very crucial for glacier studies since different methods measure or estimate different aspects of glacier changes. For this thesis, this distinction is particularly relevant because annual mass balance is used as the target variable in the machine-learning model, while glacier volume evolution is estimated later through dynamic volume-area scaling. Therefore, mass-balance prediction and volume projection are connected in the workflow, but they are not treated as the same quantity.

More recent global studies have greatly improved the baseline knowledge of glacier thickness, volume, and historical mass change. (Farinotti et al., 2019) produced a global consensus estimate of glacier ice thickness and volume by combining several models and calibrating them with available ice-thickness observations. Their study estimated the total volume of glaciers outside the ice sheets at $158 \pm 48 \times 10^3$ km³. This work is important because reliable estimates of initial glacier volume and ice thickness are necessary for future glacier evolution models. It also shows the value of combining multiple data sources and modelling approaches when direct observations are incomplete.

Similarly, (Hugonnet et al., 2021) used high-resolution digital elevation models to provide a globally consistent assessment of glacier mass change during the early twenty-first century. Their study estimated that glaciers lost mass at an accelerating rate from 2000 to 2019 and provided one of the most important geodetic benchmarks for modern glacier mass-balance studies. This type of dataset is crucial because it gives physically observed evidence of recent glacier loss and supports the calibration and validation of both physically based and data-driven glacier models.

Together, these studies show a clear methodological evolution in glacier research. The field has moved from inventory-based geometric estimation to remote sensing and geodetic observation, and then to global datasets of glacier volume and mass change. This evolution is directly relevant to the present thesis. The workflow used in this study builds on glacier

inventory attributes, historical climate variables, annual mass-balance data, and volume-area scaling. It does not replace detailed geodetic or ice-dynamic modelling, but it uses the logic developed by previous research. Glacier projection requires both physical constraints and data-driven methods that can work with incomplete but spatially extensive datasets.

This background also explains why volume-area scaling remains useful in regional glacier studies. Direct ice-thickness measurements are rarely available for every glacier in a regional sample, especially when many glaciers are included. Volume-area scaling offers a simplified but physically reliable way to estimate glacier volume from glacier area and then update volume through time (Bahr et al., 1997, 2015; Huss & Farinotti, 2012). In this thesis, this approach is used after predicting the mass balance with different machine-learning models. This allows calculating the future projected glacier volume through predicted mass balance by the machine learning models.

1.3 Global models and local-scale limitations

In the last few decades, global glacier models have improved a lot, and this development is very important in modern glaciology. With the help of these models, it is now possible to simulate glacier evolution in many different glaciers and to estimate the amount of possible future ice loss under different climate scenarios. These models are now very important to understand glaciers' sea-level contribution and large-scale patterns of glacier retreats. However, their strength at the global scale also creates limitations when the objective is to understand local or regional glacier behavior.

A major example of this development is the Open Global Glacier Model, or OGGM. (Maussion et al., 2018) Introduced this model as an open-source model design to simulate future and past glacier change at the global scale. They use glacier outlines, topography, climate data, ice thickness estimation, ice flow modelling, and mass balance modelling in constructing this model. This model is also able to represent glacier dynamics through the shallow ice approximation along connected flowlines. In comparison with earlier large-scale approaches, this model was a major improvement because it was possible to consistently simulate dynamic glacier evolution for many glaciers around the world.

Despite this, bringing global models to the regional glaciers requires simplification. Even the most advanced global models are not able to fully explain the behavior of each regional mountain glacier with different characteristics and in different circumstances. These include local shading, microclimate differences, glacier geometry, short-term extreme events, wind-driven snow distribution, debris cover, and avalanching. Thus, the global modes may be very useful for large-scale global projections, but they may not provide good results and details for hydrological interpretation or local-scale glacier assessment.

The importance of global projections is clearly shown by (Rounce et al., 2023a). Their study projected that glaciers could lose between 26 ± 6% and 41 ± 11% of their mass by 2100, relative to 2015, depending on the level of global temperature increase. This result strongly shows that every increase in temperature matters for future glacier preservation. It also confirms the importance of climate mitigation. However, this type of global result does not

fully explain how individual Alpine glacier systems will respond under local climatic and topographic conditions.

The spatial distribution of observational data is another limitation. In a research, (Gardner et al., 2013) provided an adapted estimation of glacier melt contribution to sea level rise during the years from 2003 to 2009. They combined satellite altimetry, satellite gravimetry, and other measurements. Their achievement was of significant importance because it increased the consistency of global glacier mass loss estimations. Meanwhile, they emphasized that the global glacier observations are not uniform. Some regions and glaciers are better monitored, and this can lead to a bad performance of global models on the regional scale, especially in mountainous area.

This issue is also very relevant for the European Alps. Alpine Glaciers are usually small and topographically complex. They are strongly under the influence of local elevation, aspect, accumulation conditions, and extreme summer events. Global models may be able to capture the broad warming signal, but they may miss some local variables that affect annual mass balance. For this reason, local and regional modelling remains necessary, especially when the objective is not only to estimate global ice loss, but also to understand regional glacier volume evolution.

(Zekollari et al., 2024a) addressed this problem in their research. They investigated the effect of glacier-specific mass-balance observations in twenty-first-century glacier projections. Their results showed that using glacier-specific observations can produce differences of up to several tens of percent at the scale of individual glaciers. However, these differences become smaller when they are averaged at regional or global scales. This finding is important because it shows that global totals can remain relatively stable, while local glacier projections may still change substantially depending on the calibration data used.

Therefore, the main limitation is not that global models are incorrect. Rather, their outputs must be interpreted at the right scale. They are very strong in global and regional glacier assessment, but on the regional scale, more studies and assessments on each specific glacier behavior are necessary. This issue in Alpine glaciers is particularly important, since in a small distance there can be huge differences in elevation, climate exposure, and glacier geometry.

In this thesis, we tried to work on this gap. Instead of replacing global glacier models, we develop a regional data-driven workflow on a selected area of Alpine in north west of Italy. In this workflow, we use some specific glacier attributes, historical climate variables, reconstructed annual mass balance, future climate scenarios, and dynamic volume-area scaling. In this way, we tried to complement global projections by adding more local characteristics and variables to our assessment of the future glacier mass balance and volume change.

1.4 Machine learning and AI in glacier mass-balance modelling

The limitations of global glacier models have increased interest in more flexible data-driven approaches. When the relationship between mass balance and climate variables and glacier attributes is non-linear, using Machine learning methods in evaluating glacier changes can be

especially useful. This is important for mountain glaciers because several parameters, like summer temperature, winter precipitation, elevation, topography, and local climate, can together have a major effect on annual mass balance. Therefore, explaining this complex relationship with just simple linear models is very difficult.

A major contribution in this direction was made by (Bolibar et al., 2022b). Their study used deep learning to model glacier evolution in the French Alps and showed that neural networks can capture the non-linear response of glacier mass balance to air temperature and precipitation. This is important because glacier mass balance does not always respond proportionally to climate forcing. Extreme years, changes in snow cover, and interactions between accumulation and melt can produce responses that are stronger or weaker than a linear model would suggest. (Bolibar et al., 2022b) therefore demonstrated that deep learning can be a useful tool for representing complex glacier-climate relationships.

This point is directly relevant to the present thesis. The historical dataset used in this study combines annual summer temperature, winter precipitation proxy, and glacier-specific attributes. These variables do not affect all glaciers in the same way. A warmer summer may have different effects depending on elevation, area, slope, and accumulation conditions. A machine-learning model can help capture these interactions without requiring all relationships to be specified in advance. This is one reason why non-linear models were tested in this thesis.

Recent studies also show that machine learning can support mass-balance prediction for glaciers with limited direct observations. By using seasonal and annual mass balance measured points in the Norwegian glaciers, (Sjursen et al., 2025) developed a machine learning model. Their finding showed the ability of machine learning models to generalize across different glaciers and climate conditions. Therefore, they proved that machine learning models can be useful in providing predictions for unmonitored glaciers. This was very important in assessing the mountain glacier evolutions, because many of them do not have long-term in situ measurements. Therefore, a machine learning model can help to transfer data from observed or reconstructed datasets to the glaciers where direct measurement is limited like Alpine glaciers.

(van der Meer et al., 2025) also showed the value of simpler machine-learning models for glacier mass-balance estimation. Their miniML-MB model was designed for annual point surface mass balance and for situations where available datasets are small. This is relevant because glacier mass-balance data are often limited compared with other environmental datasets. Their study also highlights an important limitation: machine-learning models may struggle with extreme years when those conditions fall outside the training range. This point is consistent with the results of the present thesis, where 2022 and 2023 strongly affected validation performance.

(Ren et al., 2024) in a different study highlighted the importance of model choice. They compared several machine learning models for simulating glacier mass balance in a wide area of High Mountain Asia. Their results showed that the performance of machine learning models can change across different climate conditions and glacier types. This indicates that there is no single model that can be universally applied. Instead, different models should be

tested under the same validation framework. This idea is followed in the present thesis, where Linear Regression, Random Forest, Gradient Boosted Trees, MLP Neural Network, and LSTM were compared before selecting the final model.

Machine learning should not be considered as a replacement for physical glacier knowledge. Its strength is that it can learn complex empirical relationships from data. The main drawback of them is that they may not fully explain the physical processes that are not in the input variables of the model. For example, the data such as avalanche accumulation, radiation, or debris cover are not always in the regional dataset to be considered as the input of the models. Therefore, the outputs of machine learning models should be considered with the physical conditions of the glaciers, and also a level of uncertainty should be considered in their interoperations.

For this reason, the approach used in this thesis combines data-driven prediction with a physical volume constraint. Machine learning is used to predict annual glacier mass balance from climate and glacier attributes. Then, dynamic volume-area scaling is used to convert predicted mass-balance changes into glacier volume trajectories. This creates a workflow that is not purely statistical. It connects flexible non-linear prediction with a physically grounded method for estimating volume evolution.

Ultimately, the recent studies have suggested the use of machine learning models to assess the regional glaciers and to predict their mass balance and volume changes, especially when there is a lack of in-situ observational data. They also support the use of these models in case of the need to capture the non-linear relationships. Meanwhile, they indicate that the machine learning models should be carefully validated, especially when there are extreme climatic conditions in the historical dataset used as input for the model. Thus, it will be a powerful methodological justification for the model comparison strategy used in this thesis.

1.5 Physics-informed and hybrid AI approaches

Recent glacier research has not only used machine learning as a statistical prediction tool, but has also started to combine artificial intelligence with physical glacier modelling. This development is important because purely data-driven models can capture complex patterns, but they may also produce results that are difficult to interpret physically. Physics-informed and hybrid approaches try to reduce this problem by combining the flexibility of AI with physical constraints such as ice flow, mass conservation, or glacier geometry.

A major example is the work of (Jouvet & Cordonnier, 2023), who developed an ice-flow model emulator based on physics-informed deep learning. Their approach used a convolutional neural network to emulate computationally expensive ice-flow calculations while remaining linked to the physical equations that describe glacier dynamics. The model was embedded in the Instructed Glacier Model framework. This is important because it shows how deep learning can be used not only to predict glacier variables, but also to accelerate physically based glacier evolution modelling.

The studies like the one mentioned above are a part of a wider shift toward hybrid modelling. In recent studies, researchers are increasingly using AI to make physical models faster and

more flexible. Thus, they are trying not to treat machine learning and physical modelling as separate approaches. Recent studies also suggest that using AI can lead to the application of physical models at a high resolution more easily. This is very important in glacier modelling because simulating a detailed ice flow can be computationally expensive. Therefore, one of the most challenging problems in previous glacier models, which is applying complex physical equations over large regions and long time periods, can be solved with the help of physics-informed deep learning models.

In the estimation of ice thickness, physics-informed machine learning models have been used. (Steidl et al., 2025) used deep learning combined with physical knowledge to estimate ice thickness for glaciers in Svalbard. Their study incorporated mass conservation and other physically derived constraints into the model. Since ice thickness is one of the most important variables in the estimation of glacier volume and its future response, this study is of significant importance for glacier evolution studies. Calculating the ice thickness directly on site is very difficult and requires specific tools and technologies. It is also time-consuming and expensive. Physics-aware machine learning application, therefore, offers a promising way to estimate important glacier properties in data-limited regions, such as ice thickness.

Another important milestone in the study of glaciers is using deep learning for mapping glaciers and detecting their boundaries, because for estimating the volume, modelling the mass balance, and future projection, a precise outline detection is crucial. This is especially difficult for debris-covered glaciers, where glacier ice can be spectrally similar to surrounding rock debris. Kaushik et al. (2025) addressed this problem by using a geospatial foundation model, Prithvi, together with multisource remote sensing data. Their results showed strong performance in mapping supraglacial debris and glacier termini. This demonstrates how modern AI models can improve the quality of glacier boundary information, which is a key input for many glacier modelling workflows.

These studies show that the future of glacier modelling is likely to involve both data-driven and physically constrained methods. Since physical models are based on real glacier mechanics, they are so powerful, but at the same time, they can be computationally demanding and sensitive to uncertain inputs. On the other hand, however, data-driven models are flexible, but they are very sensitive to the quality and representativeness of the training data. Hybrid approaches try to benefit from both sides by using AI while keeping the results connected to physical knowledge.

The present thesis does not develop a full physics-informed neural network or an ice-flow emulator. However, it follows the same general direction by combining machine-learning prediction with a physical volume constraint. In this study, machine learning is used to predict annual glacier mass balance from climate variables and glacier attributes. Then, dynamic volume-area scaling is used to translate predicted mass-balance changes into glacier volume trajectories. This means that the workflow is not only a statistical prediction exercise. It connects data-driven mass-balance modelling with a physically grounded method for estimating volume change.

Therefore, physics-informed and hybrid AI approaches provide an important context for this thesis. They show that modern glacier research is moving toward methods that are faster, more flexible, and more physically consistent. The workflow developed in this thesis represents a simpler regional version of this broader direction. It does not attempt to replace detailed ice-flow models, but it uses machine learning and volume-area scaling to create a transparent regional framework for future glacier volume projection.

1.6 Research gap and contribution of this thesis

The literature reviewed in the previous sections shows that glacier modelling has developed strongly during the last few decades. Inventory-based methods provided the first regional estimates of glacier volume and climate sensitivity. Then, emerging remote sensing and geodetic methods helped to have more observations and data on glacier areas, elevation, and mass balance changes. More recently, (Farinotti et al., 2019; Hugonnet et al., 2021) provided datasets that became globally very important for the estimation of glacier thickness, volume, and historical mass change. At the same time, (Maussion et al., 2019; Rounce et al., 2023a) introduced global models like OGGM and PyGEM. These models also make it possible to predict glacier changes under different future climate scenarios at a very large scale.

Despite this, in the literature, it was mentioned that, although global models perform well for large-scale projection, there is still a need for studies on the regional and local scale. Global models are good for predicting total glacier loss and sea level rise contribution, but they are not suitable for assessing the glacier behavior in complex mountain regions. Glaciers in the European Alps are very sensitive to elevation, topography, and climate variability, to name but a few. In addition, it should be mentioned that these factors can change over a very short distance in the Alpine area. For this reason, regional modelling is still needed when the objective is to understand glacier response in a specific Alpine area.

This issue is especially important because glacier-specific observations can strongly affect local projections. (Zekollari et al., 2024b) showed that the use of glacier-specific mass-balance observations can change projections at the scale of individual glaciers, even when global totals remain more stable. This means that global results can be robust at a large scale, while local glacier trajectories may still contain considerable uncertainty. Therefore, a key research gap is the need for regional workflows that can use glacier-specific attributes and historical climate–mass-balance information to produce locally focused future projections.

Machine-learning studies provide one possible response to this gap. (Bolibar et al., 2022b; Sjursen et al., 2025) in their studies demonstrated that deep learning and machine learning methods are effective in capturing the nonlinear relationship between the climate variables, glacier attributes, and mass balance change. (van der Meer et al., 2025) also suggested that since the direct observational data in mountainous glaciers are limited, machine learning models can be useful, but the models should be carefully validated, especially for the unusual extreme climatic conditions. This is relevant for Alpine glaciers, since in 2022 and 2023, they experienced extreme conditions and lost mass unusually, and this extreme condition is very challenging for predictive models.

At the same time, a purely statistical approach is not sufficient for glacier volume projection. Mass-balance prediction must be linked to a physically meaningful representation of glacier volume change. Volume-area scaling provides a practical way to do this when direct ice-thickness measurements are not available for all glaciers in a regional sample (Bahr et al., 1997; Huss and Farinotti, 2012; Bahr et al., 2015). Therefore, a useful regional workflow should combine the flexibility of machine learning with a physically grounded method for estimating volume evolution.

This thesis addresses this gap by developing an integrated regional workflow for Alpine glacier mass-balance and volume projection. The workflow combines glacier inventory attributes, ERA5-Land historical climate variables, reconstructed annual mass-balance data, future climate scenarios, machine-learning model comparison, and dynamic volume-area scaling. The aim is not to replace global glacier models or detailed ice-flow simulations. Instead, the thesis provides a transparent regional approach that can complement global projections by focusing on a selected Alpine glacierized area.

The contribution of this thesis is threefold. First, it constructs a regional glacier-year dataset that links glacier attributes, historical climate predictors, and annual mass balance for the 100 largest glaciers in the selected study area. Second, it compares several regression, machine-learning, and neural-network models under a strict temporal validation framework. This allows model performance to be tested on recent years rather than on a random split of the same historical period. Third, it applies the selected model to future climate scenarios and converts predicted annual mass balance into glacier volume trajectories using dynamic volume-area scaling.

By doing this, the thesis connects three parts of the literature that are often treated separately: machine-learning mass-balance prediction, future climate scenario analysis, and glacier volume estimation. This connection is the main contribution of the research. It allows future climate forcing to be translated into annual mass-balance projections and then into regional volume change. The resulting workflow is simple enough to be applied at a regional scale, but still grounded in the physical relationship between glacier area and volume.

Therefore, the research gap addressed by this thesis is not the absence of global glacier projections. Rather, it is the need for a regional, data-driven, and physically constrained workflow that can evaluate future glacier response in a specific Alpine setting. This provides the basis for the methodology developed in the next chapter.

1.7 Aim, objectives, and thesis structure

Based on the research gap identified in the previous section, the main aim of this thesis is to develop a regional workflow for predicting future glacier mass balance and volume evolution in a selected Alpine glacierized area. In this thesis, we tried to find a connection between climate variables, glacier attributes, the prediction of mass balance with machine learning models, and physically limited volume modelling. Our objective is in line with the need mentioned in the previous section, which is the inability of global glacier models to precisely understand the behavior of regional and local glaciers, especially in a complex mountainous

area like Alpine (Rounce et al., 2023a; Zekollari et al., 2024b). Therefore, a model that is proposed in this thesis can be a complement for global projections and is able to provide more detailed information about the selected study area.

The aim of this research is not to provide a model to replace global models or fully dynamic ice flow simulations. Instead, it develops a simpler and transparent regional approach. The workflow uses available glacier inventory data, historical climate variables, reconstructed annual mass-balance data, future climate scenarios, and dynamic volume-area scaling. In this way, the thesis connects data-driven prediction with a physical method for estimating glacier volume evolution.

The main objectives of the thesis are:

1. To select a representative regional sample of Alpine glaciers from the RGI/GLIMS glacier inventory.
2. To construct a historical dataset from 2001 to 2025, consisting of ERA5-Land climate variables, annual mass balance, and glaciers attributes.
3. To compare different machine learning and regression models in predicting glaciers' mass balance, including Random Forest, Gradient Boosted Trees, MLP Neural Network, Regression, and LSTM.
4. To assess the model's performance by using a strict temporal validation strategy. By partitioning the years from 2001 to 2020 for the training set and 2021 to 2025 for the validation set.
5. To analyze the effect of recent extreme years, especially 2022 and 2023, on model validation performance.
6. To apply the selected model to future climate scenarios under SSP2-4.5 and SSP5-8.5 for the period 2026–2100.
7. To convert predicted annual mass-balance values into glacier volume trajectories using dynamic volume-area scaling.
8. To assess both single-glacier and regional-scale volume evolution until 2100.

The thesis is organized into four chapters. Chapter 1 introduces the research problem and reviews the main literature on glacier monitoring, global glacier models, machine learning, and hybrid AI approaches in glaciology. Chapter 2 presents the methodology, including glacier selection, historical data preparation, model training and validation, future climate scenario preparation, and dynamic volume-area scaling. Chapter 3 presents the results, which include the comparison of the models, future mass balance projections, sensitivity analysis, and modeled volume evolution. Chapter 4 is the final conclusion, discussing the main findings, assessing the methodological limitations, and providing suggestions for future research.

2 Methodology

2.1 Research design

This research develops a regional workflow to evaluate glacier mass-balance change and glacier volume evolution under future climate scenarios. The workflow is data-driven because the annual mass balance is predicted using machine-learning models. It is also physically constrained because predicted mass-balance values are converted into volume trajectories by using dynamic volume-area scaling. This follows the main gap identified in the literature review. That is the need for methods that can capture the non-linearity in climate responses of regional and local glaciers, despite the need for global models in large-scale glacier assessments. (Bolibar et al., 2022b; Zekollari et al., 2024)

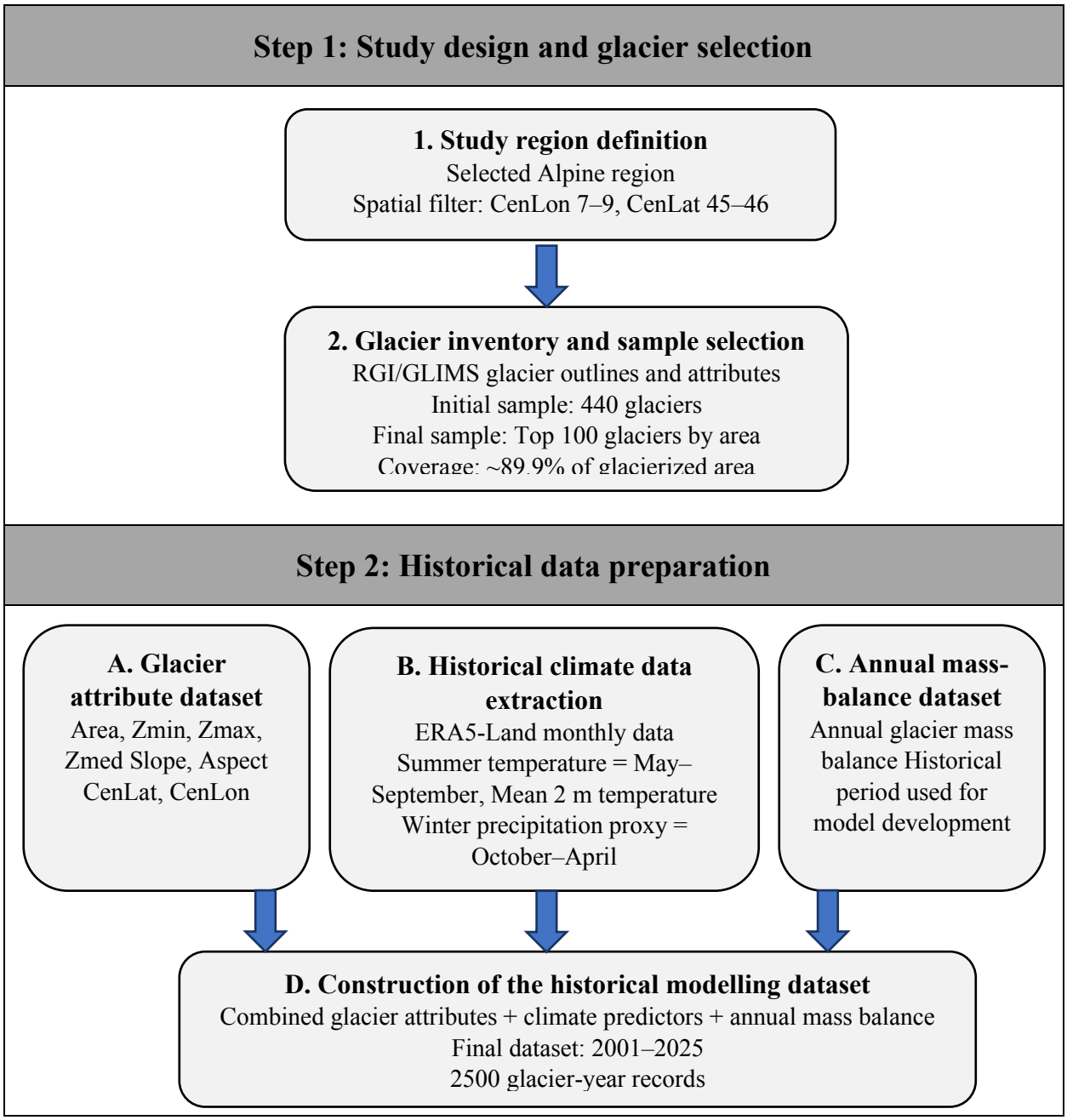
This methodology is designed to connect historical observations, climate variables, model evaluation, and future climate scenarios in one consistent workflow. The analysis begins with a regional glacier sample selected from glacier inventory data. A historical glacier-year dataset is then created by combining glacier attributes, ERA5-Land climate variables, and annual mass-balance values for 2001–2025. Several regressions, machine-learning, and neural-network models are trained and validated using a strict temporal split. The best-performing model is then applied to future climate scenarios for 2026–2100. Finally, the predicted annual mass-balance series are converted into glacier volume trajectories. This structure was chosen because the final objective is not only to predict annual mass balance. The thesis also aims to show how annual mass-balance change may translate into long-term glacier volume loss at both single-glacier and regional scales. Table 2.1 summarizes the main stages of the workflow.

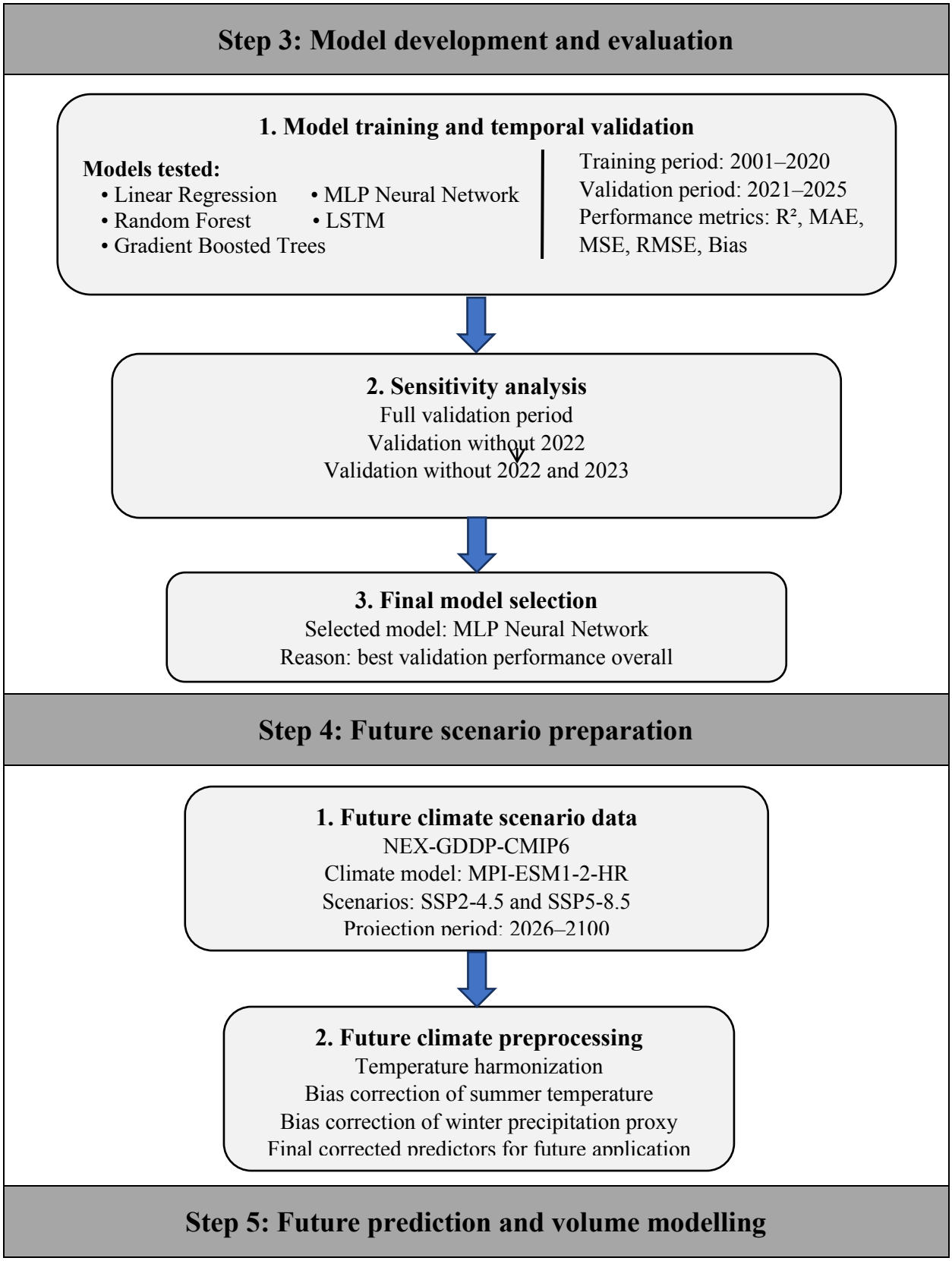
Table 2-1: Summary of the methodological workflow

Stage	Purpose	Main output
1. Glacier selection	Define a regional sample of Alpine glaciers	Top 100 glaciers by area within the selected bounding box
2. Historical dataset construction	Combine glacier attributes, ERA5-Land climate variables, and annual mass balance	2,500 glacier-year records for 2001–2025
3. Model training and validation	Compare regression, machine-learning, and neural-network models	Selected MLP model based on temporal validation performance
4. Future projection	Predict annual mass balance under SSP2-4.5 and SSP5-8.5	15,000 future glacier-scenario-year predictions
5. Volume modelling	Convert annual mass-balance trajectories into glacier volume evolution	Single-glacier and regional volume trajectories to 2100

To provide a clear overview of the methodological structure, Figure 2.1 summarizes the complete workflow of the thesis. The workflow begins with glacier selection and historical data preparation, continues with model development, validation, and sensitivity analysis. Then applies the selected model to future climate scenarios. Finally, the predicted annual mass-balance values are converted into glacier volume trajectories using dynamic volume-area scaling.

Overall Methodological Workflow of the Thesis




Step 3: Model development and evaluation
1. Model training and temporal validation
Models tested:
• Linear Regression
• Random Forest
• Gradient Boosted Trees
• MLP Neural Network
• LSTM
Training period: 2001–2020
Validation period: 2021–2025
Performance metrics: R², MAE, MSE, RMSE, Bias
2. Sensitivity analysis
Full validation period
Validation without 2022
Validation without 2022 and 2023
3. Final model selection
Selected model: MLP Neural Network
Reason: best validation performance overall
Step 4: Future scenario preparation
1. Future climate scenario data
NEX-GDDP-CMIP6
Climate model: MPI-ESM1-2-HR
Scenarios: SSP2-4.5 and SSP5-8.5
Projection period: 2026–2100
2. Future climate preprocessing
Temperature harmonization
Bias correction of summer temperature
Bias correction of winter precipitation proxy
Final corrected predictors for future application
Step 5: Future prediction and volume modelling

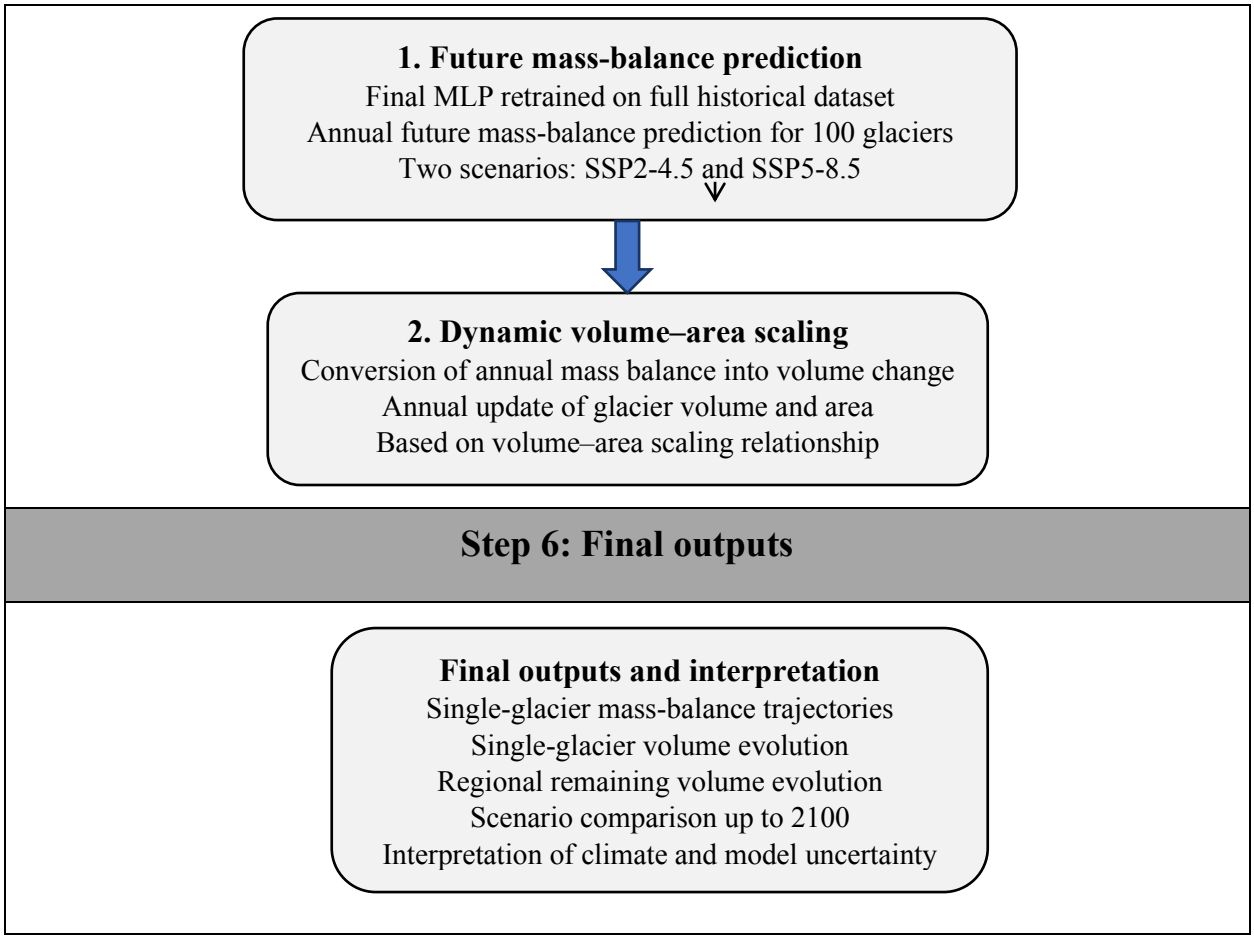


Figure 2-1: Overall methodological workflow of the thesis.

2.2 Study area and glacier selection

The study focuses on a glacierized sector of the north-western Alpine area. This sector includes part of the north-western Italian Alps and adjacent transboundary Alpine areas. Glacier outlines and inventory attributes were obtained from the Randolph Glacier Inventory / GLIMS glacier outlines. RGI 6.0 provides a global inventory of glacier outlines and is widely used for glacier-scale and regional-scale analyses (Arendt et al., 2017).

The study region was defined using glacier centroid coordinates. A geographic bounding box was applied to the inventory:

7.0° E <= Cen Lon <= 9.0° E

45.0° N <= Cen Lat <= 46.0° N

This filter selected 440 glaciers from the original inventory. Because the aim of the thesis is to evaluate regional volume evolution, the final analysis focused on the 100 largest glaciers within this area. The selection was based on glacier area, not on random sampling. The 100 selected glaciers are approximately 89.9% of the total glacierized area inside the selected area.

This makes the sample more manageable and easier to assess, while it still keeps the enough number of glaciers that represent the behavior of the whole selected region.

The retained glacier attributes were RGIId, Area, CenLat, CenLon, Zmin, Zmax, Zmed, Slope, and Aspect. Area represents the glacier surface area. Zmin, Zmax, and Zmed describe the elevation range and median elevation of each glacier. Slope and Aspect represent topographic conditions. CenLat and CenLon identify the centroid location of each glacier. These variables were used to represent glacier-specific differences in size, elevation, location, and terrain setting.

2.3 Historical climate data extraction

The historical climate features were all prepared for the whole selected 100 glaciers. They were all gained from the ERA5-Land monthly dataset. This dataset is a high-resolution land reanalysis that includes water and energy processes. It is published in the Copernicus Climate Data Store (Muñoz-Sabater et al., 2021). The reason why this dataset is selected is that it is spatially consistent and covers the whole historical period needed for this study. For each glacier, the climate extraction was based on the glacier centroid. A small bounding box of approximately ±0.05° around each centroid was used to retrieve monthly climate values. The extracted variables were 2 m temperature and total precipitation. The monthly 2 m temperature was converted from Kelvin to Celsius. The monthly values were then aggregated into glaciological-year predictors.

The glaciological year was defined based on the climate of the studied region, with winter which is for snow accumulation and summer for the melt season. Therefore, the glaciological year is set from January to September, and from October to December of the previous year.

Two annual climate predictors were computed:

• summer_t2m: mean 2 m temperature from May to September.

• winter_tp: total precipitation from October to April.

The variable summer_t2m represents warm-season temperature conditions that influence ablation. The variable winter_tp represents cold-season total precipitation and was used as a proxy for winter accumulation. It is important to note that winter_tp is total precipitation, not snowfall. Therefore, it is defined as a related approximate indicator of snow accumulation, not as a direct measurement.

In this way, a historical climate dataset consisting of 100 glaciers over 25 years is made. Which prepared 2500 records for the years from 2001 to 2025.

2.4 Historical mass-balance data and dataset assembly

Annual glacier mass balance was used as the target variable for model training and validation. The annual mass-balance data used in this thesis were obtained from the World Glacier Monitoring Service (*WGMS, 2026): Annual Mass-Change Estimates for the World's Glaciers (Version 2026-02-10). Https://Doi.Org/10.5904/Wgms-Amce-2026-02-10*, n.d.). The specific

file used for this study was CEU_mwe.csv, corresponding to the Central Europe glacier region. The file provides annual glacier-specific mass-change values in meters water equivalent (m w.e.) for glaciers identified by their RGI 6.0 outline identifiers.

The dataset is not a direct field-measurement record for every glacier and every year; it is a reconstructed observation-based mass change product. Dussaillant et al. (2025) produced the annual glacier-specific time series by combining annual glaciological in situ mass-balance observations with glacier geodetic elevation change observations derived from satellite and airborne data. In their workflow, annual mass-balance anomalies from sparse in situ observations were spatially interpolated and then calibrated to long-term glacier-wide geodetic mass-change trends. This data-fusion approach makes it possible to estimate annual mass-change time series for individual glaciers, including glaciers without continuous direct field measurements.

The data product was generated using the global glacier mass-balance data-fusion workflow developed by (*Dussaillant, I.& Hugonnet, R. (2025). Global Glacier Mass Balance Data Fusion [Computer Software]. Zenodo. Https://Doi.Org/10.5281/Zenodo.15344003*, n.d.). This software implements the geostatistical modelling, spatial interpolation, calibration, and uncertainty-propagation procedures used to produce the WGMS annual glacier mass-change estimates. In this thesis, the WGMS/Dussaillant annual mass-change series were used only as the target variable for machine-learning model training and validation; they were not independently recalculated.

The original mass-balance table was in wide format, with one row per glacier and annual columns from 1915 to 2025. For the modelling workflow, the dataset was transformed into long format, producing one record per glacier-year combination. The data were then filtered to match the climate dataset period, 2001–2025, and joined with glacier attributes and ERA5-Land climate predictors using RGIId and Year as join keys.

Because the target variable comes from a reconstructed and calibrated observation-based product, the term annual mass balance in this thesis refers to glacier-specific annual mass change expressed in metres water equivalent. It should not be interpreted as a direct in situ measurement for every glacier-year record.

The selected target variable for training and testing the models was the annual mass balance of each glacier. The dataset that was used in this study for annual mass balance was a wide-format dataset where each row was assigned to one glacier, and columns were assigned to the years from 1915 to 2025. Then, it was changed to the long format in a way that each row represented one glacier observation; thus, it became consistent with the previous historical climatic dataset.

A small number of glacier identifiers appeared more than once in the original mass-balance table. To avoid duplicate glacier-year records, the mass-balance dataset was grouped by RGIId and Year. When duplicate values were present, their mean mass-balance value was retained. The cleaned dataset was then filtered to match the climate period 2001–2025.

The cleaned mass-balance data were joined with the historical climate variables and glacier attributes using RGIId and Year as join keys. The final historical modelling dataset contained 2,500 rows and 13 columns. This dataset forms the basis for the main model comparison and future projection workflow. Table 2.2 summarizes the role of each column.

Table 2-2: Variables included in the final historical modelling dataset

Column	Role in the workflow
RGIId	Glacier identifier; retained for joining, filtering, and aggregation
Area	Static glacier area from the inventory; used as predictor and volume-scaling input
Zmin, Zmax, Zmed	Elevation attributes used as glacier-specific predictors
Slope, Aspect	Topographic predictors
CenLat, CenLon	Glacier centroid coordinates
Year	Temporal identifier; used for splitting and plotting but excluded as model input
summer_t2m	Warm-season temperature predictor
winter_tp	Cold-season total precipitation proxy
Mass_Balance	Target variable for model training and validation

2.5 Model input variables and preprocessing

The target variable for all models was Mass_Balance, and the selected predictor variables were summer_t2m, winter_tp, Area, Zmin, Zmax, Zmed, Slope, Aspect, CenLat, and CenLon, because they were the available parameters in the datasets that explain the features and variables that influence the glaciers' behavior.

RGIId was not used as a model input because it is an identifier rather than a physical variable of the glaciers. Year was also excluded from the predictor set. This avoided training the models to learn a simple numerical time trend and then extrapolate that trend into the future. Instead, future projections were driven by climate variables and static glacier attributes.

For neural-network models, input predictors were standardized before training. The target variable was also scaled during training and then transformed back to the original mass-balance unit for evaluation and projection. This preprocessing step was necessary because neural networks are sensitive to differences in variable scale. Tree-based models are less sensitive to scaling, but the same predictor structure was kept across models to make the comparison consistent.

2.6 Model training and temporal validation strategy

A temporal validation strategy was used instead of a random split. This was important because the purpose of the model is to estimate future glacier mass balance from historical training

data. A random split would mix years from the same climate period into both training and validation sets. This could produce overly optimistic performance estimates. A temporal split provides a more realistic test of whether models trained on earlier conditions can generalize to later years.

The main split was defined as follows:

- Training period: 2001–2020, producing 2,000 training records.
- Validation period: 2021–2025, producing 500 validation records.

The validation period includes recent years with very negative mass-balance conditions. The year 2022 was an extremely warm year for the European Alps. Therefore, the snowfall in winter was very low, and the summer temperature was unusually high. (*European State of the Climate 2022 | Copernicus*, n.d.). The year after, 2023 was also an exceptional year in regard to ice loss in the European Alps, because the winter snow accumulation was below the average and there was a strong summer melt condition (*Copernicus: 2023 Is the Hottest Year on Record, with Global Temperatures Close to the 1.5°C Limit | Copernicus*, n.d.; *European State of the Climate 2023 | Copernicus*, n.d.). For this reason, the validation period was very challenging for the models, and the test results of them were meaningful.

Five model families were tested. They were selected to compare a simple linear baseline, tree-based non-linear models, a tabular neural network, and a sequence-based deep-learning model. This comparison is consistent with recent glacier mass-balance studies that emphasize the importance of testing machine-learning models under clear validation settings, especially when data are limited or climatic extremes are present(Bolibar et al., 2022b; van der Meer et al., 2025).

Table 2-3: Model families tested in the mass-balance prediction workflow.

Model family	Purpose of the comparison
Multiple Linear Regression	Baseline model for linear relationships
Random Forest Regressor	Non-linear ensemble model for tabular data
Gradient Boosted Trees Regressor	Boosted tree-based model for complex non-linear patterns
Multi-Layer Perceptron Neural Network	Flexible non-linear neural-network model for tabular regression
Sequence-based LSTM	Temporal deep-learning model using multi-year input sequences

Model performance was evaluated using R^2, MAE, MSE, RMSE, and bias. Bias was defined as the mean predicted mass balance minus the mean observed mass balance. Mean Absolute

Percentage Error was not used as a key metric because glacier mass-balance values can be negative, zero, or close to zero. Percentage errors would therefore be unstable or undefined.

2.7 Sensitivity analysis for extreme validation years

The years 2022 and 2023 were very influential during the validation. In 2022, the mass balance experienced the most negative value. The year 2023 also showed a strongly negative mass balance and very low winter precipitation in the study dataset. These years are important because they test whether the models can handle conditions that are more extreme than most of the training period.

To examine this effect, sensitivity tests were conducted for the Random Forest, Gradient Boosted Trees, and MLP models. Three validation settings were compared:

- Full validation period: 2021–2025.
- Validation without 2022.
- Validation without 2022 and 2023.

This sensitivity analysis did not replace the main temporal validation design. The full validation period remained the primary basis for model selection because it represents the complete recent validation window. The sensitivity analysis was used only to interpret how strongly extreme years affected model error and bias.

2.8 Extended temporal modelling experiment

In addition to the main 2001–2025 workflow, an extended temporal modelling experiment was conducted. This experiment tested whether a longer historical record could improve sequence-based modelling. It was designed as a supplementary robustness test, not as a replacement for the main projection workflow.

The motivation for this experiment was the weak performance of the initial LSTM model. LSTM models are designed to learn temporal dependencies, but they generally require sufficient sequence length and enough examples to identify useful temporal patterns. A short 25-year dataset may therefore limit their predictive skill. To test this issue, the dataset was extended backward using ERA5-Land climate data and the available mass-balance records.

For this experiment, ERA5-Land monthly climate data were extracted for 1950–2025 over the same regional bounding box. Since winter precipitation was calculated over the October–April season, the first complete glaciological year was 1951. The final extended climate-mass-balance dataset therefore covered 1951–2025. The same 100 selected glaciers were used. Then, in this case, 7,500 records were available.

The predictor variables were the same as the last dataset, summer_t2m, winter_tp, Area, Zmin, Zmax, Zmed, Slope, Aspect, CenLat, and CenLon. The target variable remained annual Mass_Balance. The extended experiment used the following temporal split:

- Training period: 1951–2010.
- Validation period: 2011–2025.

This produced 6,000 records for training and 1,500 records for validation in the extended tabular MLP experiment. Three additional models were tested: an extended MLP trained on 1951–2010 and validated on 2011–2025, an extended LSTM using 10-year input sequences, and an extended LSTM using 5-year input sequences.

For the LSTM models, sequences were constructed separately for each glacier. Each input sequence contained the climate and glacier-attribute predictors for the previous years, and the target was the Mass_Balance value of the following target year. The results of this experiment were used only to assess whether longer temporal context improved predictive skill. The main future projection workflow remained based on the selected model from the 2001–2025 analysis.

2.9 Final model selection and retraining

For the final prediction of the mass balance, the MLP Neural Network was selected, because in the main validation results, this model showed the best performance among the chosen models. It has the highest validation R^2 and the lowest RMSE among the models. After this model was selected, it was retrained using the whole historical dataset. This provide a 2500 records for the model to be trained based on the whole historical dataset, which includes extreme years such as 2022 and 2023. Including these years was important because future climate conditions may include more frequent or more intense mass-loss years. In the configuration of the final MLP model, two hidden layers with 64 and 32 neurons were used. Input predictors were standardized, and the target variable was scaled during training. Early stopping was applied to reduce overfitting. After prediction, model outputs were transformed back into the original mass-balance unit.

2.10 Future climate scenario preparation

Future climate projections were derived from the NASA NEX-GDDP-CMIP6 dataset. NEX-GDDP-CMIP6 provides downscaled historical and future climate projections derived from CMIP6 global climate model simulations (Thrasher et al., 2022). Future climate data were extracted for the study area using a representative regional point at 8.0° E and 45.5° N. The selected climate model was MPI-ESM1-2-HR.

Two Shared Socioeconomic Pathway scenarios were retained: SSP2-4.5 and SSP5-8.5. SSP2-4.5 represents an intermediate forcing pathway, while SSP5-8.5 represents a high-emission pathway. Using these two scenarios allowed the thesis to compare a moderate future trajectory with a severe warming trajectory. The projection period was 2026–2100.

The raw future scenario file initially included the year 2101. This year was removed so that the final future period covered 75 complete years, from 2026 to 2100. The final future climate dataset contained 150 scenario-year records, which are related to 2 scenarios and 75 years. These scenario-year records were cross-joined with the 100 selected glaciers, producing 15,000 future glacier-scenario-year records.

2.11 Temperature harmonization and bias correction of future climate variables

The raw future climate variables were not directly used as model inputs because their temperature and precipitation ranges were not fully consistent with the ERA5-Land historical variables used for model training. This mismatch was especially clear for the summer temperature. The raw NEX-GDDP-CMIP6 summer temperature values extracted from the representative regional point were approximately 22–25°C in the future period, while the historical glacier-level ERA5-Land summer temperature values used in the training dataset were much lower. Directly applying the final model to the raw scenario temperatures would therefore have required the model to extrapolate beyond the historical training distribution.

To reduce this mismatch, the future summer temperature was processed in two steps. The first step was an elevation-related temperature harmonization. The future scenario temperature was extracted from a representative regional climate point, while the selected glaciers are located at much higher elevations. The area-weighted median elevation of the selected glacier sample is approximately 3204 m. Therefore, a constant temperature offset of 14°C was subtracted from the raw future summer temperature values before applying the baseline bias correction.

The value of the 14°C offset was selected as an empirical elevation-harmonization constant based on the difference between the raw future scenario temperatures and the glacier-level historical temperature range used for model training. It is also physically consistent with a lapse-rate-based interpretation. Using a standard lapse rate of about 6.5°C km^{-1}, a 14°C temperature reduction corresponds to an approximate vertical temperature adjustment of 2.15 km. This value is reasonable for harmonizing a regional near-surface climate with high-elevation glacier conditions. However, this correction should not be interpreted as fully distributed climate downscaling or as a direct calculation from a known climate-grid elevation. It was used as a practical preprocessing step to bring the raw future temperatures closer to the range of the historical glacier-level training data. Lapse-rate-based temperature adjustments are commonly used in mountain and glacier modelling, but constant lapse rates remain a simplification because near-surface temperature gradients vary in space, time, season, and surface conditions. (Dutra et al., 2020; Gardner et al., 2009; Minder et al., 2010)

The equivalent elevation difference represented by the 14°C offset was calculated as:

$$\Delta z_{equiv} = \frac{\Delta T_{elev}}{\Gamma} \qquad \textit{Equation 2-1}$$

Where Δz_{equiv} is the equivalent elevation difference, ΔT_{elev} is the applied temperature offset, and Γ is the assumed lapse rate. Using $\Delta T_{elev} = 14$℃ and $\Gamma = 6.5\ \frac{℃}{km}$, the equivalent elevation difference is:

$$\Delta z_{equiv} = \frac{14}{6.5} \approx 2.15\ km \qquad \textit{Equation 2-2}$$

The elevation-related temperature harmonization was then applied as:

$$T_{harm} = T_{future,\ raw} - \Delta T_{elev} \qquad \textit{Equation 2-3}$$

where (T_{harm}) is the elevation-harmonized future summer temperature, ($T_{future,\ raw}$) is the raw future summer temperature from NEX-GDDP-CMIP6, and (ΔT_{elev}) is the applied elevation-related temperature offset. In this thesis, ($\Delta T_{elev} = \mathbf{14}$℃).

The second step was a baseline bias correction. This step was applied to align the harmonized future temperature series with the historical training distribution. A historical baseline was defined as 2016–2025, and a future baseline was defined as 2026–2035. The additive temperature correction was calculated as:

$$T_{corrected} = T_{harm} - (\overline{T}_{harm,future\ baseline} - \overline{T}_{future\ baseline}) \qquad \textit{Equation 2-4}$$

where ($T_{corrected}$) is the final corrected summer temperature used as model input, ($\overline{T}_{harm,future\ baseline}$) is the mean harmonized future summer temperature during 2026–2035, and ($\overline{T}_{future\ baseline}$) is the mean historical ERA5-Land summer temperature during 2016–2025.

For winter precipitation, no elevation-related harmonization was applied. Instead, a multiplicative ratio correction was used to make the future winter precipitation proxy more consistent with the historical training distribution:

$$P_{corrected} = P_{future,raw} \times \frac{\overline{P}_{historical\ baseline}}{\overline{P}_{future\ baseline}} \qquad \textit{Equation 2-5}$$

where ($P_{corrected}$) is the final corrected winter precipitation proxy used as model input, ($P_{future,raw}$) is the raw future winter precipitation proxy, ($\overline{P}_{historical\ baseline}$) is the mean historical winter precipitation proxy during 2016–2025, and ($\overline{P}_{future\ baseline}$) is the mean future winter precipitation proxy during 2026–2035.

After these steps, the corrected future variables retained the same names used during model training: (summer_t2m) and (winter_tp). The raw future variables were also preserved in the dataset for documentation and comparison. This is why the results chapter reports both raw and corrected climate values. The corrected variables were then cross-joined with the 100 selected glaciers and used as inputs to the final MLP model.

2.12 Future mass-balance prediction

The final retrained MLP model was applied to the corrected bias future scenario dataset. For each glacier in different years and scenarios, one prediction of mass balance was generated by the model. The final generated table contains 15000 records, because the dataset covers 100

previously selected glaciers for 75 years from 2026 to 2100, and 2 different future climate scenarios.

These mass balance values generated by the model are not treated as the final amount of the glacier's volume. Instead, they were used as the annual forcing for the volume evolution model. This separation is important because mass balance and volume are different quantities. Annual mass balance describes gain or loss per unit area, while volume evolution also depends on glacier area and its change through time.

2.13 Dynamic volume-area scaling

After predicting the annual mass balance, the glacier's volume was calculated through volume are scaling method. Dynamic area scaling is an empirical formula that introduces a relationship between surface area and the ice volume of glaciers. When direct measurement of every single glacier's ice thickness is not available, this method is used (Bahr et al., 1997, 2015; Huss & Farinotti, 2012).

The basic relationship equation between surface area and volume of a glacier is:

$$\boldsymbol{V = c \times A^{\gamma}} \qquad \textit{Equation 2-6}$$

In the above formula V stands for Volume and A for the area. c and γ are constants, c is the scaling coefficient, and γ is the scaling component. In this study, their values are 0.034 and 1.375 respectively.

Since in the RGII dataset the area of glaciers is available, first, the volume of each glacier in the year 2001 was calculated.

$$\boldsymbol{V_{2001} = c \times A_{2001}^{\gamma}} \qquad \textit{Equation 2-6}$$

Annual volume change was then calculated as:

$$\boldsymbol{\Delta V_t = (b_t \div 1000) \times A_t} \qquad \textit{Equation 2-7}$$

Where b_t is the annual mass balance in m w.e. and A_t is the glacier area in km^2. The reason why the b_t is divided by 1000 is to convert the meter to the kilometer; therefore, the annual volume change is presented in km^3.

After that, the glacier volume was updated annually with the following equation.

$$\boldsymbol{V_{t+1} = V_t + \Delta V_t} \qquad \textit{Equation 2-8}$$

By inverting the dynamic volume area relationship, for each following year, the glacier area was recalculated using the following equation.

$$\boldsymbol{A_{t+1} = (V_{t+1} \div c)^{\frac{1}{\gamma}}} \qquad \textit{Equation 2-9}$$

This created a feedback loop. As glacier volume declined, glacier area also declined. The smaller area then influenced subsequent annual volume changes. The volume of the largest glacier, RGI60-11.02822, was first calculated through this model, and then it was applied to all other glaciers.

2.14 Regional aggregation and visualization

For the single-glacier analysis, annual observed and projected mass-balance series were plotted for glacier RGI60-11.02822 from 2001 to 2100. From the year 2001 to 2025 is the historical series, and from 2026 to 2100 is the future predicted series. For volume analysis, the dynamic volume-area scaling output was used to plot modelled glacier volume in km^3 and remaining glacier volume as a percentage of the 2001 volume. For regional analysis, annual volumes from all 100 glaciers were summed by year and scenario. The regional remaining volume percentage was calculated as:

$$\text{Regional remaining volume} = (\Sigma \boldsymbol{V_t} \div \Sigma \boldsymbol{V_{2001}}) \times \mathbf{100} \qquad \textit{Equation 2-10}$$

A final regional plot was produced to show the remaining volume of the 100 selected glaciers from 2001 to 2100 under the historical and future scenario trajectories. This allowed the results to be interpreted at both single-glacier and regional scales.

2.15 Methodological limitations

Several limitations should be considered when interpreting the results. First, future climate data were extracted from a representative regional point rather than individually for each glacier. As a result, glacier-specific future climatic variation was represented mainly through static glacier attributes rather than through fully spatially distributed future climate fields.

Second, winter_tp represents total cold-season precipitation rather than snowfall. It was used as an accumulation-related proxy, but it does not separate rain from snow. This limitation is important because the snow-rain partition can strongly affect glacier accumulation, especially under warmer future conditions.

Third, glacier volume was estimated through volume-area scaling rather than direct ice-thickness measurements. The results should therefore be interpreted as modelled volume trajectories, not as observed glacier volumes. Volume-area scaling is useful for regional studies, but it cannot represent all details of glacier thickness distribution or ice dynamics.

Fourth, the validation analysis showed that all models struggled with extreme years, especially 2022. This indicates that even the best-performing model remains uncertain under rare or highly negative mass-balance conditions. Under the continuing global warming trend, the extreme melt years may become more common, thus, this limitation is very important for future prediction.

Fifth, the future scenario analysis used two SSP2-4.5 and SSP5-8.5 pathways, and these scenarios cover a comparison between intermediate and high-emission futures, and they do not provide any possible climate in the future.

Finally, although the extended 1951–2025 experiment tested to see if longer temporal sequences could improve LSTM performance, but still, the LSTM models performed worse than the MLP model. This suggests that the available predictor structure and glacier sample may not provide enough useful temporal sequence information for LSTM-based modelling to outperform tabular neural networks in this workflow.

3 Results

3.1 Overview of the final modelling dataset

The final historical dataset used for modelling consists of glacier inventory attributes, ERA5-Land climate variables, and annual mass balance. The 100 largest glaciers were kept after applying the geographical filter. Their area is 321.003 km^2, which covers almost 89.9% of the total glacier's surface area in the selected region. Therefore, the sample keeps almost the most glacierized parts of the selected area, while it keeps the workflow shorter and more manageable. Thus, the dataset includes 2001 to 2025 attributes of the top 100 glaciers; consequently, it has 2,500 glacier-year records. The geometry of each glacier and its topographic attributes are the predictors of each record correspond to its annual mass balance. The final predictors were summer temperature, winter precipitation proxy, area, minimum, maximum and median elevation, slope, aspect, and glacier centroid coordinates. Annual mass balance was used as the target variable.

Table 3-1: Final historical modelling dataset

Dataset Component	Value
Number of the selected glaciers	100
Historical period	2001-2025
Number of years	25
Total records	2,500
Total selected glacierized area	321,003 km^2
Share of glacierized area represented by selected glaciers	89.89%
Target Variable	Annual mass balance
Main climate predictors	Summer_t2m, winter_tp
Glacier attributes	Area, Zmin,Zmax, Zmed, Slope, Aspect, CenLat, CenLon

The data were split temporally, from 2001 to 2020 for testing and from 2021 to 2025 for validation. In this way, 2000 records were assigned to the testing of the models and 500 for the validation of them. Since the split was chronic, not random, and in the validation part, there were 2022 and 2023 extreme years, it was a robust validation for the models and avoided generalization.

3.2 Annual climate and mass-balance conditions during validation

By comparing the historical annual mass balance and climate variables, an anomaly was clear in the validation period. In the whole 100 glaciers, the average annual mass balance change in the year 2021 was -0.776 m w.e., but, in the year 2022, this was -3.043 m w.e., and in the year 2023, it was -1.841 m w.e. The annual mean balance change in 2022 was the lowest amount among the whole historical dataset, which was coincident with the highest mean summer temperature, which was 7.586 °C. In 2023, the mean summer temperature was still high, 7.131°C, and the winter precipitation proxy reached the minimum amount in the whole historical dataset.

The mentioned patterns were then validated with other independent references; they were all consistent with the Alps climate records. The amount of precipitation in the winter of 2023, which followed high temperatures in the 2022 summer, was below average, and the heat wave also continued in the 2023 summer. (Cremona et al., 2023; *European State of the Climate 2022 | Copernicus*, n.d.; *European State of the Climate 2023 | Copernicus*, n.d.). Therefore, the validation period was not only for recent years, but also it was not uniform with the range in the training years; thus, it was challenging for the models. The same problem for 2022 and 2023 has also been reported in recent machine learning models used to predict mass balance in Alpine glaciers in other studies (van der Meer et al., 2025).

Table 3-2 :Climate and mass-balance diagnostics for the validation years

Year	Mean mass balance (m w.e.)	Mean summer_t2m (°C)	Mean winter_tp
2021	−0.776	5.570	0.024
2022	−3.043	7.586	0.020
2023	−1.841	7.131	0.011
2024	−0.960	6.258	0.026
2025	−0.990	7.034	0.030

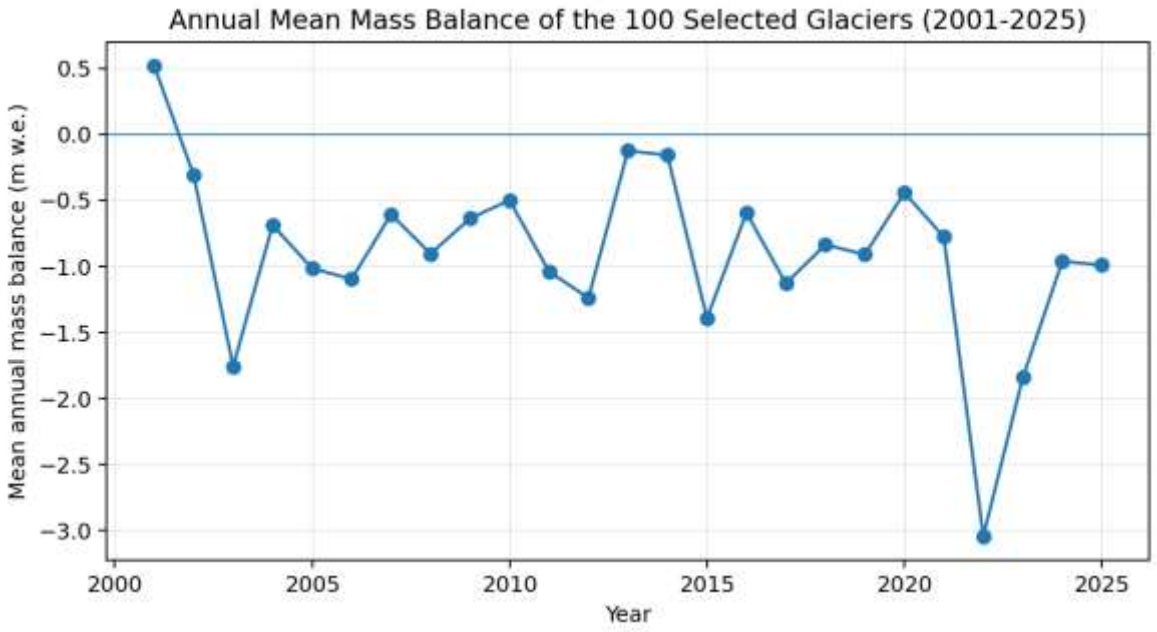


Figure 3-1: Annual mean mass balance for the 100 selected glaciers during 2001–2025. The validation period includes the exceptionally negative mass-balance years 2022 and 2023.

3.3 Model performance comparison

For estimating the annual mean balance of the selected regional glacier in this study, five model has been chosen and examined. These models are Multiple Linear Regression, Random Forest, Gradient Boosted Trees, a Multi-Layer Perceptron (MLP) neural network, and a sequence-based Long Short-Term Memory (LSTM) network. The Linear Regression has been chosen only for a simple baseline. Other models were included to test whether non-linear tabular or sequence-based approaches could better represent the relationship between climate, glacier characteristics, and annual mass balance.

The performance results of the models are showed in the table 3.3. As, it is clear, the MLP model had the best performance among the models. The maximum R^2 and the minimum MAE, MSE, and RMSE is for this model.

Table 3-3: Training and validation performance of the tested models

Model	Split	R^2	MAE	MSE	RMSE	Bias
Linear Regression	Train 2001-2020	0.365	0.367	0.220	0.469	0.000
Linear Regression	Validation 2021-2025	0.045	0.615	0.790	0.889	0.472
Random Forest	Train 2001-2020	0.928	0.123	0.025	0.158	-0.002

Model	Split	R^2	MAE	MSE	RMSE	Bias
Random Forest	Validation 2021-2025	0.091	0.621	0.752	0.867	0.444
Gradient Boosted Trees	Train 2001-2020	0.863	0.160	0.048	0.218	0.005
Gradient Boosted Trees	Validation 2021-2025	0.106	0.622	0.740	0.860	0.452
MLP Neural Network	Train 2001-2020	0.802	0.206	0.068	0.262	-0.023
MLP Neural Network	Validation 2021-2025	0.334	0.549	0.551	0.742	0.301
LSTM Sequence	Train 2003-2020	0.877	0.133	0.032	0.179	0.011
LSTM Sequence	Validation 2021-2025	-0.045	0.762	0.865	0.930	0.735

Note. Bias is defined as mean predicted mass balance minus mean observed mass balance. Positive values indicate predictions that are, on average, less negative than the observations.

The Linear Regression baseline explained little of the variability in the validation period (R^2 = 0.045; RMSE = 0.889 m w.e.). This result suggests that the response cannot be represented adequately by a single linear relationship across all glaciers and years. The models that were tree-based, were fitted in training period, but for the validation their performance was very poor. The Random Forest model had R^2 of 0.928 in training period but for validation it was only 0.091. Gradient Boosted Trees also had such a similar performance, with just a slightly smaller gap between training and validation periods. Its R^2 for validation was 0.106 while it was 0.836 for training period. The large gapes between training and validation period shows overfitting of the models to historical climate variables and glacier attributes.

The results of LSTM for training were also good, but its performance for validation period was the weakest among the whole other models, with R2 = -0.045 and RMSE = 0.930 m w.e. The negative R2 for this model indicate that its performance is worse than a prediction based on only mean validation observation. The result indicates that the three-year sequences did not provide a stable temporal signal that could be transferred to the recent period.

The MLP model has the best performance among the models, with the minimum gap between generalization and being fit. Its R2 was 0.334, while its MAE was 0.549, RMSE = 0.742 m w.e., and bias = 0.301 m w.e. However, the value of R2 was not too high, but the magnitude of errors is close to the recent machine learning models applied in different regions with different validation design (Sjursen et al., 2025; van der Meer et al., 2025). Direct numerical

comparison should therefore be made cautiously. More importantly for this study, the MLP was the best model under the same conditions applied to all five candidates and was selected for the future projections.

Table 3-4: Validation ranking of the tested models

Rank	Model	Validation R^2	Validation RMSE	Interpretation
1	MLP Neural Network	0.334	0.742	Best validation performance
2	Gradient Boosted Trees	0.106	0.860	Slightly better than Random Forest
3	Random Forest	0.091	0.867	Strong training fit, weaker validation
4	Linear Regression	0.045	0.889	Baseline model
5	LSTM Sequence	-0.045	0.930	Negative validation R^2

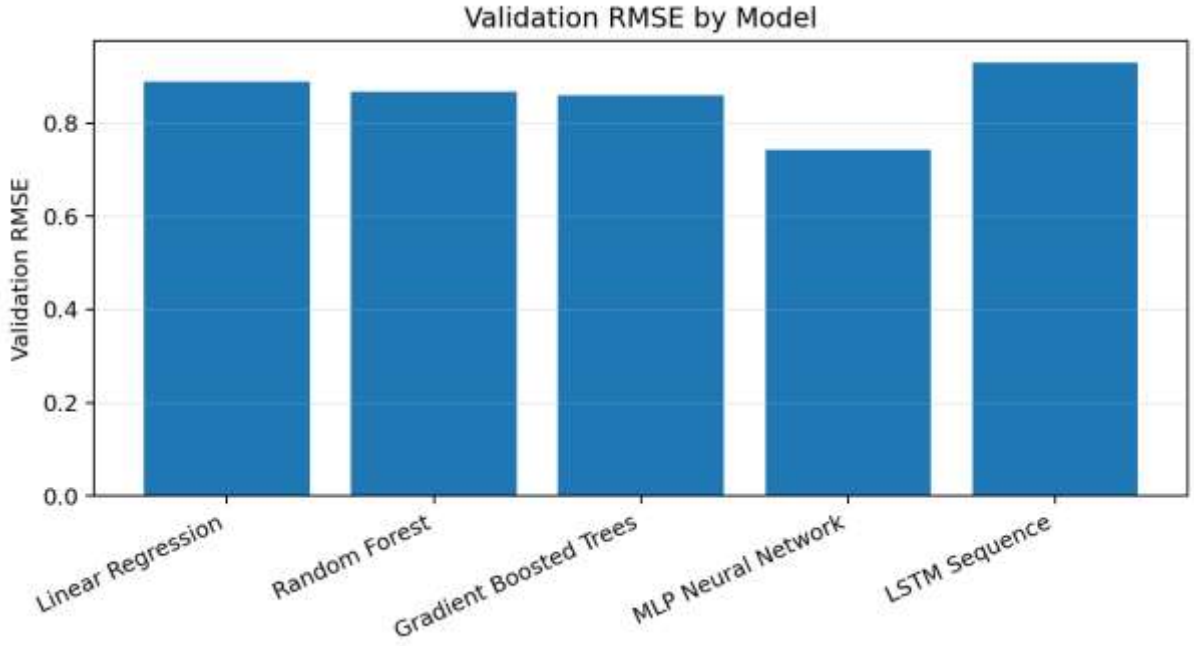


Figure 3-2: Validation RMSE for the five tested models. The MLP neural network achieved the lowest validation RMSE and was selected for the projection stage.

3.4 Sensitivity analysis for the extreme validation years

The annual diagnostics identified 2022 as the most influential extreme year and 2023 as a second challenging year. Sensitivity tests were therefore run for Random Forest, Gradient Boosted Trees, and MLP using three subsets: the full 2021–2025 validation period, the period without 2022, and the period without both 2022 and 2023. These tests were used to interpret model error, not to replace the original validation design. Because each exclusion changes both the sample size and the variance of the observations, changes in R^2 are not expected to follow changes in RMSE exactly.

3.4.1 Random Forest sensitivity

For Random Forest, excluding 2022 reduced RMSE from 0.867 to 0.449 m w.e. Removing both 2022 and 2023 reduced it further to 0.310 m w.e. Bias also moved from 0.444 to −0.038 m w.e., showing that most of the systematic underestimation of mass loss was concentrated in the two extreme years.

Table 3-5: Random Forest model sensitivity analysis

Validation setting	R^2	MAE	MSE	RMSE	Bias
Full validation 2021-2025	0.091	0.621	0.752	0.867	0.444
Without 2022	0.304	0.352	0.202	0.449	0.131
Without 2022 and 2023	0.275	0.252	0.096	0.310	-0.038

3.4.2 Gradient Boosted Trees sensitivity

Gradient Boosted Trees showed the same overall pattern. RMSE decreased from 0.860 m w.e. for the full validation period to 0.480 m w.e. without 2022 and 0.333 m w.e. without both extreme years. The almost final zero bias indicates a much more balanced fit for the remaining validation years.

Table 3-6: Gradient Boosted Trees sensitivity analysis

Validation setting	R^2	MAE	MSE	RMSE	Bias
Full validation 2021-2025	0.106	0.622	0.740	0.860	0.452
Without 2022	0.205	0.367	0.230	0.480	0.155
Without 2022 and 2023	0.161	0.261	0.111	0.333	-0.016

3.4.3 MLP neural network sensitivity

The MLP error also decreased when the extreme years were removed. RMSE fell from 0.742 to 0.484 m w.e. without 2022 and to 0.328 m w.e. without 2022 and 2023. Its R^2 decreased in the reduced subsets because the remaining observations had a narrower range, but the absolute errors became substantially smaller.

Table 3-7: MLP neural network sensitivity analysis

Validation setting	R^2	MAE	MSE	RMSE	Bias
Full validation 2021-2025	0.334	0.549	0.551	0.742	0.301
Without 2022	0.192	0.361	0.234	0.484	0.050
Without 2022 and 2023	0.189	0.268	0.107	0.328	-0.109

Taken together, the sensitivity tests show that all three non-linear models captured ordinary validation years more reliably than the two extreme years. This behavior is consistent with (van der Meer et al., 2025), who found that an ML mass-balance model trained through 2021 struggled when applied to 2022 and 2023 conditions outside its training range. The full 2021–2025 period was nevertheless retained for model selection because recent extremes are relevant to the climate conditions that future projections are expected to encounter. Under this stricter test, the MLP remained the best-performing model.

Table 3-8: RMSE comparison across the sensitivity tests

Model	Full validation RMSE	Without 2022 RMSE	Without 2022 and 2023 RMSE
Random Forest	0.867	0.449	0.310
Gradient Boosted Trees	0.860	0.480	0.333
MLP Neural Network	0.742	0.484	0.328

3.5 Gradient Boosting hyperparameter tests

To improve the performance of Gradient Boosted model and avoid generalization, some other configurations were tested. The first configuration in the model was maximum tree depth of 4,100 trees and learning rate of 0.10. Other configurations were first, reducing just the depth, second reducing the learning rate, and the third one reducing both of them.

Table 3-9: Gradient Boosting hyperparameter tests

Version	Tree Depth	Number of Models	Learning Rate	R^2	MAE	RMSE	Bias
GB original	4	100	0.10	0.106	0.622	0.860	0.452
GB v1	2	200	0.05	-0.061	0.674	0.937	0.513
GB v2	3	150	0.05	0.038	0.643	0.892	0.484
GB v3	3	100	0.10	0.097	0.625	0.864	0.458

None of the alternative settings improved validation performance. The original configuration retained the highest R^2 and the lowest RMSE. The more conservative versions reduced model flexibility too far and produced clear underfitting, particularly GB v1, which returned a negative validation R^2. The original Gradient Boosted Trees model was therefore retained for comparison, although it was not selected for projection.

3.6 Extended temporal modelling experiment

An additional experiment tested to assess if the initial result of LSTM model was mainly because of the short 2001- time series or not. Therefore, an extended dataset includes mass balance and climate variable from 1951 to 2025 was constructed for the same 100 glaciers. The new dataset consists of 7,500 glacier-year time series. This experiment was treated as a robustness check and did not replace the main workflow.

The training period for this additional extended dataset was from 1951 to 2010 and the validation period 2011 to 2025. Three models were tested in this experiment. MLP and LSTM with 10-year sequences, and another LSTM with 5-yeat sequences. The main purpose of this test is for LSTM models as they generally perform better in temporal dataset with more records, there this larger dataset with longer duration has been tested in this study. The results of these experiment are compared with the original MLP in Table 3.10.

Table 3-10: Results of the extended temporal modelling experiment

Model	Dataset	Validation period	R^2	MAE	MSE	RMSE	Bias
Original MLP	2001–2025	2021–2025	0.334	0.549	0.551	0.742	0.301
Extended MLP	1951–2025	2011–2025	0.286	0.474	0.407	0.638	0.310
Extended LSTM seq10	1951–2025	2011–2025	-0.447	0.658	0.826	0.909	0.548
Extended LSTM seq5	1951–2025	2011–2025	-0.477	0.699	0.843	0.918	0.514

The extended MLP achieved MAE = 0.474 m w.e. and RMSE = 0.638 m w.e., compared with MAE = 0.549 m w.e. and RMSE = 0.742 m w.e. for the original MLP. This suggests that a longer historical record may improve the stability of a tabular neural network. The two results are not directly interchangeable, however, because they use different validation periods and therefore different climatic conditions.

Both extended LSTM configurations remained weaker than the extended MLP. The 10-year model returned $R^2 = -0.447$ and RMSE = 0.909 m w.e., while the 5-year model returned $R^2 = -0.477$ and RMSE = 0.918 m w.e. Increasing the sequence length and the total historical coverage therefore did not resolve the poor out-of-sample performance.

For the available predictors, the most useful signal appears to be contained in the current relationship between annual climate conditions and glacier-specific attributes rather than in the short sequence memory represented by the LSTM. This does not imply that temporal neural networks are unsuitable for glacier modelling in general. It indicates that the chosen sequence structure, predictor set, and sample do not support their use in this application.

The extended experiment therefore strengthens the decision to use the MLP for projection. It also shows that adding more years is not sufficient by itself; the value of a longer record depends on whether the model can extract transferable information from the added temporal structure.

3.7 Final MLP model training

After model selection, the MLP was retrained on the complete 2001–2025 historical dataset. This allowed the final model to use all 2,500 records, including the recent extreme years, before it was applied to future climate scenarios.

The performance of this retrained model was with $R^2 = 0.838$, MAE = 0.231 m w.e., RMSE = 0.296 m w.e., and bias = 0.023 m w.e. on the full historical dataset. These values are reported only as a training sanity check. They are not an independent measure of predictive skill because the same records were used for fitting and evaluation.

The small mean bias indicates that the final fitted model did not systematically shift the historical mass-balance distribution upward or downward. Confidence in future use, however, remains based on the earlier 2021–2025 temporal validation rather than on this in-sample result.

3.8 Future climate and regional mass-balance projections

The final MLP was applied to the bias-corrected SSP2-4.5 and SSP5-8.5 climate series for 2026–2100. Predictions were generated for every glacier, year, and scenario, producing 15,000 future records. The raw scenario variables were kept for documentation, while the corrected variables were used as model inputs.

To describe changes through the century, the projection period was divided into 2026–2050, 2051–2075, and 2076–2100. Table 3.12 reports the mean corrected and raw climate variables together with the distribution of predicted annual mass balance across the 100 glaciers.

Table 3-11: Future climate and predicted mass balance for all 100 glaciers

Scenario	Period	Mean corr. summer_t2m	Mean corr. winter_tp	Mean raw summer_t2m	Mean raw winter_tp	Mean predicted MB	Min predicted MB	Max predicted MB
SSP2-4.5	2026-2050	7.002	0.025	21.975	0.653	-1.339	-5.536	1.319
SSP2-4.5	2051-2075	7.842	0.024	22.815	0.617	-1.982	-6.699	0.684
SSP2-4.5	2076-2100	8.393	0.023	23.366	0.599	-2.354	-7.409	1.064
SSP5-8.5	2026-2050	6.877	0.026	21.866	0.659	-1.231	-5.084	1.592
SSP5-8.5	2051-2075	8.858	0.028	23.847	0.697	-2.138	-6.653	1.407
SSP5-8.5	2076-2100	10.781	0.026	25.770	0.659	-3.513	-8.795	0.649

Under SSP2-4.5, the mean predicted mass balance becomes progressively more negative, changing from −1.339 m w.e. in 2026–2050 to −2.354 m w.e. in 2076–2100. Under SSP5-8.5, the mean changes from −1.231 to −3.513 m w.e. over the same periods. The two pathways overlap during the early decades, and SSP5-8.5 is slightly less negative in the first period. This short-term ordering reflects overlap in near-term climate trajectories and the combined influence of temperature and precipitation. The scenarios are clearly separated after the mid-century.

The late-century divergence is consistent with established glacier projections, which show limited scenario separation in the first half of the century and much stronger dependence on the emissions pathway thereafter (Rounce et al., 2023b; Zekollari et al., 2024b). The results therefore, indicate that the MLP responds to the stronger long-term warming signal in SSP5-8.5, while still allowing each year and early-century climate variability to influence the predictions.

3.9 Mass-balance projection for glacier RGI60-11.02822

Since the glacier RGI60-11.02822 is the largest glacier among the 100 glaciers selected for the study area, it was chosen for detailed visualization. This single glacier visualization is for understanding the behavior of the largest glacier under the performance of the selected model. Therefore, it is worth mentioning that it is not the representative of every single glacier.

The reconstructed historical series for 2001–2025 was joined to the MLP projections for 2026–2100 under both climate scenarios. The resulting annual sequence is shown in Figure 3.3.

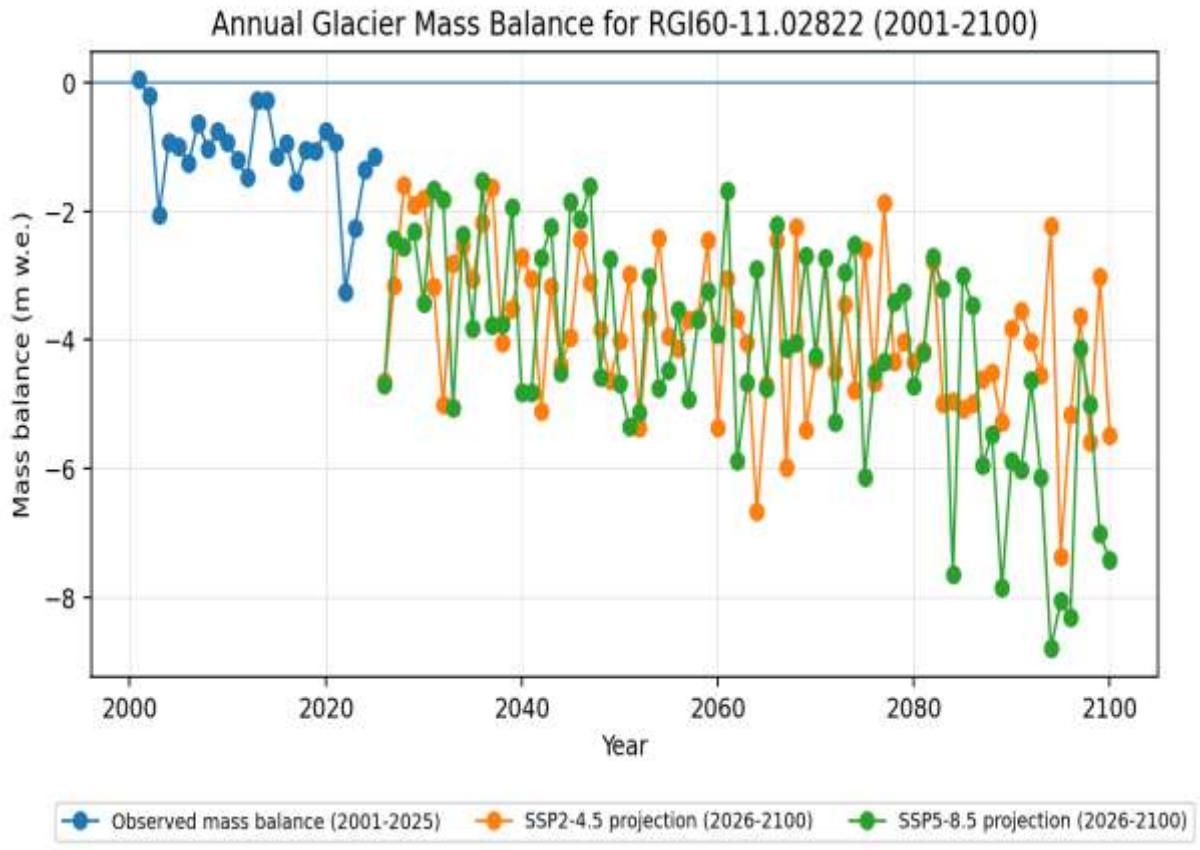


Figure 3-3: Reconstructed and projected annual mass balance for glacier RGI60-11.02822 from 2001 to 2100. The historical series covers 2001–2025, and the scenario series are MLP projections for 2026–2100.

As in the regional results, the two scenarios remain relatively close in the first half of the century and separate more clearly later. In 2076–2100, mean predicted mass balance is −4.359 m w.e. under SSP2-4.5 and −5.404 m w.e. under SSP5-8.5. The high-emission pathway is therefore about 1.05 m w.e. yr^{-1} more negative in the late-century mean. The difference is much smaller before 2075, again showing that scenario choice becomes most influential later in the projection. Table 3.12 summarizes the projected mass-balance distribution for the selected glacier.

Table 3-12:Future climate and predicted mass balance for glacier RGI60-11.02822

Scenario	Period	Mean corr. summer_t2m	Mean corr. winter_tp	Mean predicted MB	Min predicted MB	Max predicted MB
SSP2-4.5	2026-2050	7.002	0.025	-3.259	-5.100	-1.603
SSP2-4.5	2051-2075	7.842	0.024	-3.929	-6.671	-2.253
SSP2-4.5	2076-2100	8.393	0.023	-4.359	-7.364	-1.872
SSP5-8.5	2026-2050	6.877	0.026	-3.113	-5.061	-1.519
SSP5-8.5	2051-2075	8.858	0.028	-3.952	-6.137	-1.682
SSP5-8.5	2076-2100	10.781	0.026	-5.404	-8.795	-2.712

3.10 Modelled volume evolution of the selected glacier

The historical and projected mass-balance series were converted into annual volume trajectories by using dynamic volume-area scaling. The 2001 volume was estimated from the inventory area, the historical trajectory was updated through 2025 using reconstructed mass balance, and both future scenarios then started from the same modelled 2025 state.

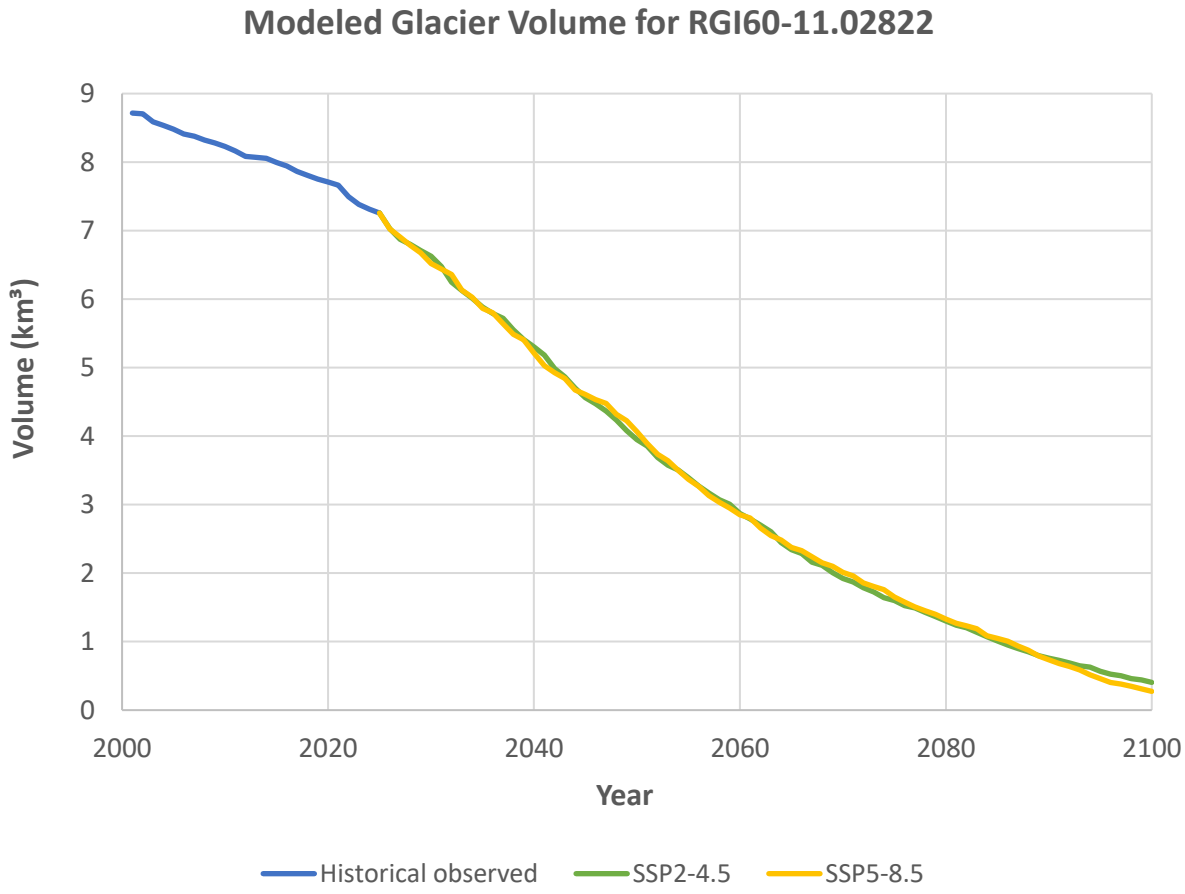


Figure 3-4: Modelled volume of glacier RGI60-11.02822 from 2001 to 2100. Historical volume is reconstructed from annual mass balance for 2001–2025; future trajectories use MLP projections under SSP2-4.5 and SSP5-8.5.

Volume declines strongly in both scenarios. As the glacier loses volume, its modelled area also decreases. This dynamic area update reduces the surface over each next years through reducing mass balance, so the absolute volume-loss rate slows as the glacier becomes smaller. This feedback also causes the two absolute volume trajectories to converge near the end of the century.

The remaining volume was therefore also expressed relative to the 2001 modelled baseline, making the long-term proportional loss easier to compare.

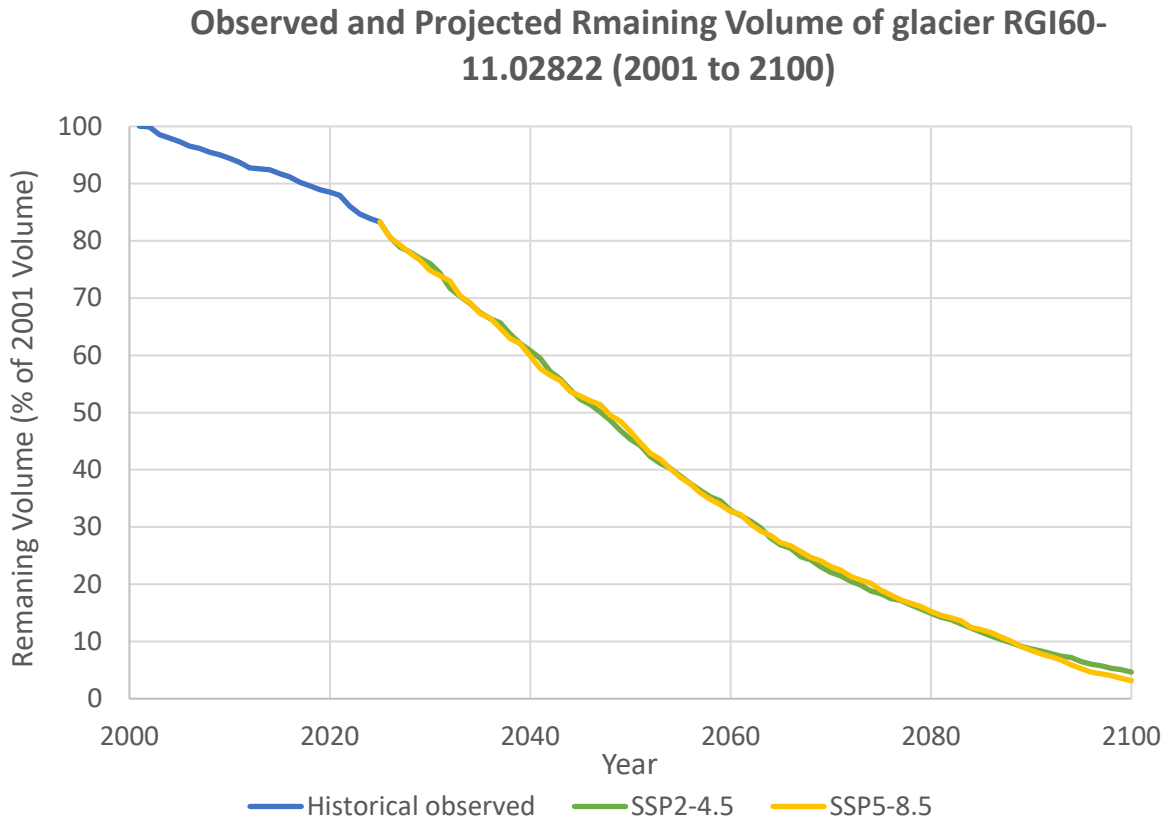


Figure 3-5: Remaining modelled volume of glacier RGI60-11.02822 as a percentage of its 2001 baseline. Future trajectories use MLP-predicted mass balance and dynamic volume-area scaling.

Table 3-13: Modelled volume summary for glacier RGI60-11.02822

Year	Series	Volume km³	Remaining volume % of 2001	Area km²	Volume change since 2025 km³
2025	Historical reconstruction	7.257	83.285	49.431	0.000
2050	SSP2-4.5	3.950	45.332	31.760	-3.307
2050	SSP5-8.5	4.068	46.691	32.450	-3.189
2075	SSP2-4.5	1.599	18.357	16.457	-5.658
2075	SSP5-8.5	1.651	18.950	16.842	-5.606
2100	SSP2-4.5	0.405	4.649	6.062	-6.852

Year	Series	Volume km³	Remaining volume % of 2001	Area km²	Volume change since 2025 km³
2100	SSP5-8.5	0.274	3.147	4.564	-6.983

This selected glacier kept 4.65% of its volume under the scenario SSP2-4.5 and 3.15% under SSP50-8.5. These results showed that this selected glacier will lose approximately all of its volume by the end of the century under both scenarios, with a little more ice lost in the high-emission pathway. These results are consistent with recent studies in the Alps, which indicate the roughly complete loss for individual glaciers and regional glacier systems. Nevertheless, the exact percentage comparison is not directly applicable because the study regions, initial years, impacting climate variables, and methodologies are different (Bolibar et al., 2022b; Hartl et al., 2025).

3.11 Regional volume evolution of the 100 selected glaciers

Dynamic volume-area scaling was then applied to all 100 glaciers. Each glacier was modelled individually from 2001 to 2025 and then continued under the two scenarios to 2100. Annual glacier volumes were summed by year and series to obtain a regional trajectory.

Regional remaining volume was expressed relative to the summed modelled volume in 2001. Both future pathways were anchored to the same historical 2025 endpoint. This was done to ensure that differences after 2025 are due to the prediction based on different scenarios, not from different initial states.

Table 3-14: Regional modelled volume summary for the 100 selected glaciers

Year	Series	Regional total volume km³	Regional remaining volume % of 2001
2001	Historical reconstruction	25.364	100.00
2025	Historical reconstruction	18.455	72.76
2025	SSP2-4.5	18.455	72.76
2025	SSP5-8.5	18.455	72.76
2050	SSP2-4.5	8.941	35.25

Year	Series	Regional total volume km³	Regional remaining volume % of 2001
2050	SSP5-8.5	9.414	37.12
2075	SSP2-4.5	2.985	11.77
2075	SSP5-8.5	2.942	11.60
2100	SSP2-4.5	0.664	2.62
2100	SSP5-8.5	0.335	1.32

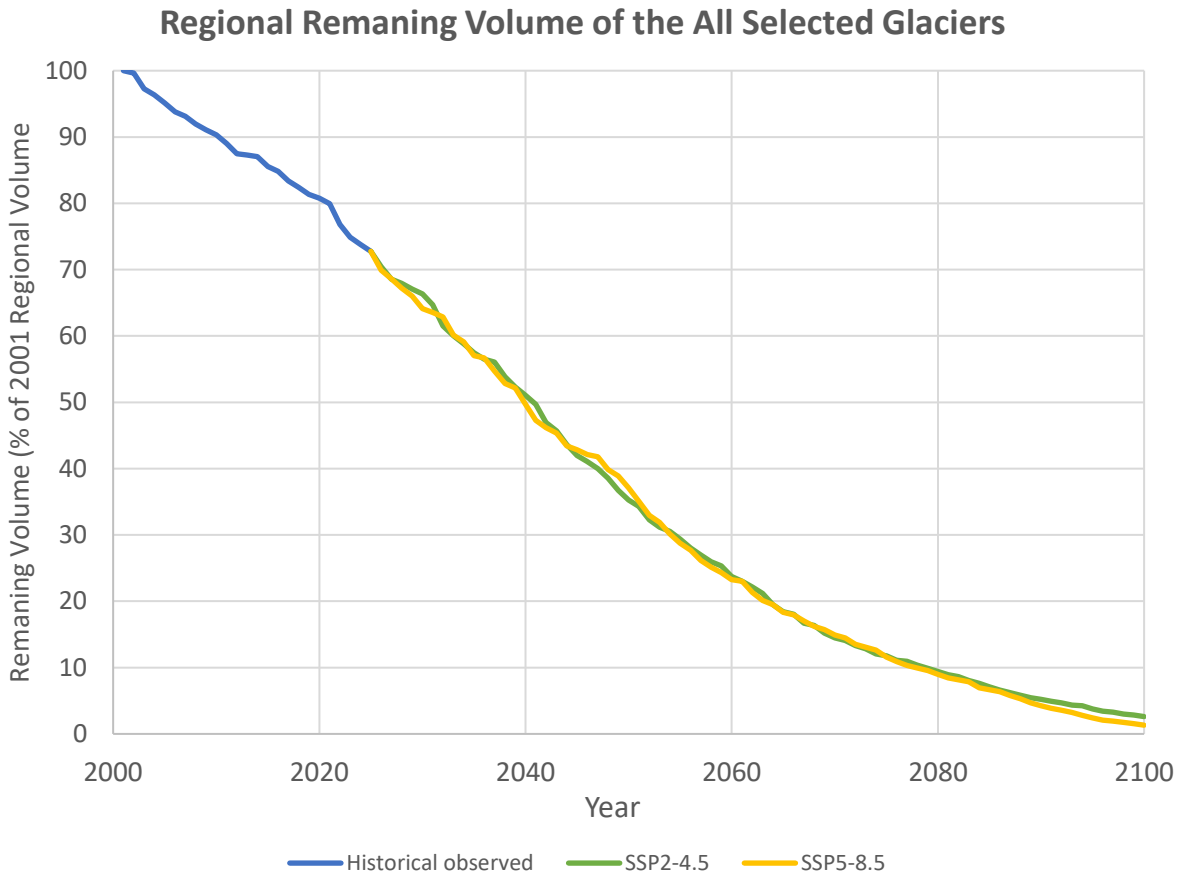


Figure 3-6: Regional remaining volume of the 100 selected glaciers from 2001 to 2100, expressed as a percentage of the modelled 2001 regional baseline.

The total volume of 100 selected glaciers, which was 25.364 km^3 in 2001, became 18.455 km^3 in 2025, which is 72.76% of the initial volume. Under the lower emission scenario, SSP2-4.5, the remaining volume related to the initial 2001 year will be 35.25% in 2050, 11.77% in 2075, and 2.62% in 2100. Moreover, for the higher emission scenario, SSP5-8.5, these amounts will be 37.12%, 11.60%, and 1.32% for the years 2050,2075, and 2100, respectively.

The slightly higher volume in 2050 in the SSP5-8.5 scenario does not mean a lower long-term climate impact. In the near future, predictions are almost similar, and they are under the impact of climate variability and precipitation. The cumulative warming effect of each scenario more influences the remaining volume later in the future. In 2100, the remaining volume under SSP5-8.5 is half of the remaining volume under SSP2-4.5. The overall predictions are consistent with recent Alpine studies and CMIP6 projections, in both scenarios the Alpine glaciers will lost a significant volume and the differences between higher emission scenarios and lower ones will be more pronounced at the end of the century (Hartl et al., 2025; Rounce et al., 2023b; Zekollari et al., 2024b).

3.12 Summary of key findings

The results lead to five main findings.

First, the MLP neural network provided the best independent validation performance. Its R^2 of 0.334 is modest, but it achieved the lowest validation errors and a smaller train–validation gap than the tree ensembles and LSTM. The result supports the use of a non-linear tabular model for this dataset, while also showing that substantial year-to-year variability remains unexplained.

Second, model error was strongly concentrated in 2022 and, to a lesser extent, 2023. Removing these years reduced RMSE substantially for all three non-linear tabular models. Retaining them in the primary validation was nevertheless important because these conditions are relevant to a warming Alpine climate and expose the limits of extrapolating beyond the historical training range.

Third, the predicted mass balance becomes more negative through the century. Scenario differences are limited in the early decades but grow after mid-century. Across the 100 glaciers, the 2076–2100 mean is −2.354 m w.e. under SSP2-4.5 and −3.513 m w.e. under SSP5-8.5.

Fourth, dynamic volume-area scaling translates these persistent negative balances into severe volume loss. The selected glacier retains 4.65% and 3.15% of its 2001 modelled volume by 2100 under SSP2-4.5 and SSP5-8.5, respectively. At regional scale, the corresponding remaining volumes are 2.62% and 1.32%.

Fifth, the extended 1951–2025 experiment improved the tabular MLP error but did not improve either LSTM configuration. For the present predictor structure, longer temporal coverage benefited the non-linear tabular model more than sequence-based learning.

Overall, the workflow projects near-complete regional volume depletion by 2100 under both pathways, with a stronger late-century loss under SSP5-8.5. These values should be interpreted as modelled trajectories rather than direct observations. Their main contribution is to show the internally consistent response of the selected regional workflow to historical extremes, future climate forcing, and dynamic area–volume feedback.

4 Conclusion

4.1 Overview of the research

This thesis developed a regional workflow for evaluating future glacier mass balance and volume evolution in a selected sector of the north-western Alps. The work was motivated by a practical problem. Global glacier models are essential for understanding worldwide ice loss, but regional applications still need methods that can represent local glacier characteristics and non-linear climate responses. Recent global assessments show that glacier loss is already accelerating. The ("Community Estimate of Global Glacier Mass Changes from 2000 to 2023," 2025), for example, estimated an average global loss of 273 ± 16 Gt per year between 2000 and 2023, with substantially higher losses in the second half of that period. These observations confirm the need for regional studies that connect historical change with future climate forcing.

This research is conducted by using ERA5-Land climate variables, glacier attribute inventory, reconstructed annual mass balance data, Machine Learning models, future CMIP6 scenarios, and dynamic volume area scaling. The sample used in this research includes the top 100 biggest glaciers regarding their surface area in the study region. These selected glaciers cover 89.9% of all glaciers in the region. This made the sample appropriate for studying regional volume change while keeping the workflow computationally manageable. The historical modelling dataset covered 2001–2025 and contained 2,500 glacier-year records.

Five models were compared using the same predictor structure and a strict temporal split. The models were trained on 2001–2020 and validated on 2021–2025. This design was more demanding than a random split because the validation period included climatic conditions that were more extreme than most of the training period. The selected MLP Neural Network was then retrained on the full 2001–2025 dataset and applied to future climate conditions under SSP2-4.5 and SSP5-8.5. Finally, the predicted annual mass balance was translated into glacier area and volume trajectories through dynamic volume-area scaling. In this way, the thesis connected statistical prediction with a physically grounded representation of glacier shrinkage.

4.2 Interpretation of model performance

The model comparison showed that non-linear methods were more suitable for the available glacier climate dataset than a simple linear baseline. Linear Regression achieved a validation R^2 of 0.045 and an RMSE of 0.889 m w.e. This weak result indicates that annual glacier mass balance could not be represented adequately as a single linear combination of temperature, precipitation, and static glacier attributes. The response of glaciers to climate is more complex.

For example, with a similar climatic anomaly, the response of the glaciers can be different. Their response is influenced by their elevation, area, topographic condition, and their condition from the previous year.

Random Forest and Gradient Boosted Trees models perform very well in the training phase, but their validation performance was much weaker. The difference between training and validation results indicates the model's overfitting. These models captured detailed patterns in the historical sample, but some of those patterns did not transfer well to the later validation years. The LSTM showed an even clearer version of this problem. It achieved a strong training fit but produced a negative validation R^2 and the largest validation RMSE. The supplementary 1951–2025 experiment did not change that conclusion. Longer sequences improved the stability of the extended MLP, but the 5-year and 10-year LSTM models still failed to outperform the tabular neural network. For this dataset, the combination of annual climate conditions and glacier-specific attributes carried more useful predictive information than the sequence structure used by the LSTM.

The MLP Neural Network achieved the best overall validation result, with $R^2 = 0.334$, MAE = 0.549 m w.e., RMSE = 0.742 m w.e., and a positive bias of 0.301 m w.e. The R^2 value is moderate, and it should not be presented as evidence of near-perfect prediction. However, the error level is reasonable for a model evaluated on an independent and unusually difficult temporal period. Recent machine-learning studies report errors of a similar order, although direct numerical comparison is limited by differences in spatial scale, target variables, input data, and validation design. (Sjursen et al., 2025), for example, reported RMSE values of approximately 0.59–1.00 m w.e. on independent test glaciers. (van der Meer et al., 2025) achieved an MAE of 0.417 m w.e. for point mass balance, but also found that the model struggled with conditions outside its training range, especially the extreme year 2022. (Bolibar et al., 2022b) similarly showed that deep learning can improve the representation of non-linear and extreme mass-balance responses compared with simpler statistical approaches.

The MLP was therefore selected because it offered the best balance between fit and generalization within this study. Its performance does not mean that neural networks are always superior to other methods. Rather, the result shows that model selection should be based on independent temporal validation instead of training fit alone. The final full-dataset metrics, including $R^2 = 0.838$ and RMSE = 0.296 m w.e., were used only as a training sanity check. They were not interpreted as independent evidence of future predictive accuracy.

4.3 Extreme validation years and model robustness

The validation period was strongly influenced by 2022 and 2023. In the regional dataset, 2022 had the most negative annual mean mass balance, at −3.043 m w.e., and the highest mean summer temperature, at 7.586 °C. The following year also had a strongly negative mean mass balance of −1.841 m w.e. and the lowest winter precipitation proxy from 2001 to 2025. These years were not ordinary fluctuations around the historical average. They represented complex conditions involving weak accumulation, high summer temperature, early snow depletion, and prolonged exposure of glacier ice.

Other observations support this interpretation. (*European State of the Climate 2023 | Copernicus*, n.d.) reported very low winter snow precipitation and an unusually warm summer, which led to the Alpine glacier's negative mass balance record in 2022. (Cremona et al., 2023) showed that some short heatwaves are responsible for about 35% of total ice loss in the summer of 2022 in the Swiss Alps. 2023 was also another unusual year for the Swiss Alps, with almost 10% glacier volume loss over both the 2022 and 2023 summers (*Copernicus: 2023 Is the Hottest Year on Record, with Global Temperatures Close to the 1.5°C Limit | Copernicus*, n.d.). These external observations confirm that the most difficult validation years in this thesis were also exceptional in the wider Alpine context.

The sensitivity analysis demonstrated how much these years affected the model metrics. Excluding 2022 from the final MLP validation period led to a reduction in RMSE from 0.742 m w.e. In another analysis, when both 2022 and 2023 were removed from the validation period, RMSE decreased to 0.328 m w.e. Other models like Random Forest and Gradient Boosted Trees showed similarly large reductions. This does not mean that the extreme years should be removed from the main evaluation. On the contrary, they are highly relevant to the climatic conditions expected in a warming future. The full 2021–2025 period was therefore retained as the main basis for model selection.

The sensitivity results have an important implication. Model error is not constant through time. It increases when the climate moves beyond the conditions represented in the training data. This is a common limitation of data-driven models and is particularly important for future glacier projections. The selected MLP can reproduce the general relationship between climate, glacier attributes, and annual mass balance, but its future outputs should be interpreted as scenario-based projections rather than precise year-by-year forecasts.

4.4 Future mass-balance and volume projections

The predictions of the future of the glacier mass balance showed a clear reduction during the twenty-first century. The mean mass balance for the selected 100 glaciers in this study under scenario SSP2-4.5 will decrease from -1.339 m w.e. to – 2.354 m w.e. from 2026 to 2100, and under scenario SSP5-8.5, it changes from -1.231 to -3.513 m w.e. During the first years of prediction, the amount of mass balance under the two scenarios is almost similar, because climate variability and bias-corrected baseline conditions at the short-term can overcome the long-term difference. This is why SSP5-8.5 does not appear worse in every early-period value. After the middle of the century, however, the scenarios separate clearly, and the stronger warming pathway produces a more negative mass balance.

The selected largest glacier, RGI60-11.02822, followed the same pattern but with more negative values than the regional mean. At the end of the century, 2076 to 2100, the predicted mean mass balance for this glacier reached -4.359 m w.e. under SSP2-4.5 and -5.404 m w.e. under SSP5-8.5. This 1.05 m w.e. more negative mass balance in the higher emission scenario highlighted the importance of this scenario at the end of the century, and this behavior is consistent with the previous studies. (Rounce et al., 2023b) in a study demonstrated the strong relationship between warming level and glacier loss. In addition, the recent CIMP6 modelling

confirms that higher emission scenarios produce more glacier loss, and model calibration for a specific glacier is very important, especially at local scales (Zekollari et al., 2024).

Dynamic volume-area scaling translated these continuous negative annual mass balances into volume reductions. The selected glacier kept 83.29% of the 2001 modeled volume in 2025 and fell to 4.65% under SSP2-4.5 and 3.15% under SSP5-8.5 in 2100. For the total 100 glaciers in the study area, this remaining volume was 72.76% in 2025, 2.62% under SSP2-4.5, and 1.32% under SSP5-8.5 scenarios.

These values indicate that by the end of the century, almost all glaciers in the study area will be wiped out. These predictions are more severe than some global average predictions, but this is not unexpected. Because the study focuses on a relatively small Alpine region, while global models combine regions with different climates, glacier sizes, and response times. Steep mid-latitudinal mountain glaciers can respond to warming rapidly. For instance, in a study conducted by Bolibar et al. (2022), they used deep learning to predict the volume loss in French Alpine glaciers, and their results predicted a 75 to 88% volume loss. Global studies also showed that even moderate warming scenarios will lead to huge glacier loss and higher warming scenarios will remove a larger share of remaining mass (Rounce et al., 2023b; Zekollari et al., 2024a). Nevertheless, since the models, baselines, periods, and glacier samples are different among the studies, a direct comparison between the results of various studies is not common. However, the direction and magnitude of change in this thesis are consistent with the wider evidence of rapid Alpine glacier decline.

The regional volume trajectories also illustrate an important geometric effect. As glaciers lose volume, their area becomes smaller. A smaller area reduces the absolute annual volume change produced by a given mass-balance value. This feedback causes the two future trajectories to approach low volumes near the end of the century, even though SSP5-8.5 has a more negative mass balance. Convergence at very small remaining volumes should therefore not be interpreted as convergence of climatic impact. It mainly reflects the limited ice left available to lose.

The difference between the scenarios remains scientifically and practically meaningful. The remaining volume under SSP5-8.5 is almost half of the remaining volume under SSP2-4.5. In general, the recent studies showed that postponing the mitigation of greenhouse gases or increasing the temperature temporarily over the target of the climate conventions can lead to glacier losses that remain irreversible for centuries (Schuster et al., 2025). Therefore, the results of this thesis are consistent with other recent studies and reinforce what modern studies have found: that is, mitigation cannot preserve all Alpine glaciers, but it still affects how much ice remains and how quickly it wipes out.

4.5 Methodological contribution

The main contribution of this thesis is the development of an integrated and transparent regional workflow. The study did not rely on just a single model or a single performance metric. It began with a consistent glacier sample and then with constructing a glacier-year dataset. Using this dataset, five modelling approaches were compared, and sensitivity to

extreme years was tested. Subsequently, the selected model was linked to the future climate scenarios and dynamic volume-area scaling. This sequence makes the assumptions and decisions visible at each stage.

The strict temporal validation design is one of the strongest parts of the workflow. Random splitting would have mixed observations from the same climatic period across training and validation sets. That approach could have produced more optimistic metrics without testing the real objective of the study, which is to use historical relationships to predict later and increasingly extreme conditions. By holding out 2021–2025, the analysis exposed the weaknesses of all models and provided a more realistic basis for model selection.

A second contribution is the explicit connection between machine learning mass balance prediction and changing glacier geometry. Many statistical applications stop after predicting mass balance. In this thesis, the annual mass balance was used to update volume, and area was recalculated after each annual step. The approach is simpler than a distributed ice-flow model, but it is physically more meaningful than applying mass-balance predictions to a fixed glacier area. The theoretical basis and limitations of volume-area scaling are well established in glacier research (Bahr et al., 1997, 2015; Huss & Farinotti, 2012).

A third contribution is the emphasis on interpretability and robustness. The study retained the raw and corrected future climate variables, separated independent validation from final full-dataset training, and treated the extended temporal experiment as supplementary rather than replacing the main workflow. This makes the results easier to audit and reduces the risk of presenting training performance as future predictive skill.

The workflow should therefore be understood as a regional screening and scenario-assessment tool. It is computationally lighter than full ice-dynamic modelling and can be applied where complete ice-thickness and long-term in-situ observations are unavailable. At the same time, it remains connected to physical glacier properties and can be improved as better data become available.

4.6 Limitations and uncertainty

The conclusions of this thesis must be interpreted together with several limitations. First, future climate data were represented by a single regional point and one CMIP6 model, MPI-ESM1-2-HR. The same future climate signal was combined with glacier-specific static attributes, but each glacier did not receive an independently downscaled future temperature and precipitation series. This limits the representation of local climatic gradients across elevation, aspect, and valley setting.

Second, future temperature required additive harmonization and an elevation adjustment before it could be used with the ERA5-Land trained model. The applied adjustment was a pragmatic way to bring the scenario data closer to high-elevation glacier conditions and to the historical predictor distribution. It should not be interpreted as a complete physical downscaling procedure or as proof of an exact source grid elevation. A fixed adjustment cannot reproduce seasonal lapse rate changes, temperature inversions, glacier boundary layer cooling, or local topographic effects.

Third, winter_tp was calculated from total October–April precipitation. It was used as a proxy for winter accumulation, but it did not separate rainfall from snowfall. This distinction will become increasingly important as warming raises the rain-snow transition elevation. The model also did not include solar radiation, snow-cover duration, albedo, debris cover, wind redistribution, avalanche accumulation, or daily heat-wave intensity. The strong impact of 2022 suggests that some of these removed processes are very important during the years that are the hardest to predict.

Fourth, most glacier attributes were treated as static model predictors. The glacier area changed within the volume-scaling model, but elevation distribution, slope, aspect, and hypsometry were not updated dynamically. As a glacier retreats to higher elevations and fragments, its climate sensitivity and geometry may change in ways that a static predictor structure cannot capture.

Fifth, volume-area scaling estimates bulk volume from surface area. It does not simulate ice flow, changes in thickness distribution, tributary disconnection, glacier fragmentation, or local bed geometry. The scaling coefficients were fixed for all glaciers, although the most appropriate parameters can differ among glacier types. The resulting values are therefore modeled volume trajectories, not direct observations or full ice dynamic simulations.

Sixth, uncertainty from the historical mass-balance dataset, climate data, model parameters, future scenarios, bias correction, and volume scaling was not propagated into a formal probabilistic uncertainty range. The projections are presented as deterministic trajectories for two scenarios. They show the behavior of the selected workflow, not the full range of plausible glacier futures.

Finally, choosing the 100 largest glaciers is appropriate since they represent the 89.90% of the total glacier surfaces in the region, but still, the remaining small glaciers, which cover 10.10% of the glacier surfaces, are not included; thus, the selected dataset does not describe the fate of every glacier in the bounding box. However, these small glaciers cover only 10.10% of the surface of glaciers, but many of them may disappear sooner than the larger glaciers, and this could be very crucial for local landscape and ecosystem change.

4.7 Recommendations for future research

Future work should first improve the spatial representation of climate forces. Daily or monthly projections could be extracted for each glacier or for several elevation bands. An ensemble of CMIP6 models would also allow climate model uncertainty to be separated from the difference between emission scenarios. Statistical or dynamical downscaling, which is supported by the elevation correction of a specific glacier, would reduce the dependence on a single representative point.

The parameter used for the precipitation predictor should also be improved. By separating rain and snow precipitation based on temperature, it is possible to convert the total precipitation to a variable for estimating snowfall. In addition, using other parameters such as albedo, radiation, debris cover, to name but a few, could improve the performance of the models in the extreme years. Using daily or monthly input data can also improve the model's performance,

and they can be very useful since the annual average data can hide short but intense melt events.

By validating each glacier individually, model evaluation could be expanded. To check if the model can generalize to glaciers that were not in the training phase, regional transfer or leave-one-glacier-out tests can be implemented. Machine learning tools for interpreting can be used to quantify how temperature, precipitation, elevation, and other attributes have an impact on each individual's predictions. This would make the MLP behave less ambiguously and identify the unrealistic physical behavior.

The volume component could be strengthened by using distributed ice-thickness datasets, glacier hypsometry, or flowline-based models such as OGGM. A hybrid workflow in which machine learning predicts mass balance and a physical ice-flow model updates the geometry of the glacier could be another suggestion. Such a workflow would have the flexible response of machine learning and ongoing changes in elevation, thickness, and glacier dynamics more realistic.

Finally, future projections should include uncertainty ensembles. Training the model with different conditions instead of using a single method can increase confidence. These changes can be different in initial circumstances, testing various configurations of machine learning models, using multiple climate models, and different bias-correction methods. This could be so crucial for using the results in other fields like water management, regional decision-making, and regional hydrological assessments, to name but a few.

4.8 Final conclusion

This thesis shows that a regional machine-learning workflow can provide useful insight into Alpine glacier evolution when it is combined with careful temporal validation and a physically grounded volume model. Many machine learning models were tested, among them the MLP Neural Network had the best performance and provided the strongest generalization for the validation period, which was from 2001 to 2025. The exceptional extreme years of 2022 and 2023 clearly affected the performance of the model. However, this limitation showed that predicting the future of glaciers becomes more difficult when the climate condition is substantially different from those of the historical range used in the training period. Despite all these challenges, the future overall situation is clear; mass balance became more negative progressively till the end of the century, and the difference between SSP2-4.5 and SSP5-8.5 will be more pronounced after the mid-century. The dynamic volume projections indicated severe loss under both pathways. By 2100, the remaining volume of 100 selected glaciers was only 2.62% of the 2001 total volume under SSP2-4.5 and 1.32% under SSP5-8.5. These amounts are not the exact volume in cubic kilometers, they are evidence of the current process of regional glaciers lost under both scenarios.

The value of the research lies in both the result and the method. The study provides a repeatable bridge between glacier inventories, climate data, machine learning, future scenarios, and changing glacier geometry. It also demonstrates why high training accuracy is

not enough, why extreme years must remain part of validation, and why data-driven models should be connected to physical understanding.

The ultimate conclusion is therefore direct. The selected glaciers in the study area of this research, the Alpine, north-west of Italy, will experience a huge and irreversible change during the twenty-first century. Under the low emission scenarios, the major loss is inevitable; nevertheless, they preserve more ice than the higher emission scenarios. For fast-responding Alpine glaciers, the difference between climate pathways is not an abstract global statistic. It determines the rate at which the remaining ice is lost and the amount that survives at the end of the century.

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