Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
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Federal Department of the Environment, Transport, Energy and Communications DETEC

Swiss Federal Office of Energy SFOE
Energy Research and Cleantech Division

Final report dated 21 November 2022

DeFROST4Hydropower

Extraction of snow water equivalent from satellite imagery for the hydropower industry



Source: © Robert Bye via Unsplash 2017

Date: 21 November 2022

Location: Bern

Publisher:
Swiss Federal Office of Energy SFOE
Energy Research and Cleantech
CH-3003 Bern
www.bfe.admin.ch

Subsidy recipients:
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SFOE contract number: SI/502279-01

The authors bear the entire responsibility for the content of this report and for the conclusions drawn therefrom.

Zusammenfassung (Deutsch)

Das Projekt DeFROST4Hydropower hat zum Ziel, die saisonalen Abflussvorhersagen durch die Assimilation von Schnee-Satellitendaten zu verbessern. Saisonale Vorhersagen ermöglichen die Vorhersage von Zuflussmengen für einen Zeithorizont von 30 bis 180 Tagen. Diese Vorhersagen verbessern die Planung und Vermarktung von Wasserkraft und sind eine wichtige Grundlage für die Bewirtschaftung von Wasserressourcen und Wasserreservoirs. Die wichtigsten Anwendungen von Vorhersagen für die Wasserkraft sind:

- Vorhersage des Zuflusses in große Stauseen, um die langfristige Füllstrategie zu verfeinern.
- Vorhersage der Wasserkraftproduktion von Laufwasserkraftwerken, um den Energiehandel (Kauf, Verkauf) zu verbessern und die richtigen Mengen zur richtigen Zeit anzubieten.
- Verringerung der mit der Erzeugung und dem Handel von Wasserkraft einhergehenden Anpassungslücken

Satellitendaten stellen die Schneebedeckung, die Schneehöhe und vor allem das Wasseräquivalent des Schnees (SWE) dar. Diese hochauflösenden Informationen können einen manchmal erheblichen Teil der Wasserzufuhr im Frühling und Sommer erklären. Obwohl diese Informationen bereits in den Ergebnissen von Regen-Abfluss-Simulationsmodellen verfügbar sind, wird erwartet, dass ihre Unsicherheit durch die neuen Satelliteninformationen reduziert wird und somit die Vorhersagbarkeit der Einträge verbessert wird.

Die Entwicklung saisonaler Vorhersagen wird in diesem Projekt für zwölf Einzugsgebiete durchgeführt, wodurch eine große Bandbreite an Einzugsgebietsgrößen und hydrologischen Regimen untersucht werden kann. Für jedes Einzugsgebiet werden saisonale Vorhersagen nach verschiedenen Methoden, ohne und mit Satellitendaten, erstellt und ihre Leistungsfähigkeit beurteilt. 9 regionale Wasserkraftproduzenten waren in diesem Projekt als Industriepartner involviert und haben die Nutzbarkeit der Technologie, die in diesem Projekt entwickelt wurde, eingeschätzt.

Die wichtigsten Erkenntnisse aus diesem Projekt und ihr strategischer Kontext für die Schweizerische Eidgenossenschaft sind folgende:

- Satelliten-SWE-Daten können erfolgreich produziert werden und können mit einem R-Wert von 0.86 im Vergleich zu Daten eines hochauflösenden Sensors sehr zuverlässig sein- insbesondere bei hoch gelegenen Einzugsgebieten, die einen Referenzpunkt besitzen (punktuelle Bodenmessung, SWE aus der Modellierung). Satellitengestütze SWE Daten in niedrig gelegenen, stark bewaldeten oder gletscherreichen Gebieten sind weniger akkurat und müssen momentanauf der Grundlage eines Regen-Abfluss-Modells kalibriert werden. Dies bedeutet, dass die in diesem Projekt entwickelten Satellitendatensätze technologiebasierte Schwachpunkte haben, die verbessert werden müssen, damit die Integration der Daten für die Wasserkraftproduzenten universal von Nutzen sein kann. Sobald diese Verbesserungen abgeschlossen sind, können die mit dieser Technologie gewonnenen Erkenntnisse zu den Zielen der Energiestrategie 2050 beitragen, mit der die durchschnittliche jährliche Stromproduktion aus Wasserkraftwerken bis 2050 auf 38.600 GWh gesteigert werden soll, wobei die schweizerische Gewässerschutzgesetzgebung zu beachten ist und eine Anpassung an die sich ändernden hydrologischen und sonstigen klimatischen Bedingungen erfolgen soll. Ein wichtiges Fazit ist, dass die Qualität der SWE ausserdem ein entscheidender Faktor für die Qualität der saisonalen Zuflussprognose und damit für die potenziellen wirtschaftlichen Auswirkungen ist.

- Saisonale Abflussvorhersagen, die mithilfe von Regen-Abfluss-Modellen und linearen Regressionen erstellt werden, können die Prognosefehler im Vergleich zur Verwendung historischer Durchschnittswerte der Zuflüsse (die üblicherweise verwendet werden) stark reduzieren. Die Abweichungen werden oft um 30% bis 50% verringert.

- Die Assimilation von SWE-Satellitendaten führt zu einer weiteren Verbesserung der Vorhersageleistung, insbesondere für die längsten Zeiträume (60-180 Tage) und große Einzugsgebiete. Die anfänglichen Abweichungen werden um weitere 5%-10% verringert. Diese Erkenntnis trägt insbesondere zu den folgenden Forschungsschwerpunkten des BFE-Wasserkraftforschungsprogramms bei:
  - Einführung von Massnahmen zur Erhöhung der betrieblichen Flexibilität.
  - Verfeinerung der Prognosemodelle im Hinblick auf eine Steigerung der Produktion und der Wirtschaftlichkeit.
  Verbesserte saisonale Prognosen tragen auch zu den Zielen des Bundesgesetzes über eine sichere Stromversorgung mit erneuerbaren Energien bei, das Wachstum der inländischen erneuerbaren Energien und die Versorgungssicherheit der Schweiz zu stärken.

- Die wirtschaftliche Bewertung zeigt, dass die Anpassungen beim Handel mit Wasserkraft durch die Verwendung von saisonalen linearen Regressionsprognosen mit Schneedaten bis zu 50 % reduziert werden können. Insgesamt hat es sich jedoch als schwierig erwiesen, die wirtschaftlichen Auswirkungen dieser verbesserten Zuflussprognose zu quantifizieren. Energiehandel und -erzeugung sind komplexe Prozesse, bei denen viele Faktoren eine Rolle spielen (Marktschwankungen, Preisschwankungen, individuelle Betriebs- und Handelsstrategien, der Faktor Mensch u.a.). Um eine Quantifizierung zu ermöglichen, wären eine oder mehrere vertiefte Einzelstudien mit Energieerzeugern notwendig.

- Generell wird das Potenzial dieser Technologie von den Industriepartnern positiv eingeschätzt. Je nach Anlage werden Umsatzsteigerungen von durchschnittlich 50.000 bis 500.000 Euro pro Jahr in Aussicht gestellt. Darüber hinaus wird die Technologie als ein Schritt in Richtung Digitalisierung und mehr Nachhaltigkeit in der Wasserkraftbranche gesehen. Insbesondere wird dies dazu beitragen, die Position der Schweizer Wasserkraft auf dem Energiemarkt zu stärken, ohne dass ein Ausbau erforderlich ist und die Wasserläufe möglicherweise beeinträchtigt werden, was das Ziel 7 für nachhaltige Entwicklung und die Schweizer Gewässerschutzgesetzgebung unterstützt. Da derzeit nur 4 Jahre an Satellitendaten zur Verfügung stehen, wird eine noch stärkere Reduzierung des Vorhersagefehlers erwartet, wenn in Zukunft mehr Daten (idealerweise 8 oder mehr Jahre) zur Verfügung stehen.

- Durch den Einsatz von Modellen des maschinellen Lernens lassen sich einige Prognosen nur geringfügig verbessern. Allerdings macht die Entwicklung solcher Modelle die Methodik komplexer, ohne dass die Leistung ausreichen verbessert wird.

Résumé (Français)

Le projet DeFROST4Hydropower a pour objectif d'améliorer les prévisions saisonnières de débit par l'assimilation de données satellite de neige. Les prévisions saisonnières permettent de prévoir les volumes d'apports pour des horizons de 30 à 180 jours. Ces prévisions permettent d'améliorer la planification et la commercialisation de l'hydroélectricité, et sontune donnée essentielle pour la gestion des ressources en eau et des réservoirs. Les applications principals des prévisions pour l'hydroélectrité sont:

- Prévoir les apports dans les grandes retenues, afin d'affiner la stratégie à long terme de remplissage
- Prévoir la production hydroélectrique des aménagements au fil de l'eau, de manière à mieux échanger l'énergie (acheter, vendre) et proposer les bonnes quantités au bon moment
- Réduire les écarts d'ajustement inhérents à la production et au commerce d'hydroélectricité

Les données satellites représentent la couverture de neige, la hauteur de neige, et surtout l'équivalent-eau de la neige (SWE). Ces informations à haute résolution permettent d'expliquer une partie parfois importante des apports hydrique au printemps et en été. Même si ces informations sont déjà disponibles dans les résultats des modèles de simulation pluie-débit, il est attendu que leur incertitude soit réduite grâce à cette nouvelle information satellite, et ainsi que la prévisibilité des apports soit améliorée.

Le développement de prévisions saisonnières est réalisé pour douze bassins versants dans ce projet, permettant d'explorer une large gamme de tailles de bassins versants et de régimes hydrologiques. Sur chaque bassin versant, les prévisions saisonnières sont établies selon plusieurs méthodes, sans et avec données satellites, et leurs performances sont évaluées. 9 producteurs régionaux d'hydroélectricité ont été impliqués dans ce projet en tant que partenaires industriels et ont évalué l'utilisabilité de la technologie développée dans le cadre de ce projet

Les principaux enseignements tirés de ce projet, ainsi que leur contexte stratégique pour la Confédération suisse, sont les suivants :

- Les données SWE par satellite peuvent être produites avec succès et peuvent être très fiables avec une valeur R de 0,86 par rapport aux données d'un capteur à haute résolution, en particulier pour les bassins versants de haute altitude qui ont un point de référence (mesure ponctuelle au sol, SWE issu de la modélisation). Les données SWE satellitaires dans les zones de basse altitude, fortement boisées ou riches en glaciers sont moins précises et doivent être calibrées pour le moment. Cela signifie que les ensembles de données satellites développés dans le cadre de ce projet ont des faiblesses basées sur la technologie qui doivent être améliorées afin que l'intégration des données puisse être universellement bénéfique pour les producteurs d'hydroélectricité. Bien que ces améliorations soient encore en cours, les connaissances générées par cette technologie contribuent aux objectifs de la Stratégie énergétique 2050, qui prévoit de porter la production annuelle moyenne d'électricité des centrales hydroélectriques à 38 600 GWh d'ici 2050, tout en respectant la législation suisse sur la protection des eaux et en s'adaptant à l'évolution des conditions hydrologiques et climatiques. Les prévisions saisonnières de débit, réalisées par modélisation pluie-débit jaugée et régression linéaire, permettent de fortement réduire les erreurs de prévisions, par rapport à l'utilisation de la moyenne historique des apports (couramment utilisée). Les écarts sont souvent réduits de 30% à 50%.

- La qualité du SWE est un facteur déterminant pour la qualité de la prévision des apports saisonniers, et donc de l'impact économique potentiel. L'assimilation des données satellite de SWE permet d'améliorer encore la performance des prévisions, en particulier pour les échéances les plus longues (60-180 jours) et les grands bassins versants. Les écarts initiaux sont encore réduits de 5%-10%. Ce résultat contribue particulièrement aux priorités de recherche suivantes du programme de recherche sur l'énergie hydraulique de l'OFEN :
  - Introduire des mesures visant à augmenter la flexibilité de l'exploitation.
  - Affiner les modèles de prévision en vue d'augmenter la production et la rentabilité.
  L'amélioration des prévisions saisonnières contribue également aux objectifs de la loi fédérale sur la sécurité de l'approvisionnement en électricité au moyen d'énergies renouvelables, qui visent à renforcer la croissance des énergies renouvelables nationales et la sécurité d'approvisionnement de la Suisse.

- L'évaluation économique montre qu'une réduction des ajustements au cours du processus d'échange d'hydroélectricité peut atteindre 50 % grâce à l'utilisation de prévisions saisonnières par régression linéaire avec des données sur la neige. Pourtant, dans l'ensemble, l'impact économique de cette amélioration des prévisions de débit entrant s'est avéré difficile à quantifier. Le commerce et la production d'énergie sont des processus complexes dans lesquels de nombreux facteurs jouent un rôle (fluctuations du marché, fluctuations des prix, stratégies individuelles d'exploitation et de commerce, facteur humain, entre autres). Une ou plusieurs études individuelles approfondies auprès des producteurs d'énergie seraient nécessaires pour permettre une quantification.

- De manière générale, les partenaires industriels perçoivent positivement le potentiel de cette technologie. Des augmentations de revenus de 50 000 à 500 000 euros par an en moyenne sont envisagées selon les installations. En outre, elle est perçue comme une étape vers la numérisation et une durabilité accrue de l'industrie hydroélectrique. Plus précisément, cela contribuera à renforcer la position de la production hydroélectrique suisse sur le marché de l'énergie sans qu'il soit nécessaire de l'étendre et de porter atteinte aux cours d'eau, soutenant ainsi l'Objectif de développement durable 7 et la législation suisse sur la protection des eaux. Étant donné que seules 4 années de données satellitaires sont actuellement disponibles, des réductions encore plus importantes de l'erreur de prédiction sont attendues avec davantage de données (idéalement 8 années ou plus) à l'avenir.

- L'utilisation de modèles d'apprentissage automatique ne permet d'améliorer certaines prévisions que de manière marginale. Cependant, le développement de tels modèles rend la méthodologie plus complexe, sans pour autant améliorer suffisamment les performances.

Summary (English)

The goal of the project is to improve the seasonal inflow forecasts by the assimilation of snow data from satellites. The seasonal forecast aims at predicting inflow volumes at lead times from 30 to 180 days ahead. The seasonal forecasts are in general needed for a better planning and trading of hydropower, as well as for reservoir and water management. The main applications of these forecasts in the context of hydropower are:

- Predict the inflow in large reservoirs, to adjust the long-term strategy of filling the reservoirs
- Predict the hydropower production at run-of-river power plants, in order to trade (sell, buy) the correct amount of energy at the right moment
- Reduce the adjustments needed during the production and trading processes

Satellite data represent snow cover, snow height, and especially snow water equivalent (SWE). This high-resolution information can explain a sometimes crucial part of the water supply in spring and summer. Even if this information is already available in the results of rainfall-runoff simulation models, it is expected that their uncertainty will be reduced thanks to this new satellite information, and thus the predictability of the inputs will be improved.

The development of seasonal forecasts is carried out for twelve catchments in this project, allowing a wide range of catchment sizes and hydrological regimes to be explored. For each watershed, seasonal forecasts are developed using several methods, without and with satellite data, and their performance is evaluated. 9 regional hydropower producers were involved in this project as industrial partners and assessed the usability of the technology developed in this project.

The main lessons learned from this project along with their strategic context for the Swiss Confederation are as follows:

- Satellite SWE data can be successfully produced and can be very reliable with an R-value of 0.86 compared to data from a high-resolution sensor, especially for high altitude catchments that have a reference point (point ground measurement, SWE from modelling). Satellite-based SWE data in low-lying, heavily forested or glacier-rich areas are less accurate and currently need to be calibrated to determine SWE based on a rainfall-runoff model. This means that the satellite datasets developed in this project have technology-based weaknesses that need to be improved for the integration of the data to be universally beneficial to hydropower producers. While these improvements are still an ongoing process, the insights which are generated through this technology could contribute to the aims of the Energy Strategy 2050, through which the mean annual production of electricity from hydropower plants is to be increased to 38,600 GWh by 2050 whilst respecting Swiss water protection legislation and adapting to changing hydrological and other climate conditions. Seasonal flow forecasts, performed by rainfall-runoff modelling and linear regression, can greatly reduce forecast errors, compared to the use of historical average inflows (commonly used). The errors are often reduced by 30% to 50%. The quality of the SWE is found to be a determining factor for the quality of the seasonal inflow forecast, and therefore the potential economic impact.

- The assimilation of SWE satellite data further improves forecast performance, especially for longer time frames (60-180 days) and large catchments. The initial deviations are further reduced by 5%-10%. This finding particularly contributes to the following research priorities of the SFOE Hydropower Research Programme:

- Introduce measures to increase operational flexibility.
- Refine forecasting models with a view to increasing production and cost-effectiveness.

Improved seasonal forecasts also contribute to the aims of the Federal Act on a Secure Electricity Supply with Renewable Energies to strengthen the growth of domestic renewable energies and of Switzerland's supply security.

- The economic assessment shows that a reduction of the adjustments during the trading process of hydropower can reach 50% through use of seasonal linear regression forecasts with snow data. Yet overall, the economic impact of this improved inflow forecast has proven difficult to quantify. Energy trading and generation are complex processes in which many factors play a role (market fluctuations, price fluctuations, individual operation and trading strategies, the human factor, among others). One or more in-depth individual studies with energy producers would be necessary to enable quantification.

- Generally, the industry partners perceive the potential of this technology positively. Revenue increases of between EUR 50,000 and 500,000 per year on average are envisaged depending on the facilities. In addition, it is perceived as a step towards digitalisation and increased sustainability of the hydropower industry. Specifically, this will help to reinforce the position of Swiss hydropower generation in the energy market without the need for expansion and potential harm to waterways, supporting Sustainable Development Goal 7 and Swiss water protection legislation. As only 4 years of satellite data are currently available, even higher reductions in prediction error are expected with more data (ideally 8 or more years) in the future.

- The use of machine learning models can only slightly improve some forecasts. However, developing such models makes the methodology more complex without sufficiently improving performance.

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Abbreviations

ARIMA	AutoRegressive Integrated Moving Average
DEM	Digital Elevation Model
ESP	Ensemble Streamflow Prediction
GWh	Gigawatt hour
HS	Snow Height a.k.a Snow Depth
LiDAR	Light Detection And Ranging
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MLP	MultiLayer Perceptron
MWh	Megawatt hour
NDSI	Normalized Difference Snow Index
PF	Perfect Fit
RADAR	RAdio Detection And Ranging
RMSE	Root Mean Square Error
RS	Routing System
SAR	Synthetic Aperture Radar
SCE	Snow Cover Extent
SLF	WSL-Institut für Schnee- und Lawinenforschung
SWE	Snow Water Equivalent
SMHI	Swedish Meteorological Hydrological Institute
STP	SSH File Transfer Protocol
UAS	Unmanned Aerial Systems

A. Introduction

a. Background information and current situation

Snow water equivalent (SWE) is a key factor in hydrological modelling for water utilities and hydropower, representing the volume of water stored in the snowpack. This variable is crucial for hydropower plants located in basins in snow-prone regions, since this is the only variable determining water inflow except for the meteorological factors of temperature and precipitation. This is the case in about 444 hydropower plants in Switzerland alone.

Spring melt inflow from February to June, when the influence of the snowpack is most important for the watershed flow, has proven to contain several uncertainties in the mid-term (the typical forecasting range is between +30 to +150 days ahead). This is even more pressing under climate change conditions that induce a higher variability in the meteorological predictability. The most frequent methods of acquiring SWE information for inflow forecasting are annual field surveys and rainfall-runoff modelling. Both approaches can be operationally expensive and prone to error (error estimated up to 30% by the SMHI).

Rainfall-runoff modelling is the sounder approach of the two. Here, the snowpack properties can be calculated by simulation models, which use ground precipitation and air temperature as input. These models are calibrated over many years at discharge gauging stations and are reliable. However, the SWE estimates, which are an internal variable of these models, cannot directly be validated through rainfall-runoff modelling and perform less reliably under extreme weather conditions or unprecedented events caused by climate change. SWE measurements are *indirectly* validated by the calculation of spring and summer inflows, and their comparison with observed values. This means that there is always a residual uncertainty regarding the SWE. This leads to increasing pressure to innovate and find novel approaches to improve the mid-term forecast accuracy.

Various methods exist for predicting the future mid-term and long-term inflows (Table A-1). The literature shows that the most cost-efficient methods are based on linear and multi-linear regressions rather than ML or ensemble streamflow forecasting (Apel et al., 2018; Tang et al., 2016 ; Rosenberg et al., 2011 ; Pagano et al., 2009 ;). Their cost is very low, and they provide similar results to more complex methods.

Short-term forecasts	Seasonal forecasts
Deterministic methods [1-7]	Hydrological models [16-25]
Physical models	Ensemble Streamflow Prediction (ESP)
Conceptual lumped models	Climate-Model-Based Seasonal Hydrological Forecast (CM-SHF)
Statistical methods [8-15]	Statistical methods [26-33]
ARIMA, Linear regressions, Multilinear	Linear regressions, Multilinear
Machine Learning	Machine Learning

Table A-1 Methods developed for seasonal inflow forecasting

b. Purpose of the project

We propose to counter the forecast uncertainty that exists due to the estimation of SWE using information derived from satellite imagery, especially RADAR imagery like the Sentinel-1 information provided by the European Space Agency. In an operational setting, this method would allow for the extraction of continuous and observed SWE data, which has been shown to improve streamflow forecasts. In the last decades, scientists have extensively investigated the potential of Synthetic Aperture RADAR (SAR) data for deriving SWE directly or through its relationship with snow height (HS). Sun et al. (2015) used microwave scattering models to analyse the scattering characteristics of C-band SAR over snow-covered areas and therefore estimated the distribution of the SWE using SAR data and snow cover data measured in the field. Conde et al. (2017) presented a methodology for mapping the temporal variation of SWE through the SAR Interferometry technique and Sentinel-1 data.

The proposed approach uses satellite-derived HS to process it to SWE, since HS is known to account for more than 90% of the variation in SWE, along with snow density accounting for approximately 10%. Snow density information, while important for the calculation of SWE, is often homogeneous over larger regions and the variable is therefore summed up in bulk density measurements which reflect the regional average. This is caused by the normal distribution of snow density values, where on average 50% of all bulk density measurements for seasonal snow lie in the narrow range of 0.244 to 0.375 g cm−3. Some scientists go even as far as to use a constant as snow density for entire mountain ranges, often selecting a value of around 0.312 g cm−3. HS information is well-established as crucial for exact SWE observation and prediction on a global scale and even less frequent HS observations than planned in this project have proven value for SWE. Wegaw's approach as explained in Section B.b allows to both directly extract snow height from SAR imagery, and to infer the snow density value by time-series based modelling of the snow ablation and accumulation process.

The methodology to extract HS information from satellite imagery is present in current scientific literature but is not finished in its development. Lievens et al. (2019) published a methodology to extract HS at 1km resolution based on SAR data on a global scale with strong results. While taking inspiration from the approach, the consortium member Wegaw has developed its own innovative approach to extract high-accuracy snow height information to be used as the basis for SWE extraction.

c. Objectives

The goal of the project was develop a product to provide mid-term water inflow forecast during the Spring melt season based on observable and precise Snow Water Equivalent (SWE) data for the last 5 years (2017-2021) and subsequently to run an energy production and discharge simulation to identify the potential of increased energy production/ trading capabilities and monetary saving for the industry partners participating in the study.

We therefore set the following technical targets:

- The inflow forecast error optimized with the project partner data will reduce the relative inflow forecasting error during spring melt by minimum 10%.

- The SWE product based on earth observation information measures SWE values with minimum 80% accuracy based on SLF area validation data on a basin level in Switzerland by the end of the project. This target was converted due to the unit of the SWE data. Continuous values do not meet the criteria to be measured in accuracy percentages. Instead, we used a 0.8 correlation coefficient (R-value) to assess our accuracy goal.

The research questions to be studied to reach the technical target are the following:

- To what extent can spatial data be used to calculate SWE and how scalable are these solutions for optimizing hydrological forecasts?
- What are the limitations of C-band SAR to extract information on SWE for Switzerland?
- What maximum improvement in accuracy can be reached by integrating SAR information in comparison to current solutions on the market?

Since operational use and economic impact are a major aspect of the project, the economic target is the following:

- Improve the annual average price per MWh by 0.5%. For context, in the Emosson basin, this translates to on average 200k CHF per year.

B. Procedures and methodology

To achieve the project objectives and answer the research question, the project and cooperation between the partners were structured as follows (Figure B-1):

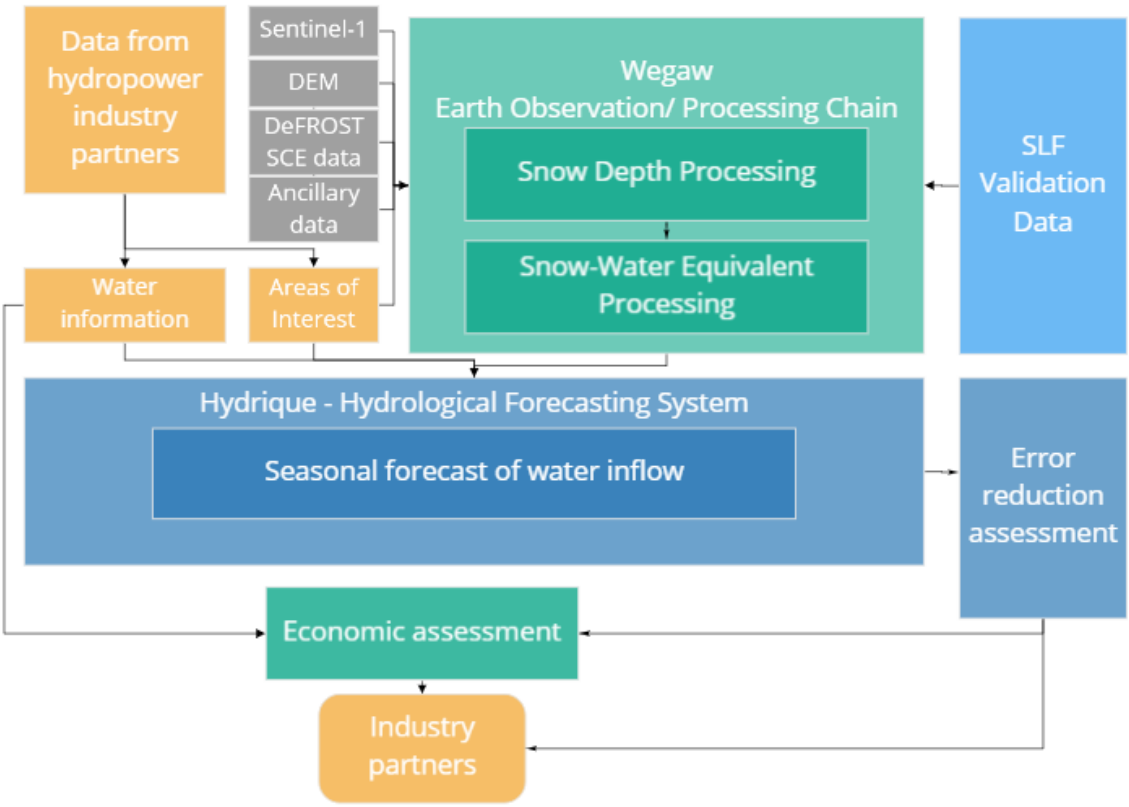


Figure B-1 Overview of consortium members (early adopters: orange, Wegaw: green, SLF: light blue, Hydrique: dark blue), data flow and core input variables (grey).

The majority of hydropower companies contributing to the project as industry partners provided the following data:

- Discharge information for the last 5 years.
- Data on critical water level, water used for energy generation, and spill for the last 5 years.
- Geospatial information for the basins to observe (shapefile and dam location).

The discharge data was used for the error reduction assessment by comparing the provided discharge data with the simulated one. The other data sets were used in the economic assessment to quantify potential savings and opportunities for the hydropower companies to leverage the information provided by Wegaw and Hydrique (e.g., potential increases in generation/ reductions in spill).

Wegaw processes SAR-based SWE information partially derived from snow height data, which were produced based on satellites and validated through ground information. The products are validated by drone flights and in-situ measurements conducted by the Institute for Snow and Avalanche Research (SLF). The SWE information is subsequently ingested by Hydrique's hydrological forecasting system which produces a seasonal forecast of water inflow for 30, 60, 90 and 120 days in the future for each

basin. The reduction of the discharge error was determined by Hydrique. The results were then redistributed back to the industry partners and used in internal assessment of the partners and the key project team.

In order to calculate the economic benefit, first industry partners analyzed internally how much water inflow error reduction impacts their trading revenues. Based on this data, the consortium was able to assess what will be the economic impact of the SWE in a seasonal hydrology model. In order to extract this knowledge, the consortium worked closely with industry partners' trading team to find out this relationship.

In order to calculate the energy generation improvement, manual analysis on short term forecasting was done, comparing the non-snow operations of the dams and snow influenced operations of the dam and how the total discharge error, water spill and water volume used for energy generation change. Based on this, the consortium analysed how much extra energy the industry partners would be able to produce when ingesting snow data in their models.

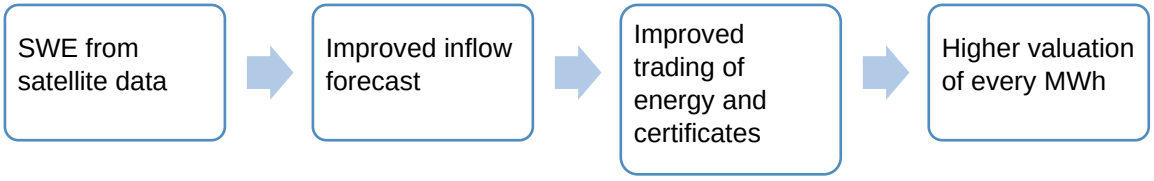


Figure B-2 General flow from satellite data to economic impact.

The objectives mentioned in Section A.c were aimed to be evaluated using the following methodologies:

Technical evaluation: Measuring the technical project goals was done by the key partners based on spatial data analysis and hydrological modelling.

1. **Evaluation of the first technical target (>0.8 correlation coefficient between SLF drone data and Wegaw measurements)**: Based on SLF validation data. Exact snow height and SWE information was derived from drone flights using laser as described in Section B.b.ii. In addition, past SWE measurements available in the SLF archive were used to extent the validation data set. These measurements were used to extract statistical values including RMSE, R^2 and correlation coefficient (R). This was done on SLF-provided datasets in the second half of the project using spatial statistics tools in Python.
2. **Evaluation of the second technical target (10% relative inflow forecast error reduction):** Hydrique Ingénieurs performed a comparison of inflow values to assess if the stated minimum 10% reduction in error is reached by comparing inflow forecasts produced with and without satellite data input. This will be performed with lead time of 30, 60, 90 and 120 days, giving a total of 4 indicators. This process was conducted by Hydrique in March-May 2022 for each of the basins provided by the industry partners.

A test on the system & modelling capabilities, as well as SWE performance was conducted during the Factory-Acceptance-Test as part of Work Package 3.

Economic evaluation: The economic impact of the project, and therefore the assessment if the target is met, was based on the information complied by the industry partners in conjunction with the consortium data.

1. **Economic improvement**: In order to calculate the trading improvement, first industry partners analysed internally how much water inflow error reduction impacts their trading revenues, based on the power futures increase. Based on this data, the consortium was able to assess what will be the economic impact of the SWE in a seasonal hydrology model. To extract this knowledge, the consortium worked closely with industry partners trading team. This was conducted in July- September 2022 by a selection of consortium members.

2. **Energy generation improvement:** To calculate the energy generation improvement, manual analysis on short term forecasting was done, comparing the non-snow operations of the dams and snow-influenced operations of the dam and how the total discharge error, water spill and water used for energy generation changed. Based on this, the consortium analysed how much extra energy the industry partners were able to produce when ingesting snow data in their models. This step was conducted in July - September 2022 by selected consortium members.

To optimally frame and execute the project, we also ran a user needs collection with the industry partners to best understand their way of operating, and gain clarity on how we can create the most added value for Swiss energy generators.

For that, we executed 1-to-1.5-hour long interviews with each individual generator to cover the following topics:

- Data requirements
- Time requirements
- Basin requirements
- SWE data usage
- Minimal accuracy
- Economic potential
- Expected Results

The results were collected (see Appendix) and integrated into the methodology described below.

a. Pilot catchments in the project

The studied catchments cover the Mont Blanc massif, the Jura, the Pre-Alps and the Alps. They have different hydrological regimes and cover a good part of the range of watershed types present in Switzerland. Table 3.1a shows the main characteristics of the catchment areas.

Catchment	Total area (km2)	Glacier area (km2)	Mean discharge (m3/s)	Min/max altitudes (m a.s.l.)
Léman	8000	680	250	372-4634
Arve	2082	108	73.19	370-4810
Lac de Gruyère	949	-	33.1	700-3000
Emosson	81	22	5.06	1650-3700
Ferden	164	32	6.97	1800-3900
Lac de Joux	156	-	4	1000-1500
Hongrin	87	-	2.89	1300-2500
Gletsch	40	19	2.72	2300-3600
Kummenbord	22	1.5	1.25	2000-3200
Zeuzier	17	0.3	2.51	1800-3000
Godet	13	-	0.89	1800-2500
Bortelsee	2	0.02	0.25	2400-3200

Table B-1 Main characteristics of the catchments studied in the DeFROST4Hydropower project

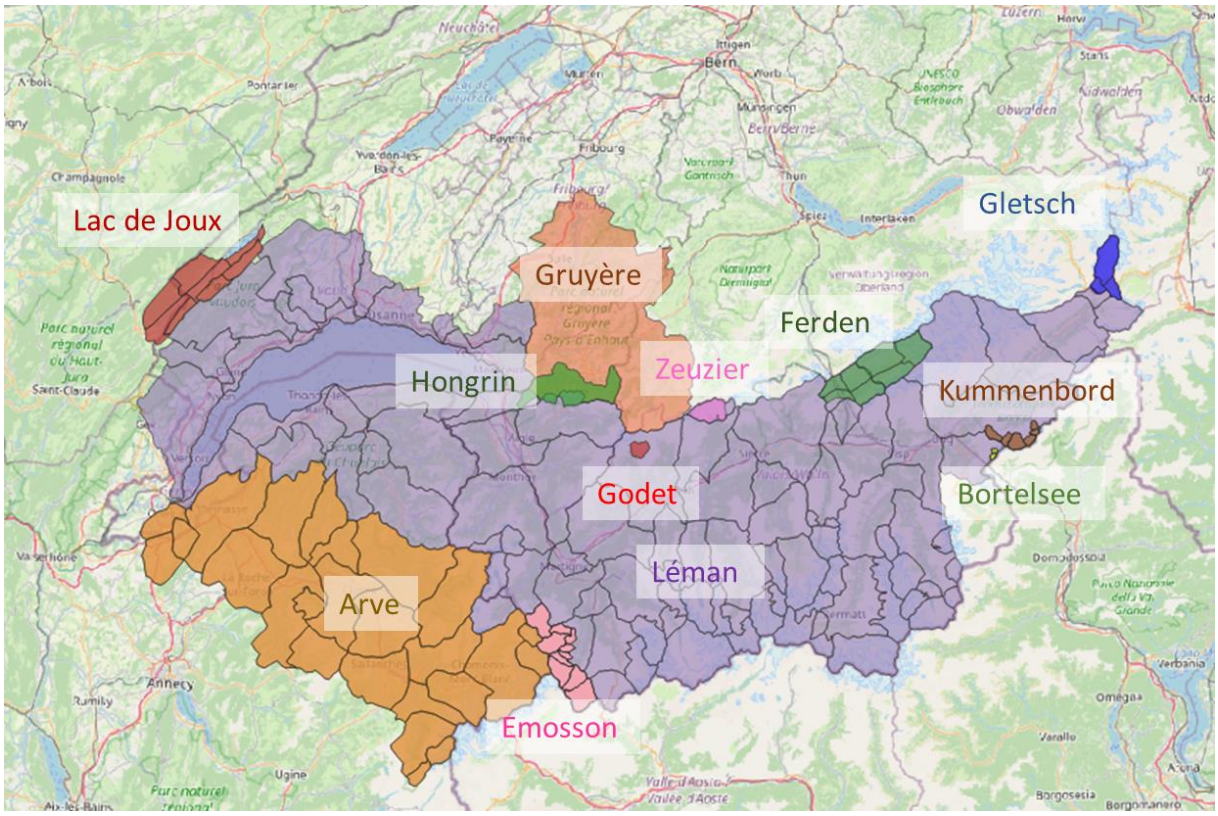


Figure B-3 Location of the catchments studied in the DeFROST4Hydropower project.

b. Earth Observation System by Wegaw

i. System Architecture

The purpose of this work was to design a system to provide a weekly map of SWE on remotely sensed data for any required catchment area.
Wegaw uses the following data to produce the SWE product:

- ESA's Sentinel-1 satellite imagery (GRD and SLC imagery)[1]
- Pre-existing DeFROST Snow Cover Extent information (based on optical imagery (Sentinel-2A/B[2], MODIS Terra/ Aqua[3], VIIRS[4]) and RADAR data (Sentinel-1A/B), ALOS Global Digital Surface Model at 30m resolution[5], meteorological information
- Global Multi-resolution Terrain Elevation Data 2010 DEM (335m) [6]
- Ancillary data includes CORINE Land Cover (CLC 2018)[7], Copernicus Pan-European High-Resolution Layer on Tree Cover Density[8]

The methodology is based on Wegaw's existing products covering snow cover extent (SCE) and snow height (HS). The SCE contains information on the location of the snow, indicating snow or no-snow at over 90% accuracy at resolutions between 2m and 500m. It is based both on optical and RADAR information to maximize precision and spatial & temporal resolution. The snow detection using optical is based on the Normalized-Difference Snow Index (NDSI) and a variety of infrared (NIR and SWIR) and other band thresholds (Blue and Green), allowing us to reliably identify snow in each pixel. The SCE is also used to extract the current altitude of the snow, the snow line.

The SCE and the snowline product are used in support of the snow height product The snow height product contains information on snow height in centimetres per pixel or scaled for a whole basin. This information is extracted from Sentinel-1's RADAR data through tracking of snow ablation and accumulation through changes in the incoming phase signal between two points in time, called time-series change detection. This data is processed together with slope, elevation, and aspect information derived from a high-resolution Digital Elevation Model (DEM) (Figure B-4).

[1] https://sentinel.esa.int/web/sentinel/missions/sentinel-1

[2] https://sentinel.esa.int/web/sentinel/missions/sentinel-2

[3] https://terra.nasa.gov/about/terra-instruments/modis

[4] https://earthdata.nasa.gov/earth-observation-data/near-real-time/download-nrt-data/viirs-nrt

[5] https://www.eorc.jaxa.jp/ALOS/en/aw3d30/index.htm

[6] https://topotools.cr.usgs.gov/gmted_viewer/viewer.htm

[7] https://land.copernicus.eu/pan-european/corine-land-cover/clc2018

[8] https://land.copernicus.eu/pan-european/high-resolution-layers/forests

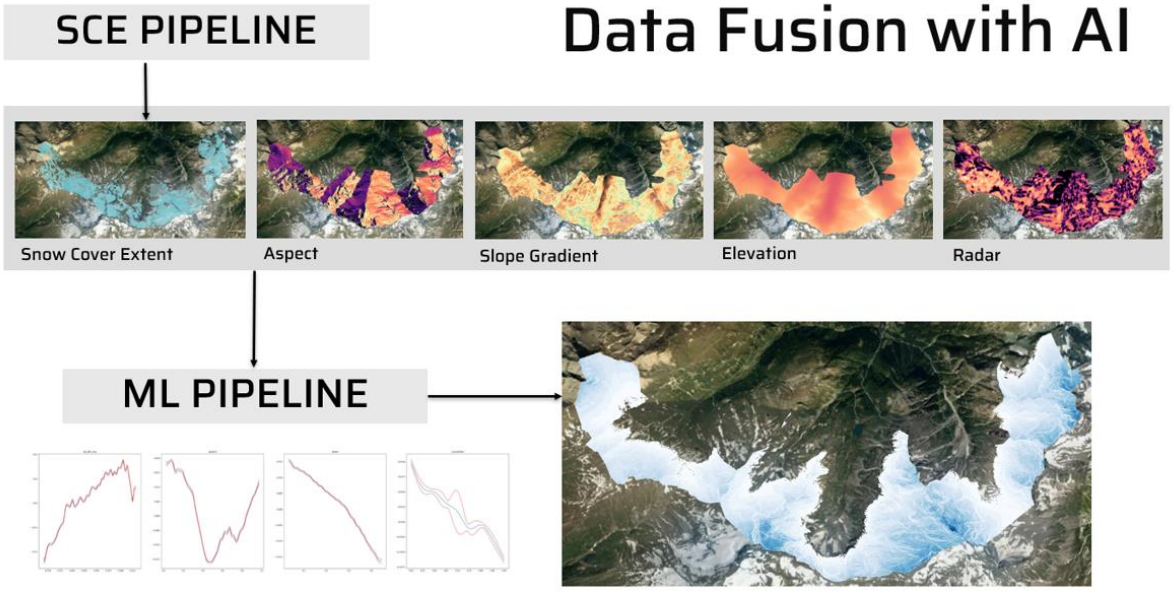


Figure B-4 Machine learning and data fusion pipeline of Wegaw visualized though spatial data.

To maximise the impact of the data set and enable the transformation to SWE, the HS information based on multiple SAR readings is combined with all other available data is ingested into our Machine Learning-based system in combination with other available information (such as station information, laser flights, etc.) to create a daily-updated “input layer”.

This input layer is combined with the “static layer” to ensure a natural distribution of the snow. This high-resolution spatial layer contains important information on the natural distribution of snow, such as redistribution due to elevation, slope, aspect and micro-geomorphological characteristics. In addition, Wegaw’s SCE and snowline products are added to exclude potential noise and outliers.

These three signals are combined within our system using cutting-edge machine learning techniques to minimize uncertainty, compensate for noises in the data, and ensure a high-accuracy output. For the final step of the transformation to SWE, the ablation and accumulation dynamics of the snow information allow us to model physical forces on the snow to quantify compression and create snow density and calculate SWE.

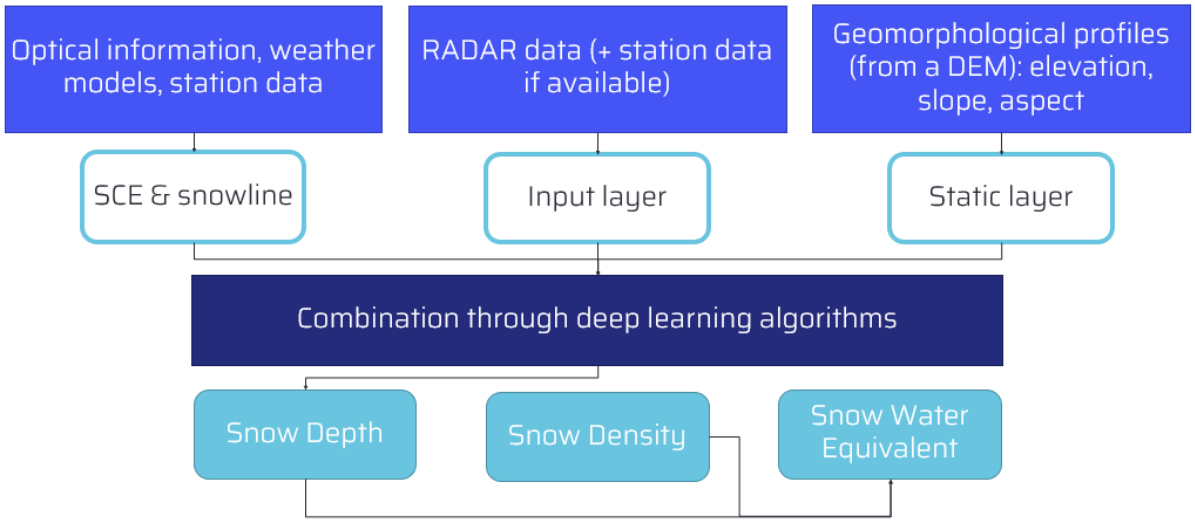


Figure B-5 Snow Water Equivalent extraction methodology by Wegaw.

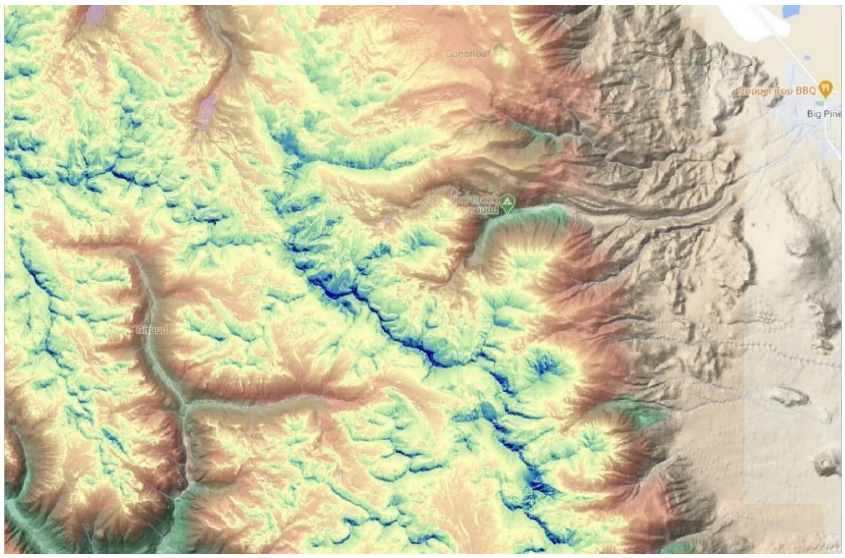


Figure B-6 Examples of snow height distribution extracted from RADAR information.

Wegaw's HS product has been validated extensively on point data in Switzerland for snow height up to 3m and on point data by the government of British Columbia, Canada, for 3m plus. Point validation of the snow height product reached average accuracies of over 80% in both Switzerland and Canada, peaking at over 90% in areas unaffected by vegetation. While a great starting point, point validation does not reflect the dynamics of snow distribution over an entire basin, but only at the measurement point. In addition, the topography has to meet specific criteria in the first place to qualify for hosting a station (low slope, low avalanche risk, etc.). This leads to the conclusion that station information, while highly reliable, is not representative for large regions, explaining the need for area validation.

Wegaw's first attempts on area validation were conducted based on 50m resolution HS information from LiDAR flights of the NSDIC DAAC Airborne Snow Observatory (ASO)[9], which provides 54 high-resolution datasets on snow height and SWE. Validation over entire basins ranges between a 90% correlation coefficient (24cm RMSE) for areas dominated by ice, glacier, and rock and 70% correlation (50cm RMSE) for areas with prominent vegetation or urban activity. While the outlook was promising, simply transferring the insights bears a high risk to add uncertainties to the Swiss model. Therefore, there was a strong need for area validation in Switzerland to ensure that the topographic micro-characteristics and dynamics specific to the European Alps are accurately reflected in the model. The drone flights conducted by the SLF delivered the insights needed to ensure a high-accuracy product for Swiss hydropower providers.

ii. Validation with SLF

To meaningfully validate HS and SWE products, spatially continuous HS measurements were required. Remote sensing from airplanes and drones has the capability to map snow height with accuracies between 5 and 30 cm and spatial resolutions between 10 and 200 cm (Bühler et al. 2016, Bühler et al. 2015).

SLF mapped HS by Unmanned Aerial Systems (UAS) in the field within the test catchments of this project. Specifically, two to three flights were flown per validation basin. One under snow-free and on under snowy conditions. This data was shared with Wegaw for use in validation of the SWE product. In addition, SLF provided access to Wegaw for past UAS flights collection spatial information on HS for additional validation.

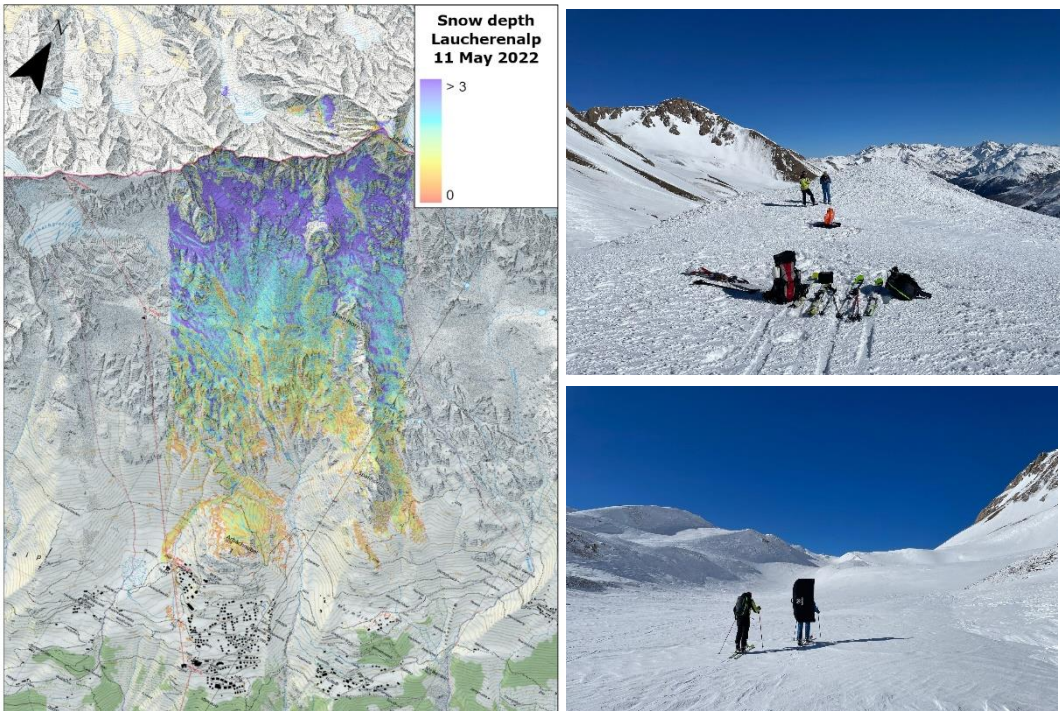


Figure B-7 Examples of snow height distribution extracted from drones (left) and field imagery (right).

[9] https://nsidc.org/data/aso

c. Rainfall-runoff model methodology by Hydrique

i. Routing System

The rainfall-runoff simulation allows to calculate the inflow in reservoirs using typically precipitation, air temperature and solar radiation data. This data is used as input of a physically based distributed simulation model. Indeed, this model computes the different hydrological processes, such as assimilation of meteorological input data, snowmelt, glacier melt, soil infiltration, evapotranspiration, runoff generation (Figure B-8). SWE can be directly derived from the model state variables but is in general not directly calibrated.

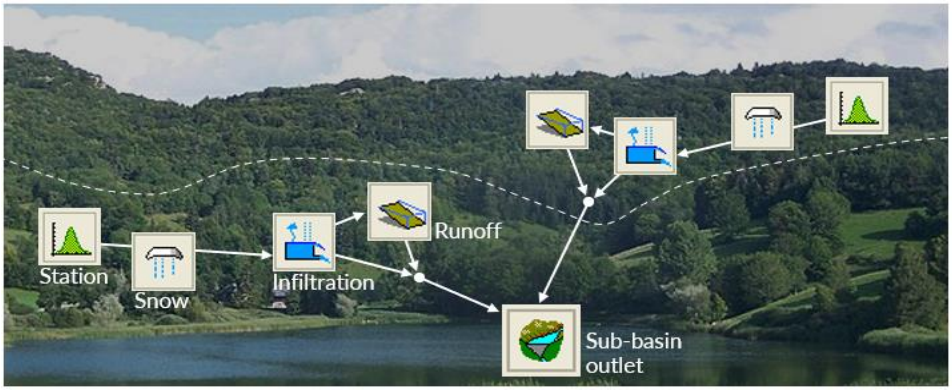


Figure B-8 Concept of the semi-distributed rainfall-runoff model with the detailed modelling of the hydrological processes such as snow melt, soil infiltration and runoff generation

The model calibration is based on the discharge observations (Figure B-9). The parameters are calibrated, in order to obtain the best correlation between simulated and measured discharge at the catchment outlet. The SWE can then be directly extracted from the state variables.

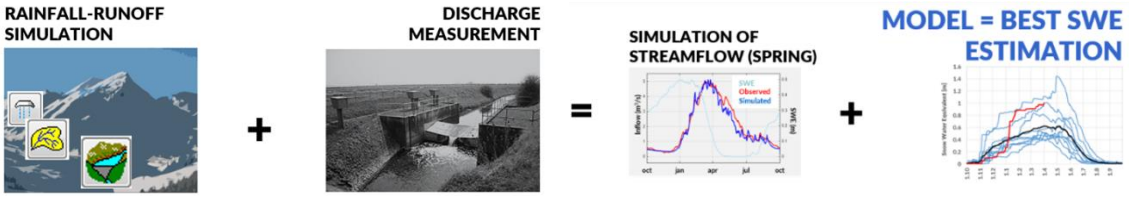


Figure B-9 Process of calculation of the SWE based on rainfall-runoff simulation.

To get a mid-term inflow forecast, today's SWE is of highest importance, as this water reserve represents between 30%-70% of the future flow volume. Thus, an error on the SWE estimation leads to important uncertainties in the flow forecast. Errors in the SWE estimation can occur, because of the lack of robust meteorological information in the catchment area, or during the calibration process, when multiple parameter combinations can produce similar simulation performance.

In this work, the SWE estimated by rainfall-runoff simulation are compared to the ones provided by the Earth Observations. The model state variables are then adapted, by assimilating this data. Finally, new forecasts are generated using this additional information. The forecast skill of both methods (with and without satellite data) is compared by countering the different inflow forecasts and their respective errors.

Finally, the automation of the workflow is achieved, to provide a pilot system, which can be directly used by the project partners hydropower companies.

ii. Rainfall-runoff model calibration

The rainfall-runoff model is considered high-quality if it is able to correctly reproduce the flows during several years, in particular the hydrological regime (seasonality) and the variability of the annual volume. By extension, the internal variables of the model are also considered high-quality. The SWE, which can be directly extracted from the simulation model, is just such an internal variable of the model and can be used as a predictor for the future flow.

Thus, the challenge is to create a rainfall-runoff model that is extremely robust in terms of the hydrological regime and interannual variability. This model is based on meteorological data at measuring stations near the catchment area. Thus, the SWE can be calculated every day according to the arrival of new input data (continuous simulation).

Figure B-10 and Figure B-11 illustrate the capabilities of the rainfall-runoff model for the Arve catchment in Geneva. The representativeness of the interannual variability is excellent. Indeed, the mean absolute error on the annual volume is 3.6%, while the interannual variability is about 35%. This means that the modeling error is 10 times smaller than the variability. The hydrological regime is also very well reproduced, and the mean absolute error of the daily flow is 7.4%, for a variability of about 35% as well.

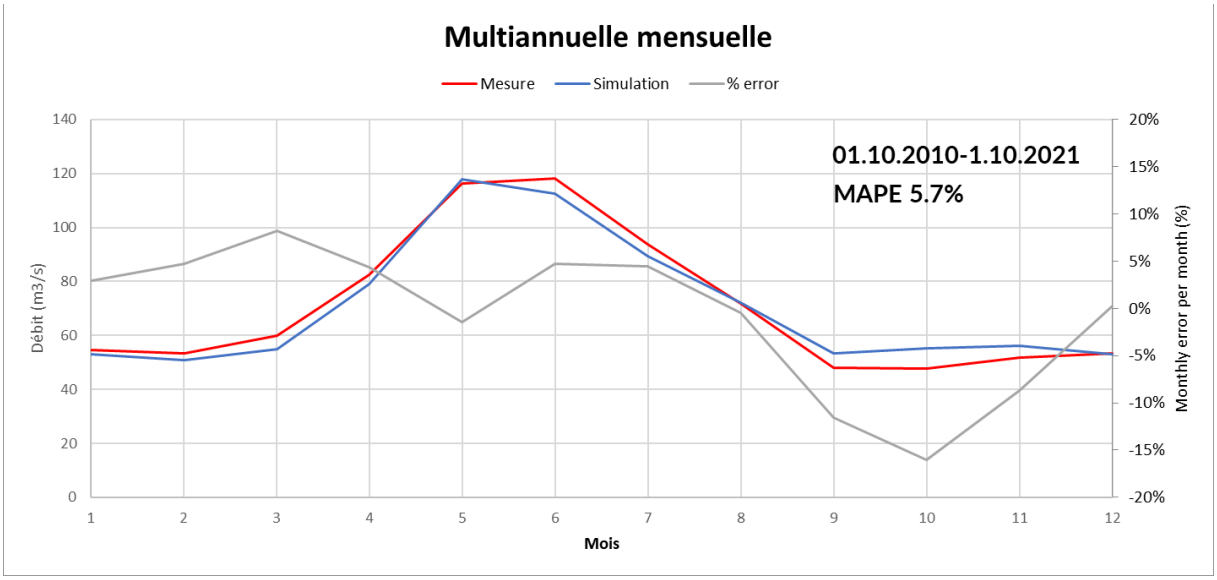


Figure B-10 Comparison between simulated and measured annual volumes in the Geneva Arve catchment. Mean annual error MAE (grey).

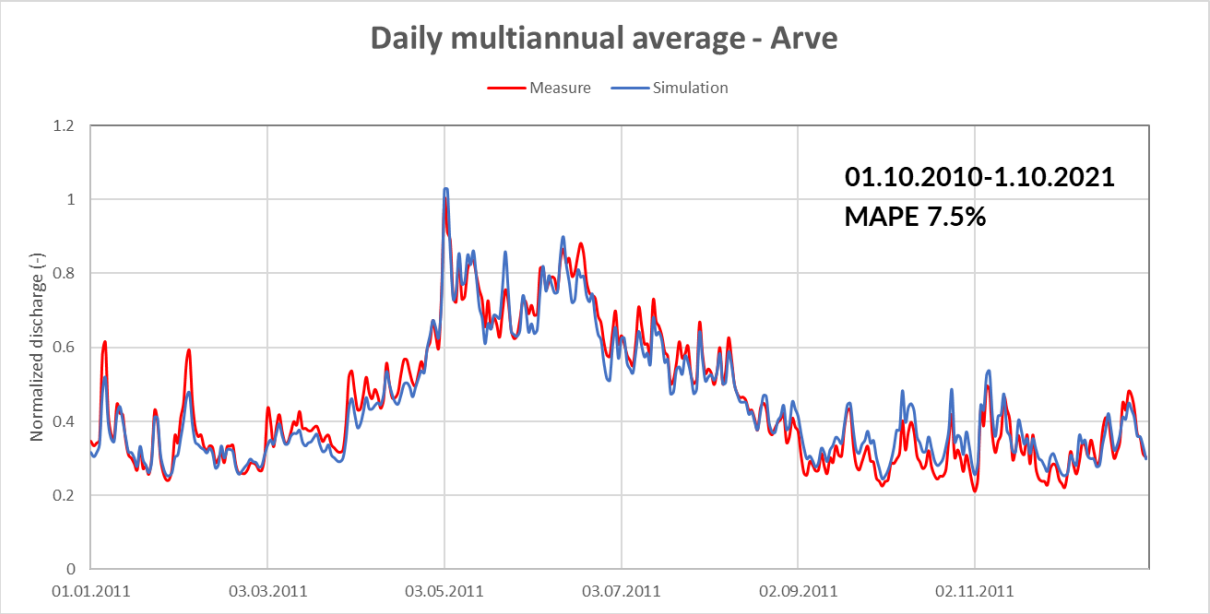


Figure B-11 Comparison between simulated and measured mean daily flows in the Arve catchment in Geneva.

iii. Seasonal forecasts - linear regression

The method used in the project is a linear regression between the quantity of water contained in the snow (SWE) and the cumulative volume during a certain period of time (30, 60, 90 or 120 days). Since the uncertainty of a flow forecast on this time scale is too great, average flows or cumulative volumes over the next 30-120 days are predicted. The linear regression method used relates the cumulative volume of the next few days to the SWE, for the same day values of all years. Thus, this method calculates one regression per day. A regression for a given day contains as many points as there are years in the SWE and cumulative flow time series.

The minimum data required for the regresion is :

- Real time and historical meteorological data (precipitation, temperature) for model calibration - min. 8 years
- Real-time and historical discharge data for model calibration and verification - min. 8 years
- Satellite SWE to be averaged in the catchment area - min. 8 years

First, a continuous simulation on a previously calibrated RS model is performed over a period of at least 8 years to extract the SWE simulated by the RS snow model. An example of simulated SWE is given for one year in Figure B-12.

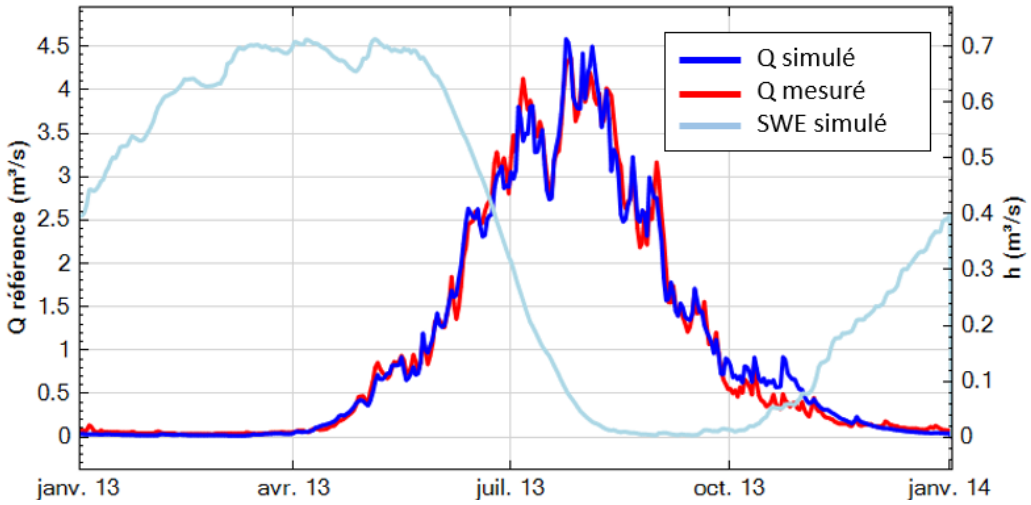


Figure B-12 Example of rainfall-runoff simulation (red = measure ; blue = simulation) and corresponding SWE (lightblue).

Figure B-13 shows the evolution of the SWE for 10 years, issued from the Routing System rainfall-runoff simulation. Each curve is representing one single year.

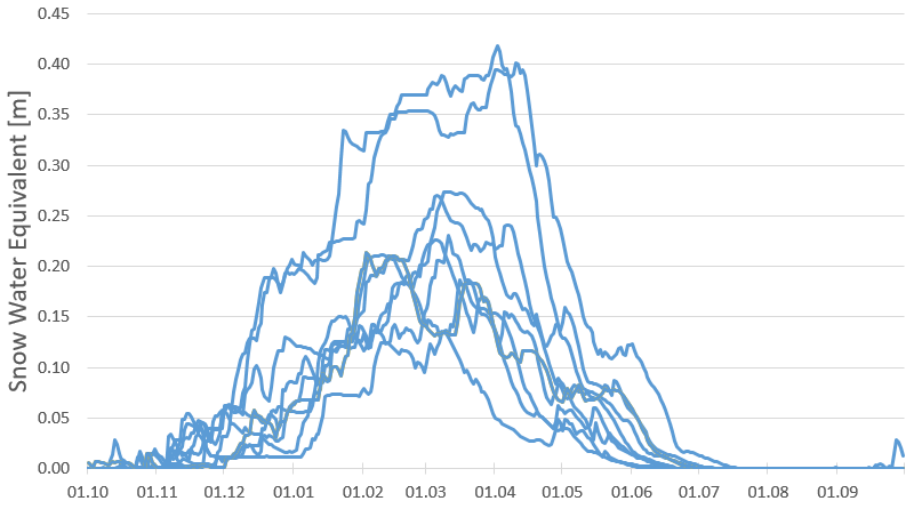


Figure B-13 Example of SWE evolution for 10 years, issued from the rainfall-runoff simulation.

Secondly, the measured flow (historical) is used to calculate a cumulative flow volume in a predetermined number of days ahead (e.g. 30, 60, 90 or 120 days), corresponding to the desired forecast horizon.

Figure B-14 is an example of a time serie of cumulative volumes over the next 30 days for a given catchment, with each curve representing a year.

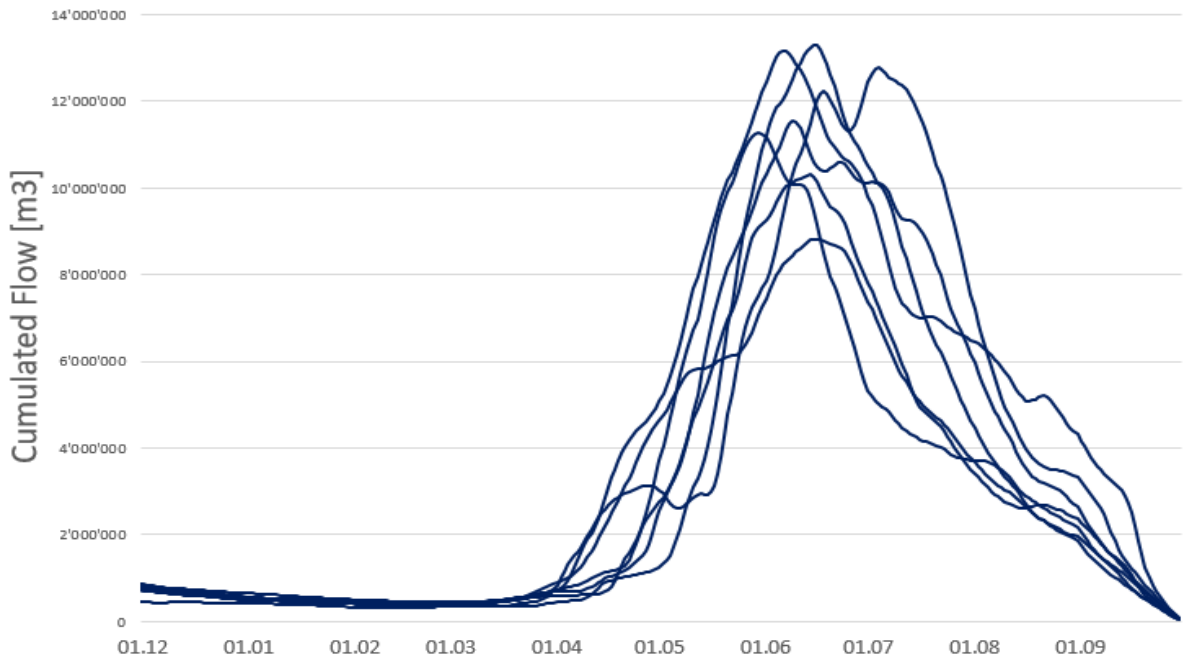


Figure B-14 Example of cumulative volumes over 30 days for 8 years of simulation. Each curve is representing a single year.

Calculation of the linear regression

For each day of the year, and for each forecasting lead time, a linear regression is calculated between the SWE and the corresponding cumulative volume. The number of points in a regression is therefore the number of years in the time series of flow and SWE. Figure B-15 shows an example of a regression for a given day of the year. The regression is composed of 8 points, because there are 8 years of data.

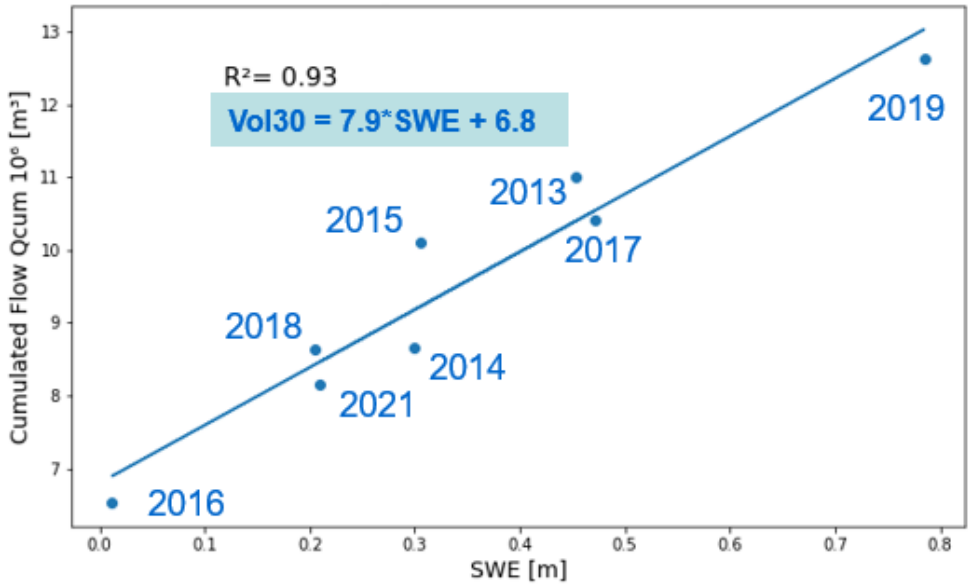


Figure B-15 Example of a linear regression between SWE and the cumulated flow volume over the next 30 days.

For each day of the year, a regression formula of the following form is obtained:

$$V_{cumulé,\Delta T}(i) = \alpha_i * SWE_i + \beta_i$$

where :

i :	Day of the year (e.g. 1st of April)
α_i	Slope coefficient of the linear regression for day i
β_i	Ordinate at origin of the linear regression for day i
$V_{cumulé,\Delta T}(i)$	Cumulated flow volume over the ΔT next days after day i (forecast)
ΔT	Number of days of the lead time of the forecast (e.g. ΔT = 30 days forecasting the flow volume over the next 30 days.

iv. Short-term flow forecasts

The real time short term forecasts can also benefit from the SWE satellite data. Such forecasts are used to predict the future inflow over a few days in advance. The short-term forecast is generally based on the hydro-meteorological cascade, using a rainfall-runoff simulation model.

The forecasting model must be first initialized. To do so, the simulation model must be constantly updated with the most recent measurements, during the continuous simulation process. The most recent rainfall and temperature observation is used as input of the model, giving as a result the discharge at the outlet of the catchment area.

In a second step, the simulation model is adjusted, in order to better reproduce the observed discharge at the outlet. An iterative process is followed by adjusting the model initial conditions, such as initial water content of the soil and of the glacier reservoirs. The goal is that the model is able to reproduce correctly the flow volume over the last 24 hours. As a result, the new adjusted initial conditions of the rainfall-runoff model are obtained.

Finally, using a numerical weather forecast, future rainfall and temperature are used as an input of the simulation model, using the new adjusted initial conditions, to provide the short-term discharge forecast of the catchment area.

d. Integration of the satellite SWE data into the regression method for seasonal forecasting

In a first step, the raw data issued from Wegaw, given in a gridded format, is converted into another format usable in routing System or in the machine learning ML. Then, a step of post-processing of the data is carried out in order to correct erroneous values.

i. Pre-processing of the satellite SWE data

Aggregation to the simulation model elevation band resolution

The gridded data is averaged at the elevation band scale using QGIS. The satellite data being in the form of a grid of points spaced 100m apart, it is to be transformed into the corresponding semi-distributed model unit, which cuts the catchment area into elevation bands of several km^2. The algebraic average of all grid points located in the elevation band is achieved

Figure B-16 shows the satellite measurements before aggregation, represented here by grid points spaced at 100m. Each elevation band contains a large number of points, thus a loss of spatial information is naturally expected. Once aggregated at the band level, the satellite measurement can then be integrated into the Routing System simulation model or as an input variable to a ML algorithm.

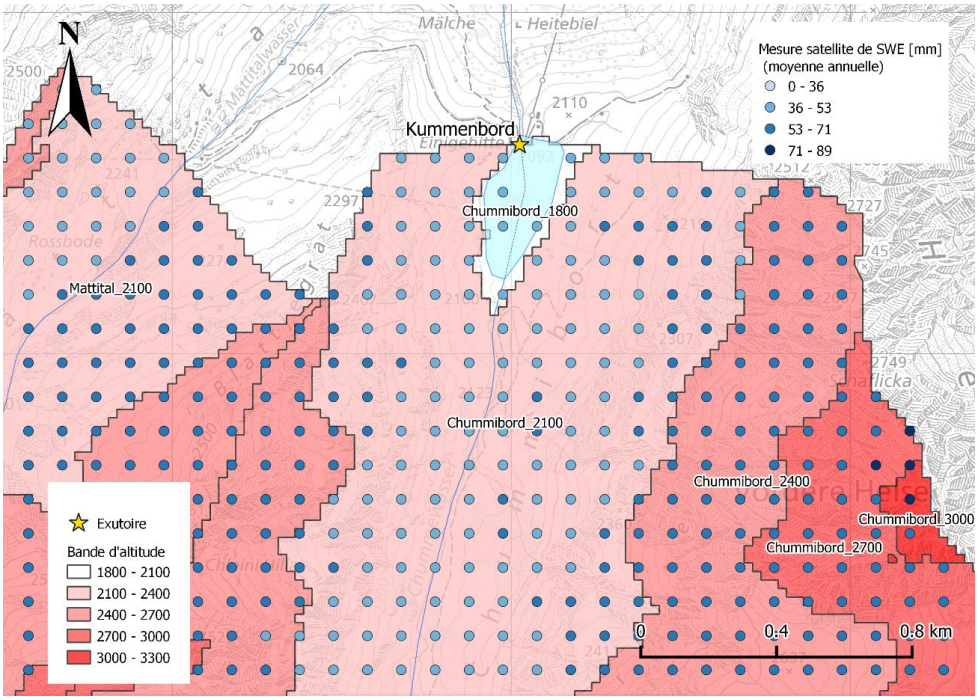


Figure B-16 Example of elevation bands (red) and the grid points from satellite data. The colours represent the average SWE value of a spring day.

Correction of outliers at the end of the snowmelt season

SWE peak values often occur at the end of the snowmelt season. These are not correlated with any rain event and may occur when it is too warm to snow. This is observed for example at the Kummenbord catchment (see the area circled in red in Figure B-17).



Figure B-17 Example of SWE peak values appearing at the end of the snowmelt season in a elevation band (red). Kummenbord, season 2017-2018.

To correct these peaks, it is first necessary to detect them: an increase in SWE that is too sharp on one day and the absence of precipitation at the same time is considered an error. Once detected, the errors are smoothed by replacing them with the average of the previous days.

The thresholds are determined in a trial-and-error process. Thus, an error is defined by an increase in SWE of 50mm in one day while the precipitation is less than 0.1mm/h (2.4mm for 24h).

Correction of outliers called « sudden drops »

At times, SWE values drop to zero suddenly, without reason, as observed in Figure B-18. These values are due to processing errors or original Wegaw measurements. The detection of these values is done by considering values smaller than the threshold of 1cm of snow, and which have neighbouring values larger than 10 cm. These thresholds are determined by a trial-and-error process.

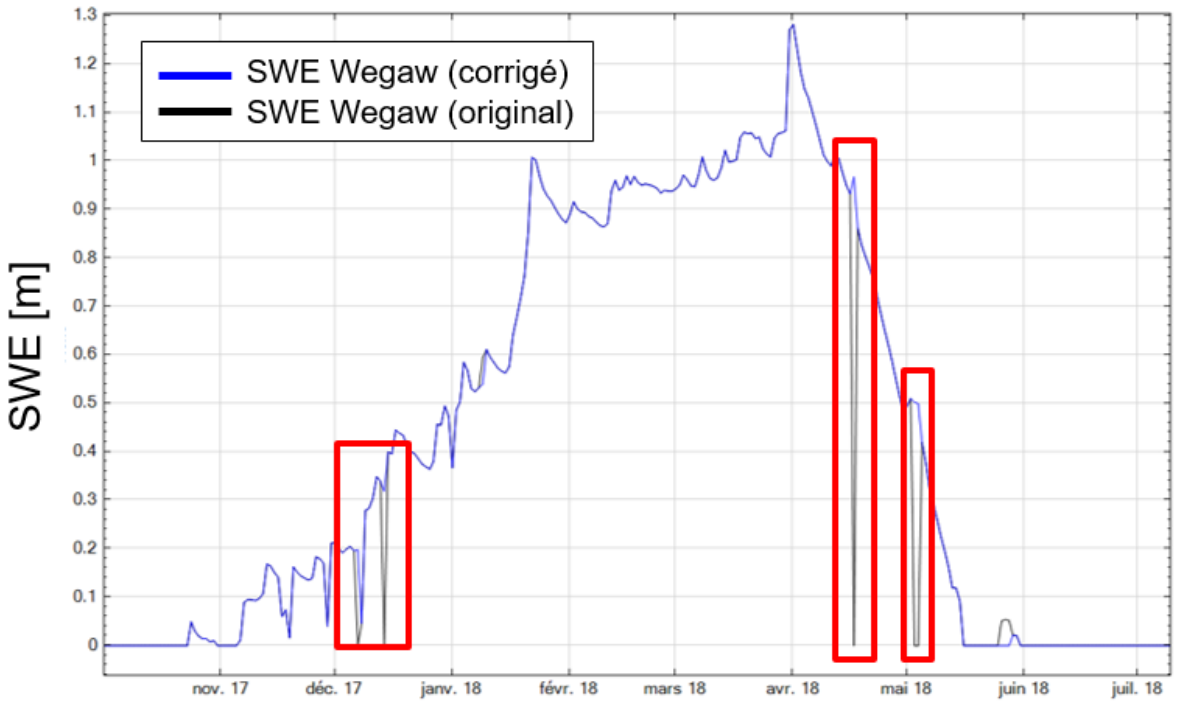


Figure B-18 Example of “sudden drops” needing a correction. SWE measured in the Gletsch catchment area, season 2017-2018.

Setting SWE values to zero at inter-season

At the end of the snowmelt season and before the new snow accumulation period (typically July-October), the received satellite measured SWE is very low, but never at zero. This is problematic for its use in the rainfall-runoff simulation, especially for glacier elevation bands, where the model assumes that glacier melt only activates when the snow cover is completely melted. To correct for this, SWE values that fall below a (watershed-dependent) threshold are replaced with 0.

The thresholds are determined for each catchment by a trial-and-error process. Indeed, some catchments have higher SWE values than others during the shoulder season. On the other hand, some catchments such as Hongrin that do not have any glacier do not absolutely require this type of correction.

ii. Integration of the SWE satellite data into the seasonal forecast

Seasonal forecasting is based on a statistical method (linear regression) that requires a long duration of data. However, the SWE satellite data is only available for 4 years (Oct. 2017 - Oct. 2021). In order to enlarge this short duration, a hybrid series of 8 years is created by combining the SWE of the RS simulation model (Oct 2012 to Oct 2017) with the satellite SWE.

A scaling factor is applied to the Wegaw SWE time series. Figure B-19 shows the result of scaling the satellite SWE data with the goal of obtaining a longer, more uniform time series. The Ferden example is used because it has much higher satellite SWE values than expected by the RS rainfall-runoff simulation. The scaling is based on the maximum SWE values (satellite vs RS). This combined series is used to make the latter called "Wegaw" seasonal forecasts.

In this example, the SWE from the simulation is provided to Wegaw, allowing to calibrate the satellite data processing realized by Wegaw. After this calibration, the new satellite SWE data is scaled with RS data in order to provide the longer SWE hybrid time series.

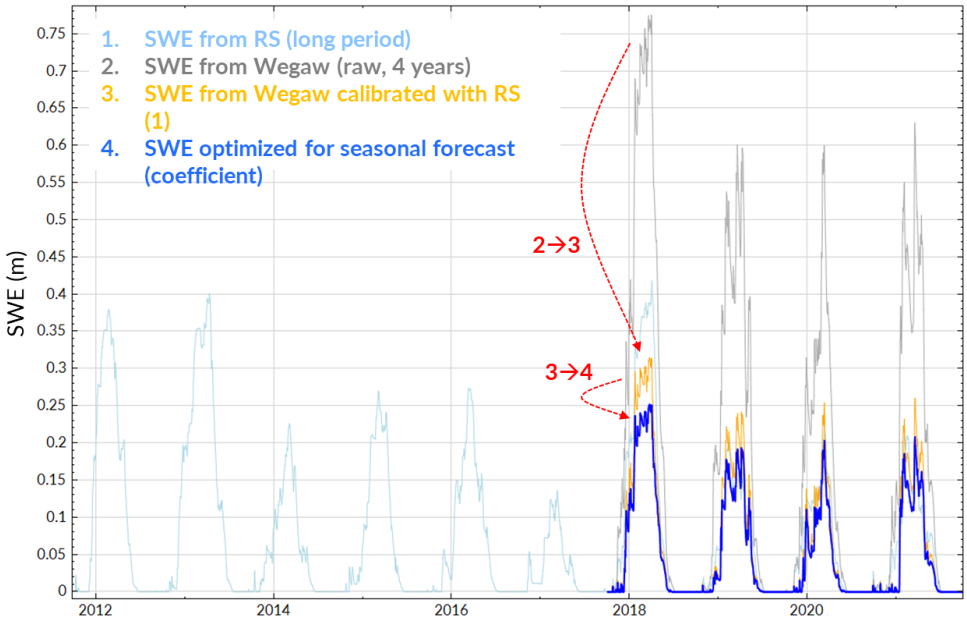


Figure B-19 Illustration of the methodology for correcting the raw SWE satellite data with the use of the rainfall-runoff SWE output. Example of the Ferden catchment.

iii. Integration of Wegaw data into the short term forecasts

The SWE obtained from the satellite measurements is integrated into the Routing System rainfall-runoff model. In particular, the SWE measurements are integrated into the RS snow model. Thus, the processes that determine the flow from snowmelt is the same as for the model.

In this case, the model calibration is done at hourly time step while the SWE measurements are provided once a day. To cope with this, the SWE value is updated once a day at midnight by the value measured by satellite. During the day, this SWE varies according to the melting intensity; once the day is over, the SWE is reset/replaced by the new SWE measurement.

Figure B-20 shows an example of the integration of the Wegaw SWE into the snow model. Every day at midnight, the SWE is reset by the satellite measurement. During the following 24 hours, the snow stock decreases according to the snowmelt intensity parameter (degree-day factor). The decrease of the snow pack is proportional to the temperature, so that the decrease of the pack is accentuated during the day and decreased at night. A limitation of this model is that it is possible to melt more than measured. This can be seen in the blue curve, which has a deliberately exaggerated melting intensity.

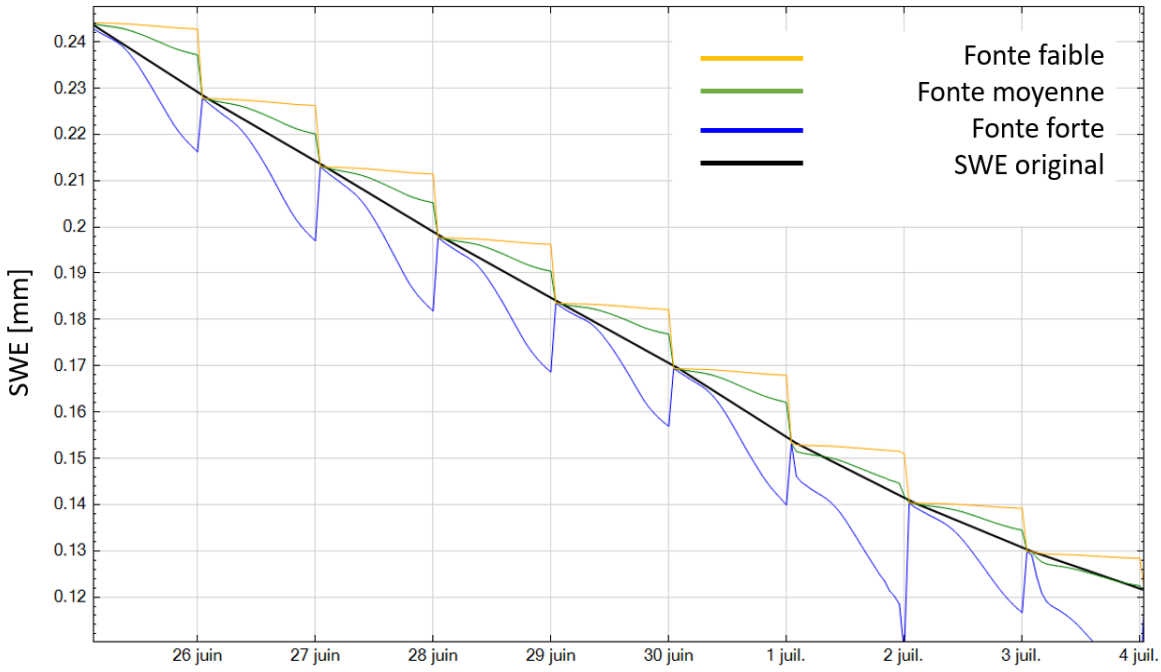


Figure B-20 Evolution of the SWE in the Hongrin catchment imn June 2019. The yellow, green and blue curves show the influence of weak, moderate and strong snow melt degree-day factors.

e. Machine learning forecasting

In order to realize seasonal as well as short-term forecast, machine learning (ML) is also implemented, specifically with a neural network. This chapter describes the general structure of the ML algorithm used, without going into the theoretical details of ML which is not the subject of this project.

The software architecture for the development of the ML models (learning, validation) is realized in Python with the libraries Sickit-learn, PyTorch, TensorFlow and Keras.

i. General architecture

The neural network used is the Multi-Layer Perceptron (MLP), shown in Figure B-21. The structure of the network (number of hidden neurons, number of layers) is determined on a case by case basis by a trial and error process. In the tests performed, the activation functions used are the sigmoid function or ReLu.

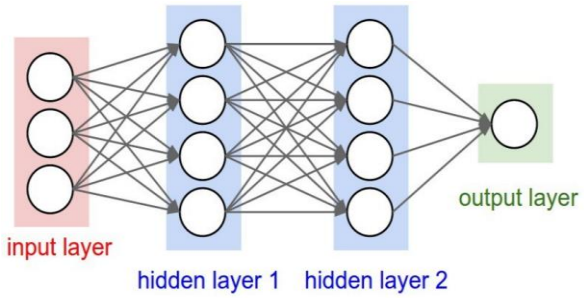


Figure B-21 Schematic of a multilayer perceptron. The input data layer is connected to the successive hidden layers, then to the output layer.

ii. Training of the ML model

A k-fold cross-validation is performed, allowing the entire training dataset to be used for training and evaluation, instead of just a portion. The k-fold cross-validation is described in Figure B-22.

The cross-validation avoids phenomena such as data overfitting, in which the model performs very well on the training dataset, but much less well on datasets that have not been used during training.

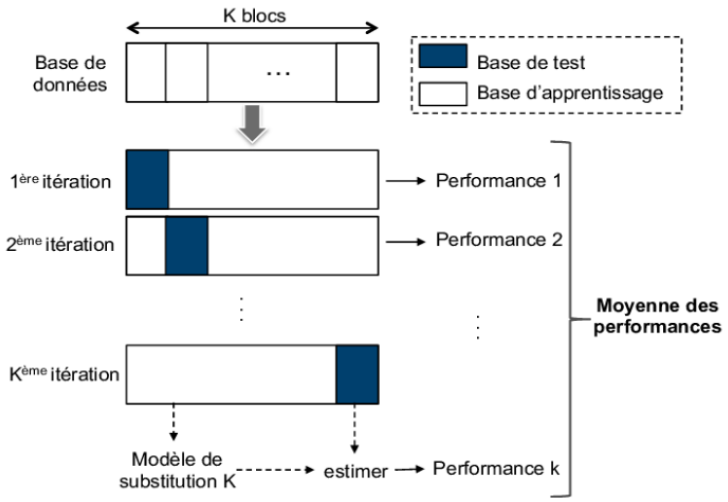


Figure B-22 K-folds cross-validation (Laqrichi, 2015) separates the dataset into k blocks, and trains the algorithm by keeping 1 block aside for validation at each iteration.

iii. Loss function

The loss function calculates the difference between the prediction and the measured value. In this case, the loss function used is the Mean Square Error (MSEloss) : $L(Q, \hat{Q}) = \frac{1}{N}\sum_{i=0}^{N} \quad (Q_i - \hat{Q}_i)^2$

iv. Optimization algorithm

An Adam-type optimization algorithm is used, which allows to adapt the training intensity. The goal of the optimizer is to find the minimum of the loss function by adjusting the parameters of the model, in a reasonable number of trials.

v. Typical input data

The typical input data used to predict flows is described here :

- Weather variables (precipitation, temperature) past and future
- Variables issued from the RS simulation model output (hybrid models)
- Persistence (flow measured in the near past)

The variables are determined on a case-by-case basis through a trial-and-error process.

f. Automatization and development of the operational processes

The automation of the calculation processes and algorithms is realized in the project as a Proof of Concept. Figure B-23 shows the operational processes of making and publishing the seasonal forecasts.

All operations presented below are performed on a virtual machine in a Cloud.

1. First, external data is continuously retrieved and stored in the database. This includes SWE data provided by the satellite (raster data), weather measurements and forecasts (time series and multidimensional rasters), and flow measurements at the forecast point (time series).
2. The data is used as input to the short-term forecast model. The short-term forecast can then be calculated by rainfall-flow simulation or Machine Learning and transferred to the MySQL database.
3. The data is used for the seasonal forecast. The seasonal forecast uses the correlations calculated during the development of the models and calculates the forecasted volumes for +30, +60, ..., +180 days. The basic data for this calculation is, each day, the SWE from satellite data, and the coefficients of the linear regression of the day.
4. The seasonal forecast volumes are then converted into flow time series. The historical average of each day's flows is used and scaled to the forecast volumes for each time-series. The method ensures continuity of forecast volumes, so that the +60 day volume calculated from the new flow series (which already incorporates V30) matches the forecast V60. This new 180-day time series is stored in the MySQL database.
5. The curve is displayed on the Cartoweb server developed by Hydrique Ingénieurs (my.hydrique.ch) for operational hydrological forecasts.
6. The curve is also transferred to an SFTP server to be directly retrieved by the operator, in order to automatically feed the optimization software.

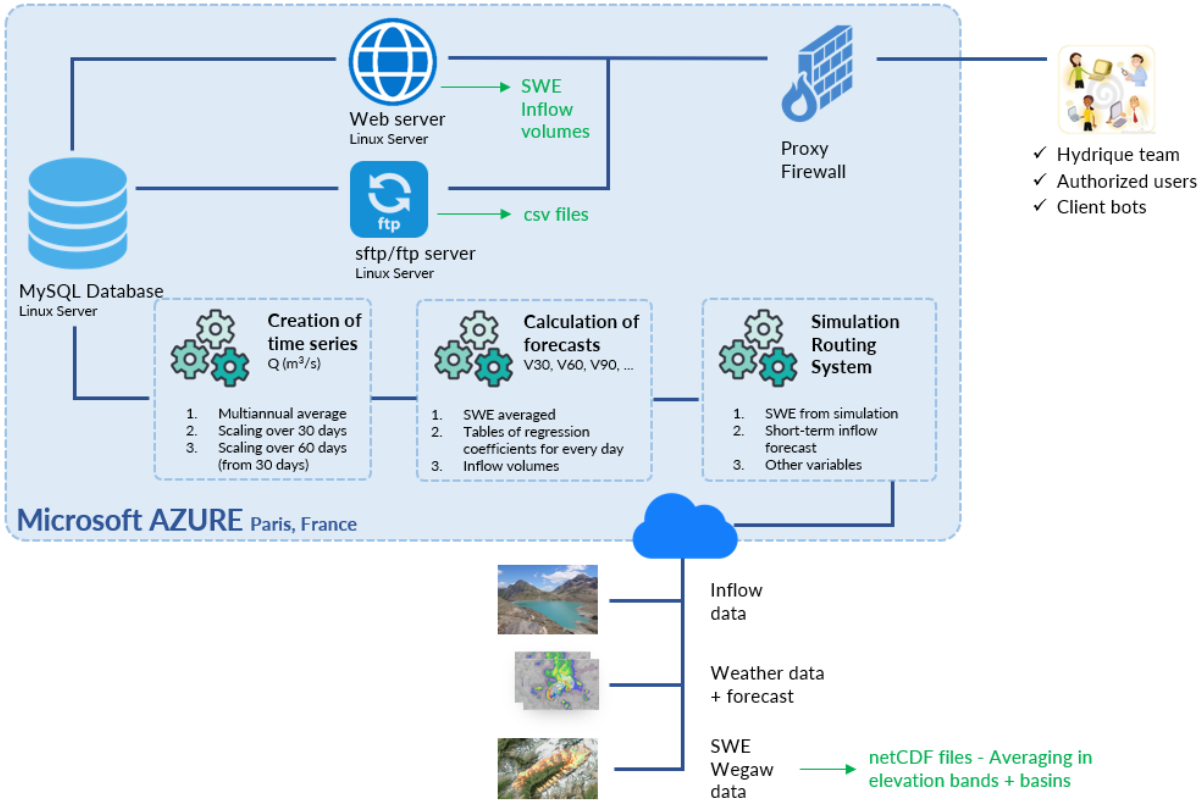


Figure B-23 Schematic of the operational seasonal inflow forecasting system for dams.

The average SWE value is very important, it is the best predictor for seasonal forecasting. For this reason, it is very useful to visualize its history and its last value. Figure B-24 shows the example of the Lake Geneva catchment, for which the web interface displays the current SWE (situation on 15.2.2022) as well as the SWEmin, SWEmax, SWEmedian statistics. The image shows that the current SWE is below the median of the last 12 years (2010-2021). This qualitative view does not constitute a forecast, but allows to easily imagine the trend of the spring inflow.

The platform also allows comparison of inflow volume forecasts with past SWE and inflow volume values (Figure B-25). The SWE of the day is positioned on the scatterplot and allows to determine graphically the volume forecast at +30, +60, ..., +180 days. This tool allows a contextualization of the forecast and helps to understand the forecast value, as well as to interpret the uncertainty.

Finally, the time series of inflows from +1 to +180 days are reconstructed from the volumes at +30, +60,..., +180 days. Figure B-26 illustrates these predicted curves, in the case of the Ferden dam, in comparison with the historical inflows (blue) and the measurement (red). The image shows that the forecast curves are systematically closer to the (a posteriori) measurement than the historical inflows. This confirms, in this case, the improvement obtained with the seasonal forecast and the SWE.

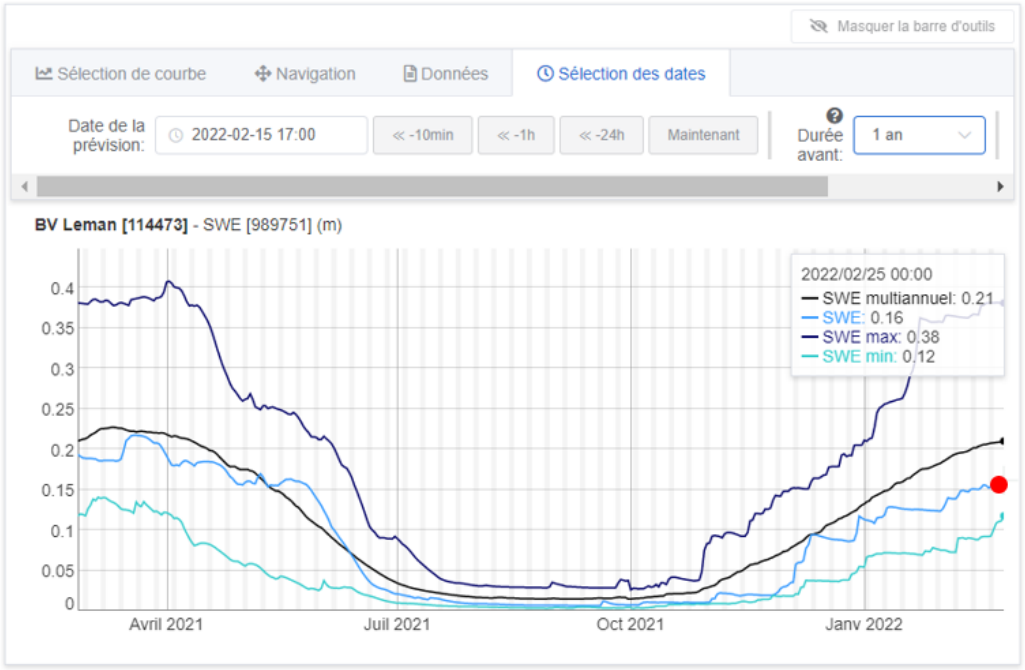


Figure B-24 Display of average SWE values over the watersheds. Comparison with historical values.

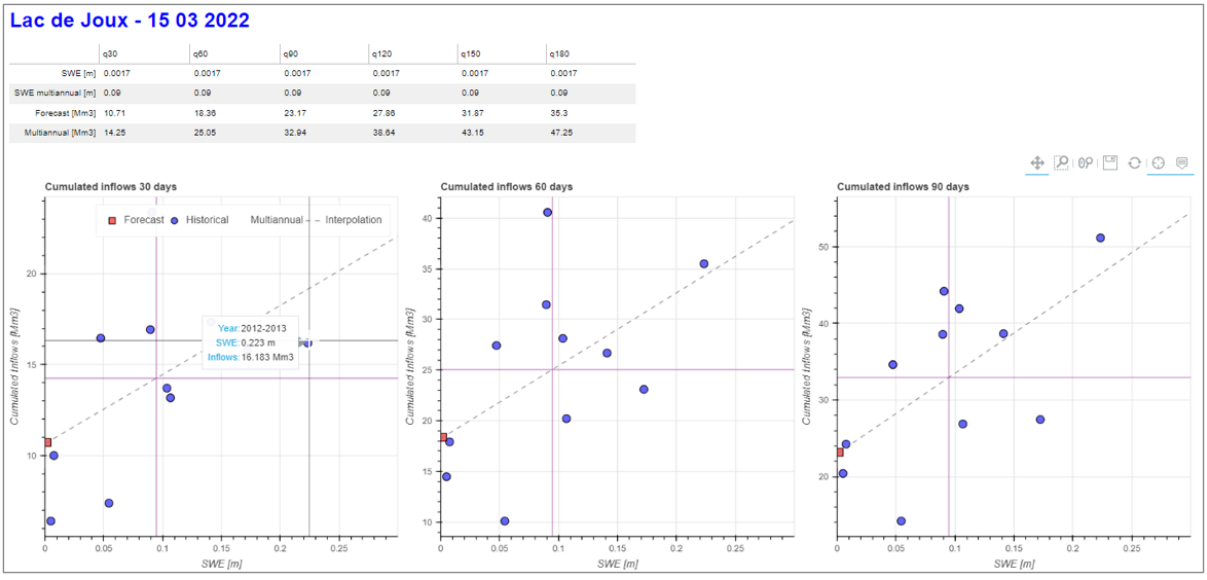


Figure B-25 Display of predicted inflow volumes, related to the historical values used in the linear regression model.

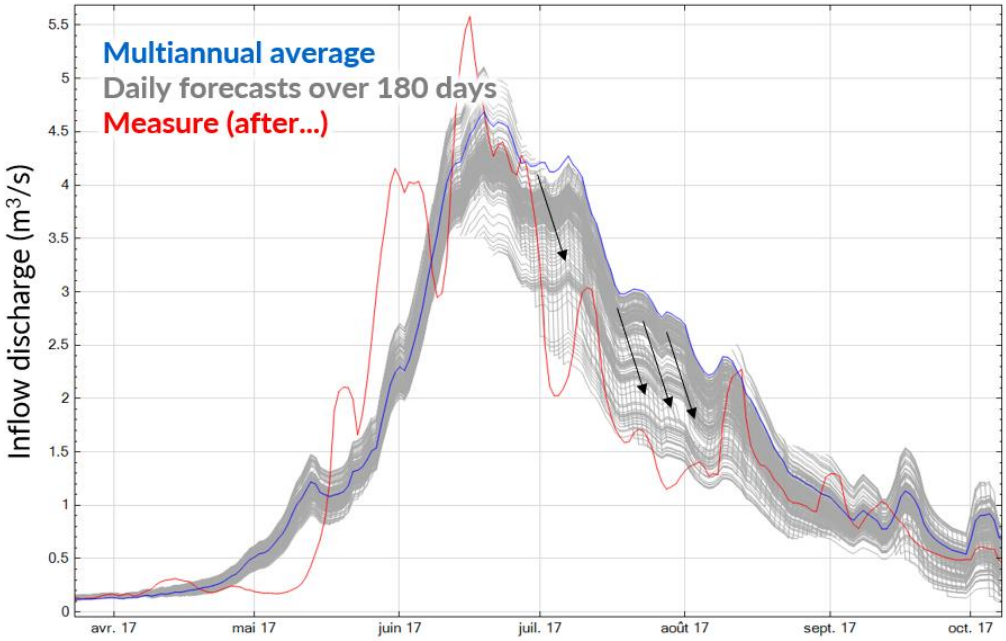


Figure B-26 Display of time-series of inflow forecasts, reconstructed from volume forecasts and historical inflows.

C. Results and Discussion

This section will present and examine the findings of the following research:

Section C.a - The validation of Wegaw's snow product using data provided by SLF.

Section C.b - The comparison of seasonal forecasting with and without Wegaw data, including with use of machine learning.

Section C.c C.b.iii - The comparison of short-term forecasting with and without Wegaw data, including with use of machine learning.

Section C.d - An economic analysis of the improvements achieved by seasonal forecasting covering trading and generation.

a. Snow Product Validation System with SLF

Details of the HS validation campaign with SLF are explained in this section of the report. The Wegaw HS product was validated in partnership with the WSL Institute for Snow and Avalanche Research (SLF), through product quality assessment against historical SLF datasets between 2017 and 2021, and targeted data acquisition campaigns across the winter and spring of 2022. This enables a broad and comprehensive assessment of the snowpack.

Snow density measurements were not collected by the SLF as part of this validation campaign, and therefore SWE cannot be comprehensively validated in the study areas of this project. Past validation campaigns of Wegaw also include SWE measurements validated in Canada, the USA and Norway. The full validation report (independent of this project) is available through Wegaw's website via the following link: Snow Water Equivalent (SWE) Validation

i. 100m Raster Validation

To evaluate the pixel-level accuracy of the Wegaw snow height product, a total of 224 689 corresponding HS estimations were made for pixels of width 100m observed by the SLF photogrammetric surveys (Eberhard et al. 2021, Bühler et al. 2021) using the UltraCam Eagle Mark 3 (Figure C-1). An R-value of 0.65 and an RMSE of 57cm was observed across all the measurements. Visual spatial comparisons (Figure C-2) show the most significant errors occur at high altitudes with complex geomorphology. These errors are most likely due to wind-driven snow redistribution and snow trapping.

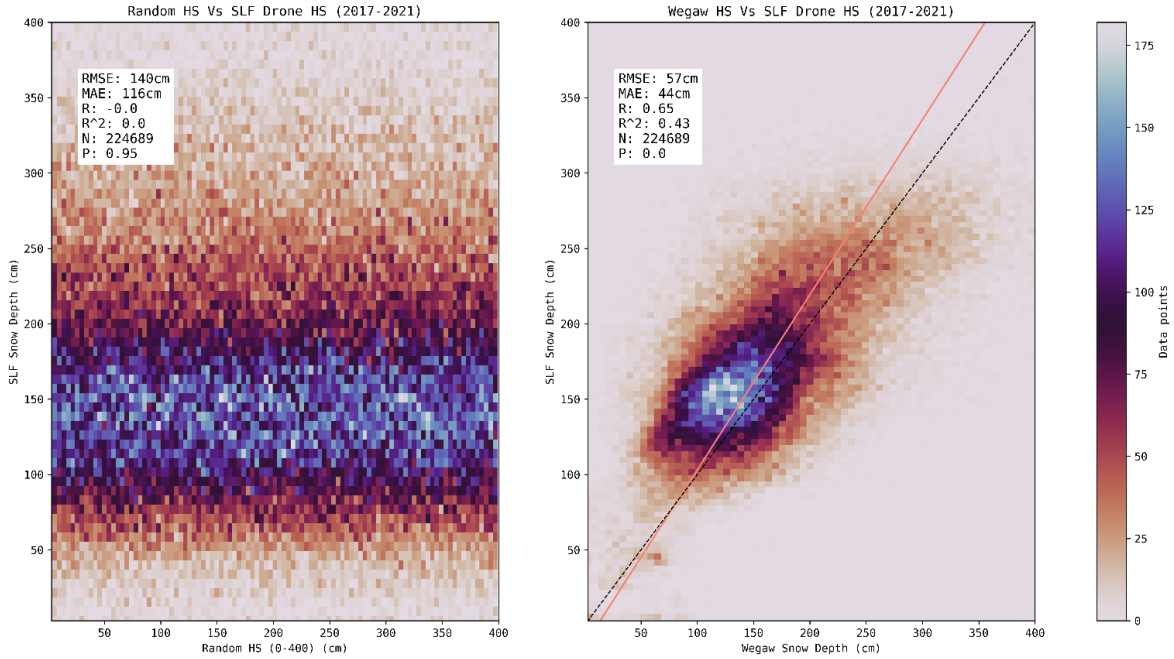


Figure C-1 Histogram of randomly generated HS values vs SLF UltraCam HS values (left) and Wegaw HS values vs SLF UltraCam HS values (right).

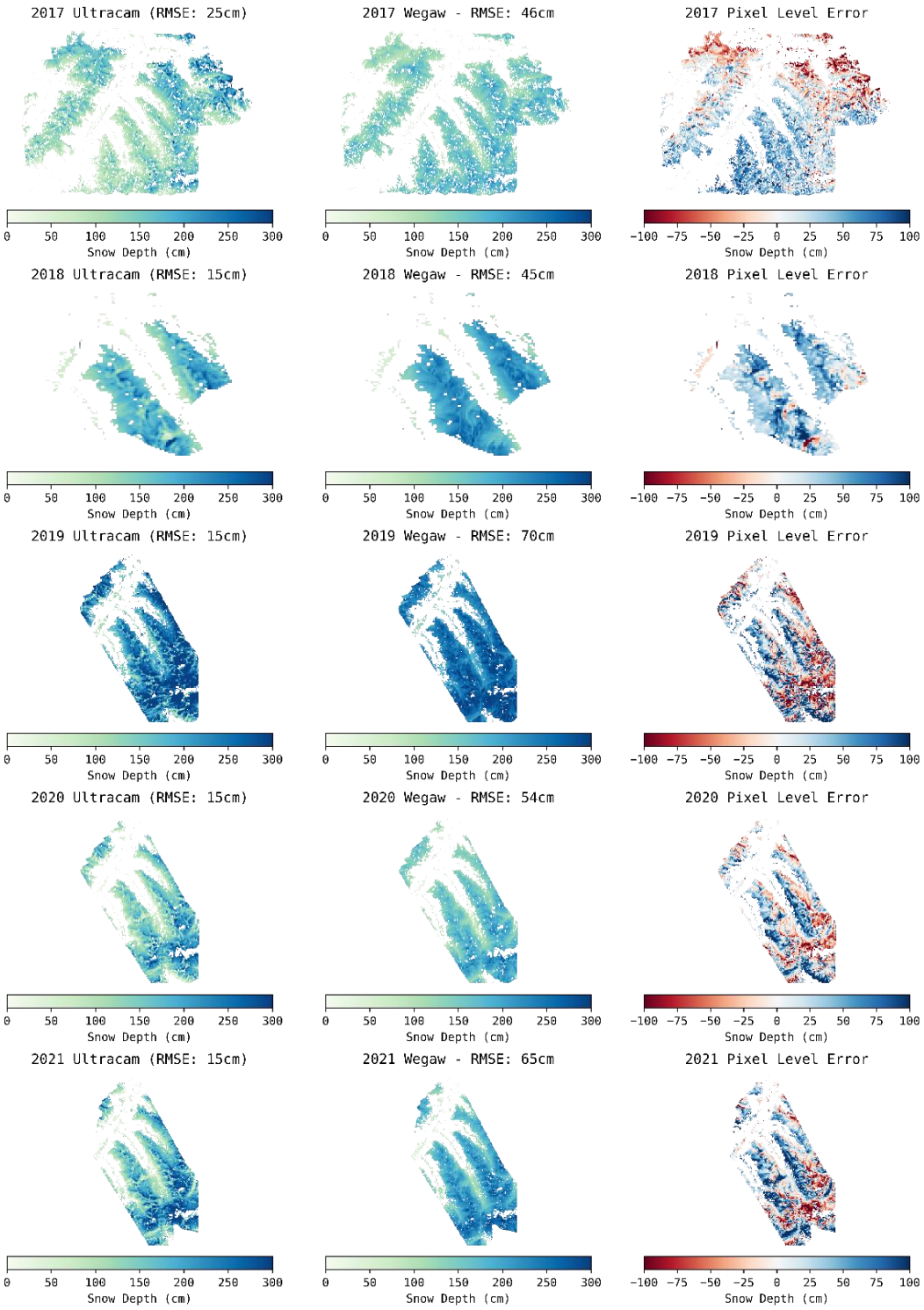


Figure C-2 Spatially-distributed comparisons of SLF UltraCam HS data (left) and Wegaw modeled HS data (center), including pixel wise differences between the two datasets (right). The RMSE stated for the SLF UltraCam data is the reported RMSE of the UltraCam.

ii. Catchment Scale Validation

For catchment scale hydrological modeling, we consider the accuracy of the HS product across entire river basins. The SLF photogrammetric HS measurements and the Wegaw HS estimations were aggregated to a mean HS value for each year Figure C-3. The R-value of the corresponding mean HS at each catchment area is 0.86, with an RMSE of 27cm. Figure C-3 indicates that performance is better in larger catchments. The size of the points indicates the number of data points used to calculate the mean value for each basin and date. The dashed line shows how a perfect correlation between the datasets would look, and the solid line shows the actual correlation.

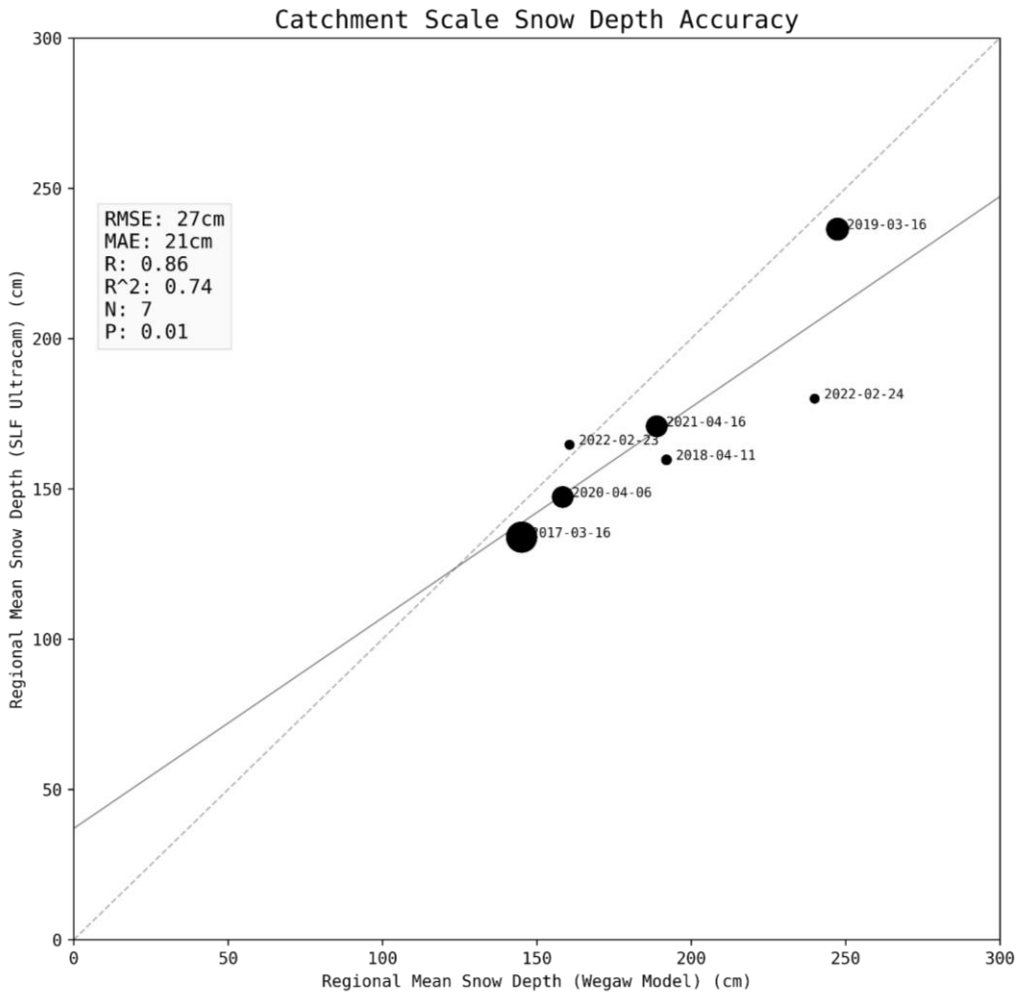


Figure C-3 Comparison of regional mean HS modeled by Wegaw and regional mean HS measured by the SLF UltraCam.

iii. High Resolution (1m) Validation

For purposes of process optimisation and ease of usage, the Wegaw HS product is down sampled to 100m. However, the maximum possible horizontal resolution of the Wegaw HS product is 1m. To assess the performance at this level, the data was compared to 1m resolution UltraCam and

photogrammetry data generated by the SLF in Lauchernerap. Figure C-4 shows images of SLF scientists collecting the data. Figure C-5 shows the validation results. Figure C-6 and Figure C-7 show the maps generated by the SLF.

The R-value of the corresponding mean snow heights at the 1m pixel level is 0.74, with an RMSE of 61cm. This demonstrates that the Wegaw HS product accuracy is slightly lower at 1m resolution than 100m resolution.



Figure C-4 SLF scientists collecting validation data in Lauchernerap. Photo credit SLF.

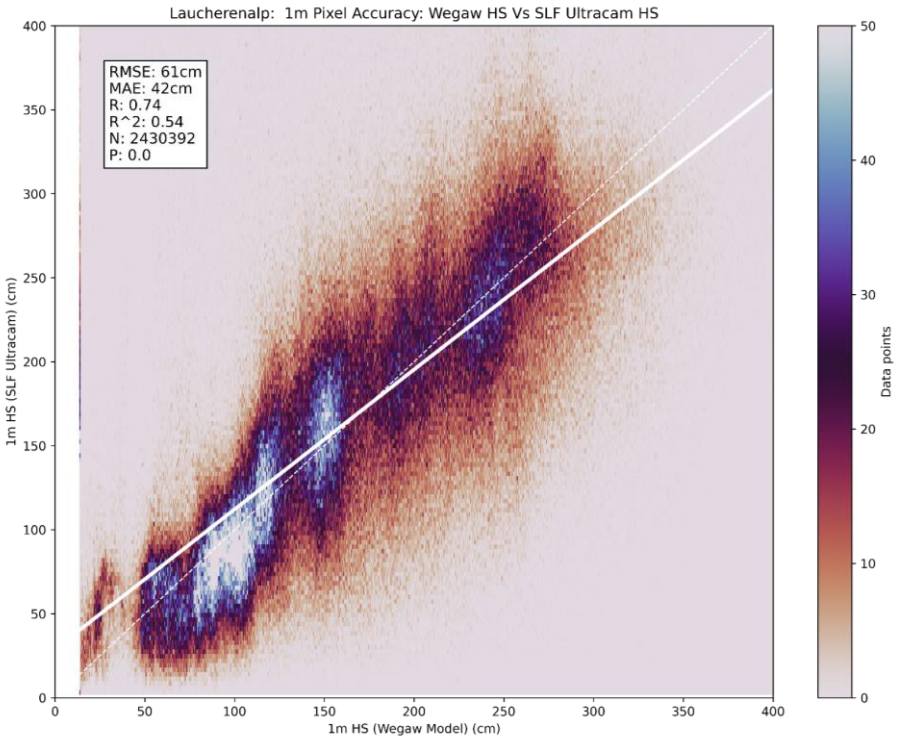


Figure C-5 Comparison of Wegaw HS data and SLF UltraCam HS data at 1m resolution in Lauchernalp.

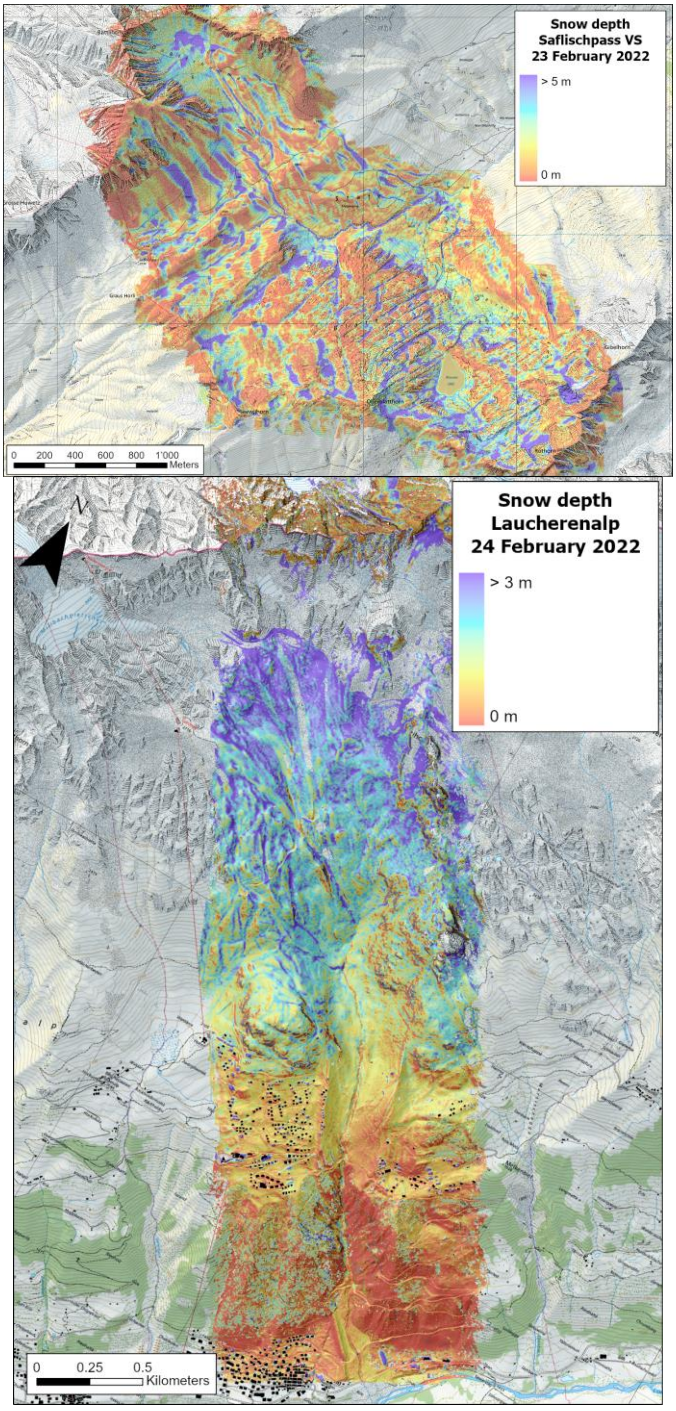


Figure C-6 SLF UltraCam HS data in February for Saflischpass (upper) and Laucherenalp (lower).

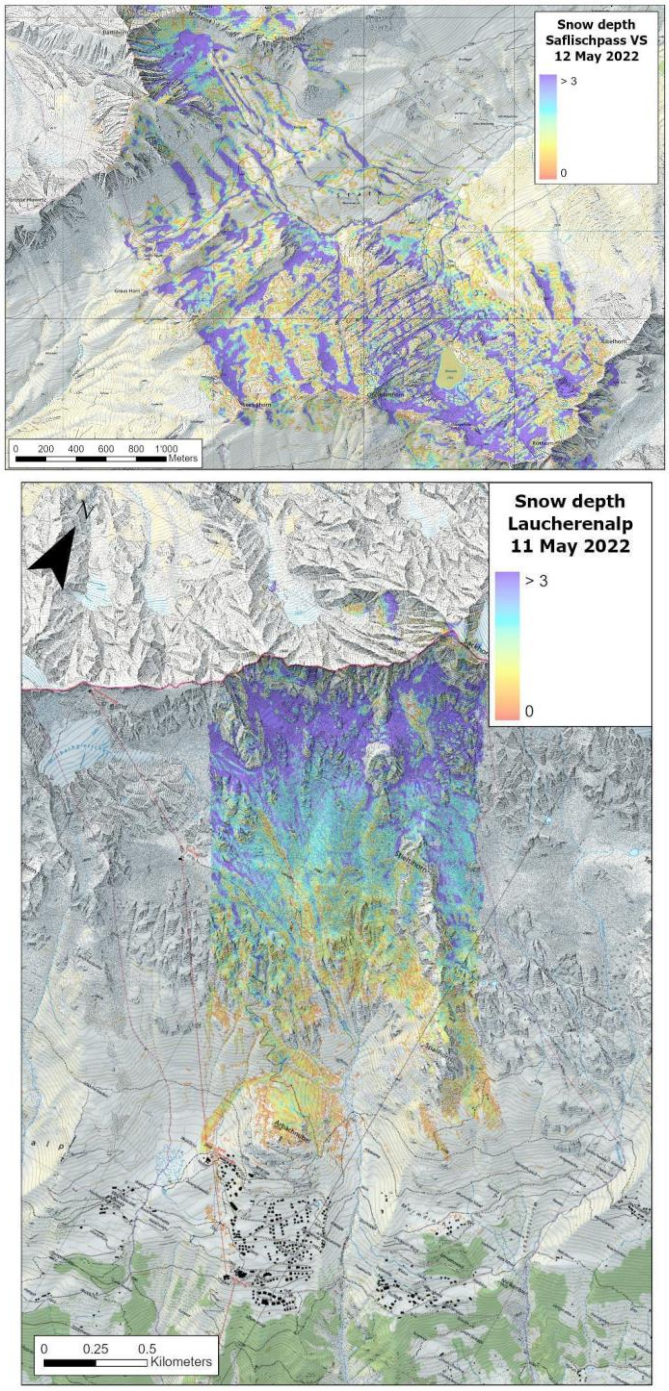


Figure C-7 SLF UltraCam HS data in May for Saflischpass (upper) and Laucherenalp (lower).

b. Seasonal forecasts

Seasonal forecasts are evaluated for all catchment areas first with the classic rainfall-runoff simulation-based methodology (“Hydrique”) and then with the introduction of satellite SWE values (“Wegaw”). In the first approach, the RS simulation model must first be created, and then the model must be calibrated

to correctly represent intra- and inter-annual flow variations. The seasonal forecasts are then analyzed by comparing the predicted and observed 30-, 60-, 90-, 120- and 180-day volumes.

i. Calibration of the Routing System simulation models

The calibration of the routing system (RS) simulation models is the most important step in the methodology. The calibration performance obtained directly influences the reliability of the SWE produced by the model. When calibrating the models for seasonal forecasts, the focus is on daily, monthly and annual flows.

The performance of the models is evaluated by comparing the simulated flows with the measured flows at the catchment outlet. The daily and annual Mean Absolute Percentage Error (MAPE) indicators are presented for all analysed watersheds in Table C-1.

Table C-1 presents the calibration performance of the different models developed in this project. Several models are really excellent and have a great potential for seasonal forecasting: Lake Geneva, Arve at Geneva, Ferden, Kummenbord, Lake Gruyere, and Zeuzier. The catchment areas of the Bortelsee, Hongrin and Lac de Joux should also give good forecast results. The situation is more difficult for Gletsch, Emosson or Godet. In the cases of Gletsch and Emosson, the interannual variability is lower and the catchments are located at the intersection of mountain ranges. In the case of Godet, the difficulty to measure precisely the inflow to the lake leads to a high uncertainty on the measurement itself.

Priority	Catchment	Period	MAPE yearly	MAPE daily
1	Gletsch	2012-2021	0.098	0.082
1	Zeuzier	2011-2021	0.048	0.089
1	Bortelsee	2008-2021	0.065	0.145
1	Ferden	2010-2021	0.035	0.056
1	Hongrin	2009-2021	0.082	0.148
1	Lac de Gruyère	2009-2021	0.037	0.102
1	Lac de Joux	2011-2021	0.071	0.154
1	Arve	2011-2021	0.036	0.074
2	Kummenbord	2013-2021	0.045	0.081
2	Godet / Lizerne	2013-2021	0.098	0.141
2	Emosson	2010-2021	0.109	0.113
3	Léman	2010-2021	0.03	0.074

Table C-1 Calibration performance of the models tested in the project.

The results are in general good, with annual MAPE values between 3.5% and 10.9% and daily MAPE values between 5.6% and 14.8%. These indicators can be strongly influenced by the quality of the measurement, especially for the daily values. The inflow to the Bortelsee, for example, is estimated by recalculation based on the reservoir level and the estimated outflow, and thus the quality of the measurement can partly explain the higher values for this basin.

Indicators alone are not sufficient to assess the quality of a calibration. The visual comparison of simulated and measured flows is essential in this evaluation. In order to identify possible calibration biases, the monthly and daily flows are averaged over all the years analysed. In this way, a systematic under- or overestimation at one time of the year is easily identified.

The measured and simulated monthly and daily multiannual averages of the Arve, Hongrin, Kummenbord, Lac de Joux and Geneva catchments are presented in Figure C-8 to Figure C-17.

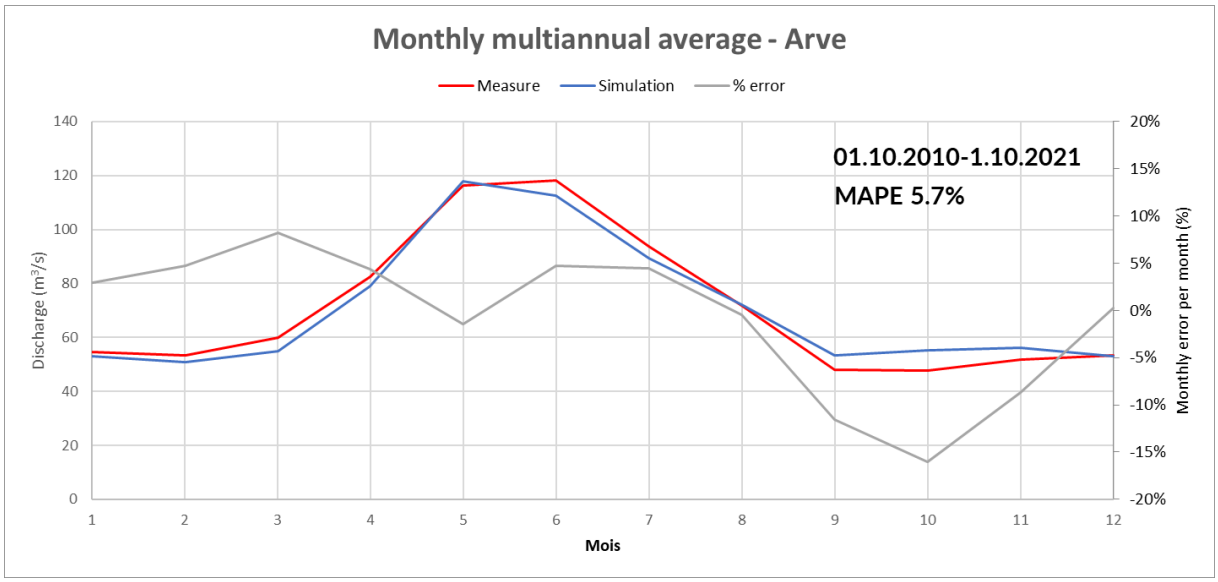


Figure C-8 Measured and simulated monthly multiannual average discharge for the Arve basin.

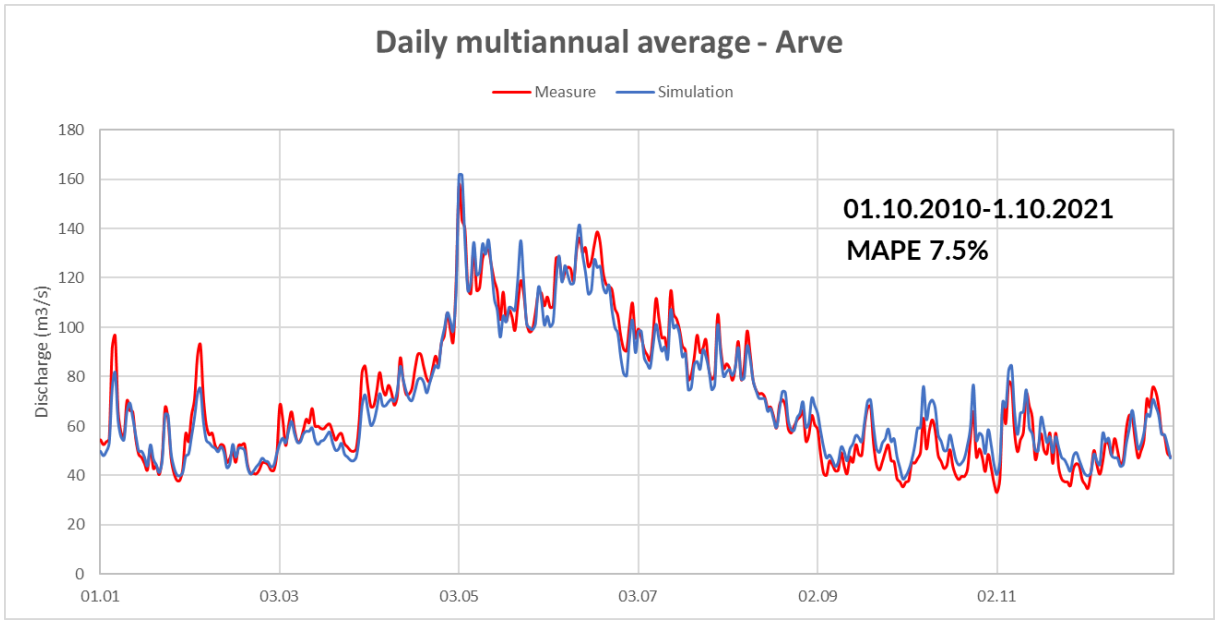


Figure C-9 Measured and simulated daily multiannual average discharge for the Arve basin.

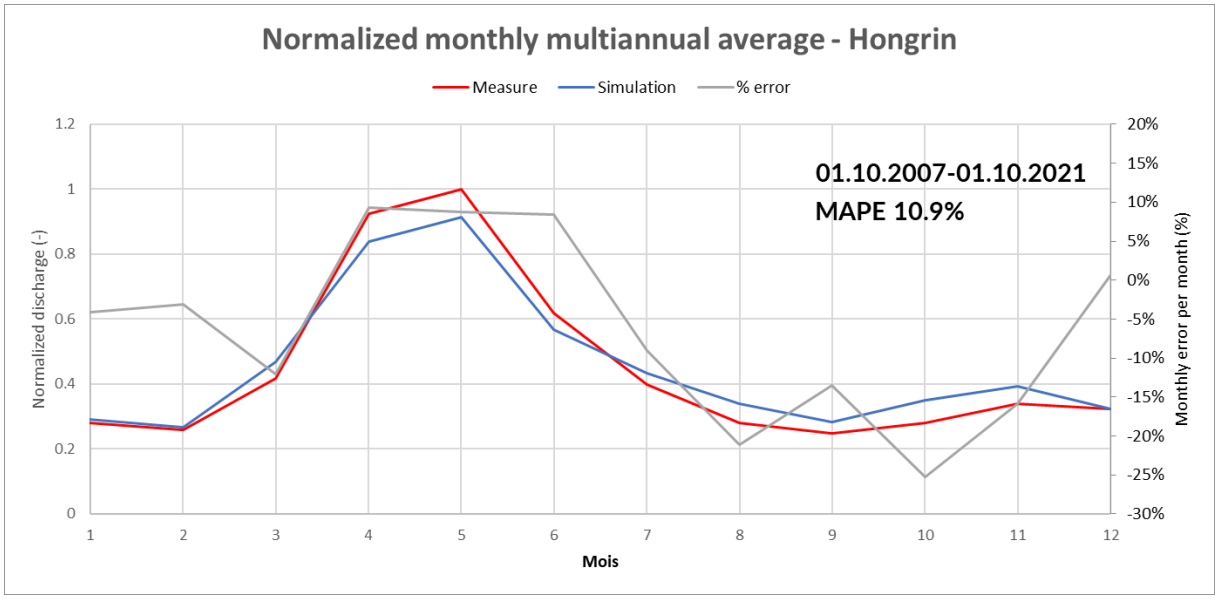


Figure C-10 Normalized measured and simulated monthly multiannual average discharge for the Hongrin basin.

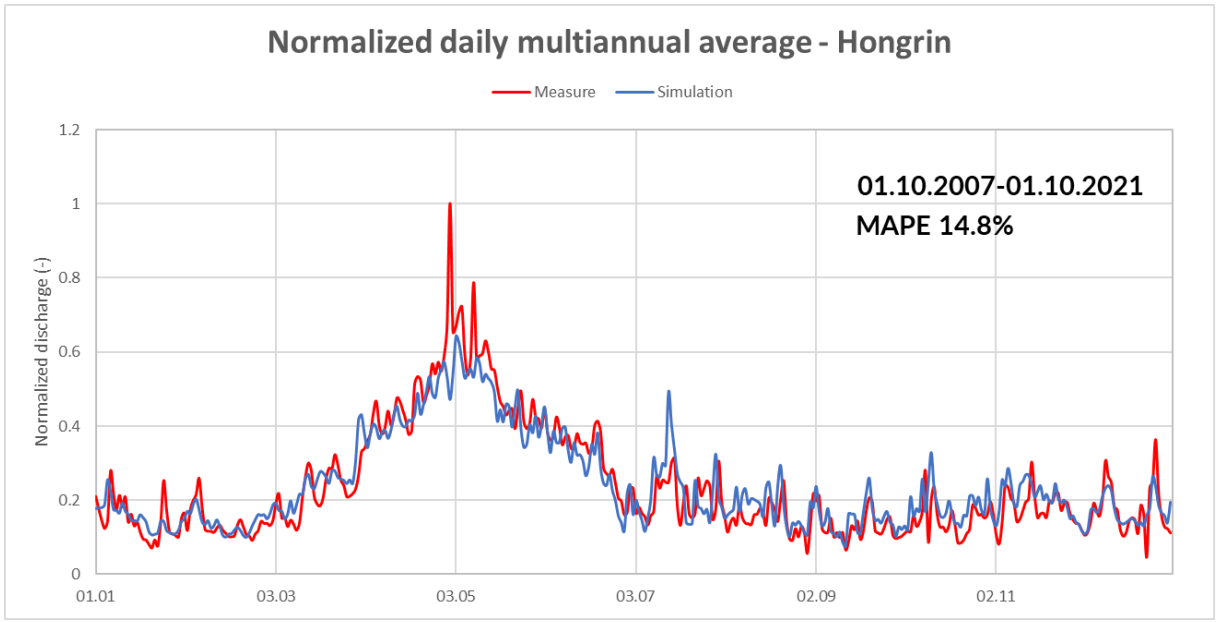


Figure C-11 Normalized measured and simulated daily multiannual average discharge for the Hongrin basin.

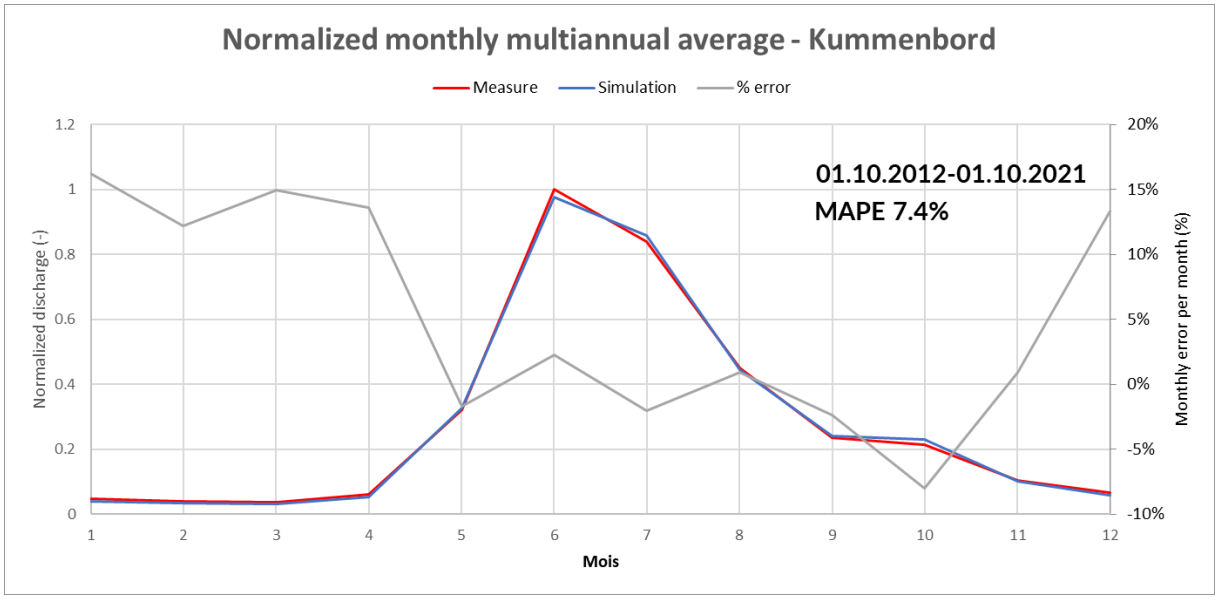


Figure C-12 Normalized measured and simulated monthly multiannual average discharge for the Kummenbord basin.

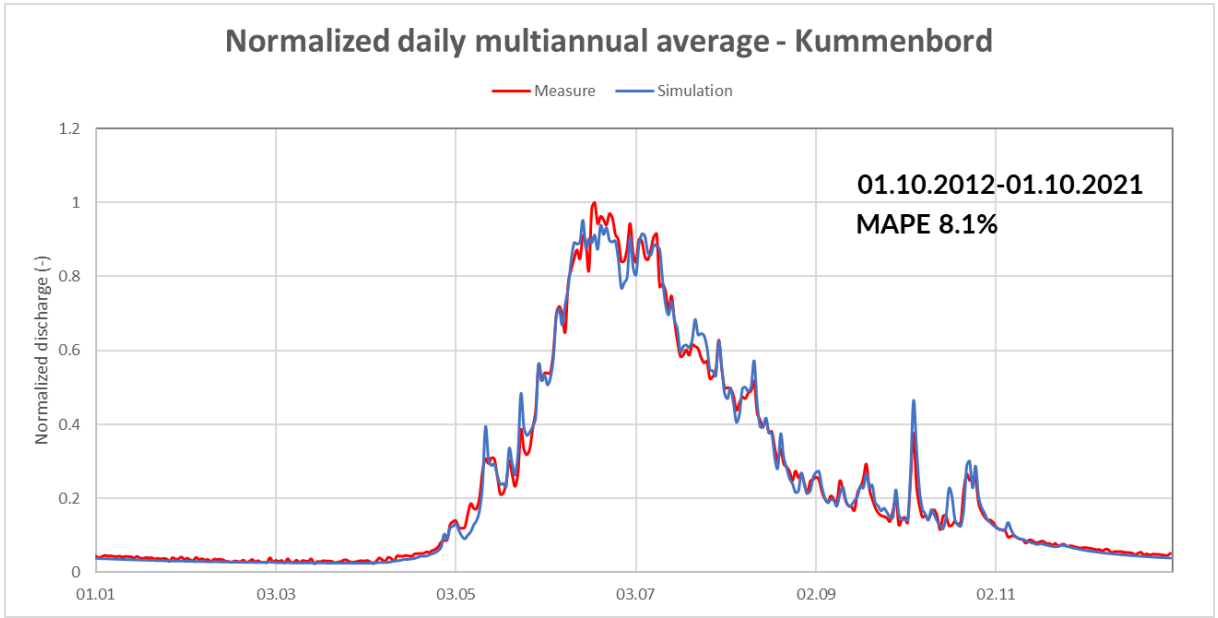


Figure C-13 Normalized measured and simulated daily multiannual average discharge for the Kummenbord basin.

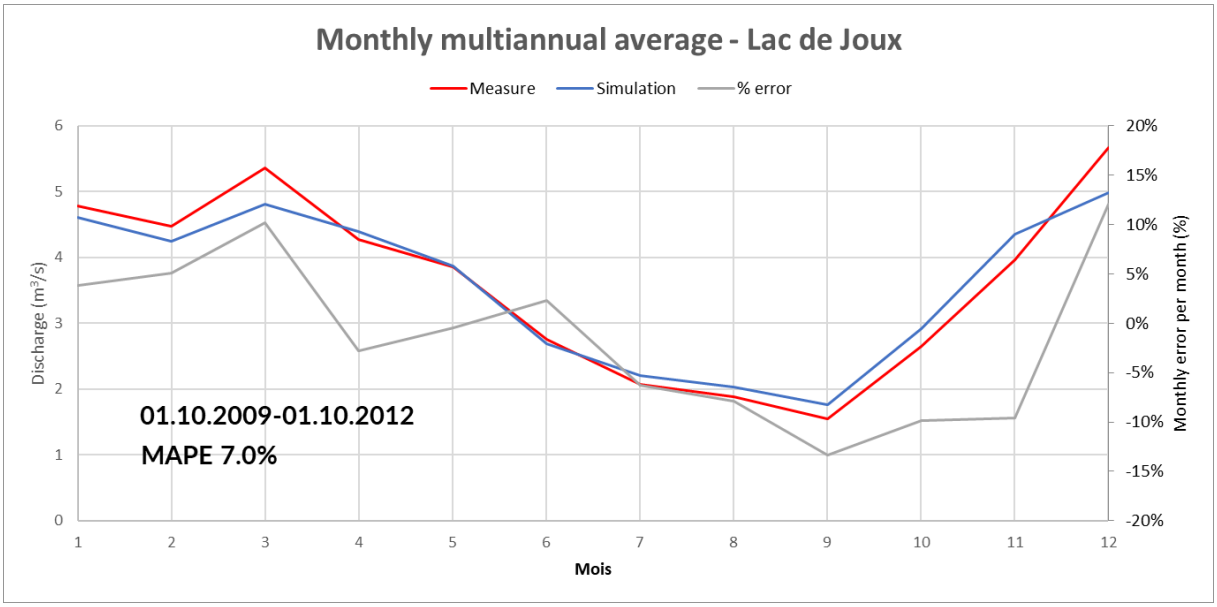


Figure C-14 Measured and simulated monthly multiannual average discharge for the Lac de Joux basin.

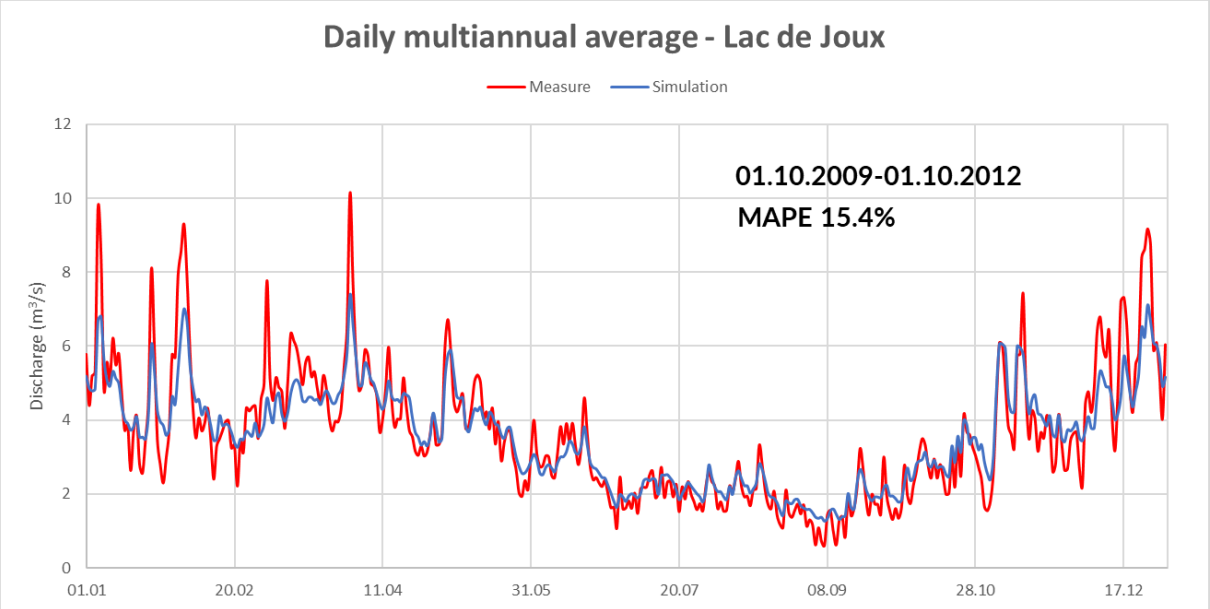


Figure C-15 Measured and simulated daily multiannual average discharge for the Lac de Joux basin.

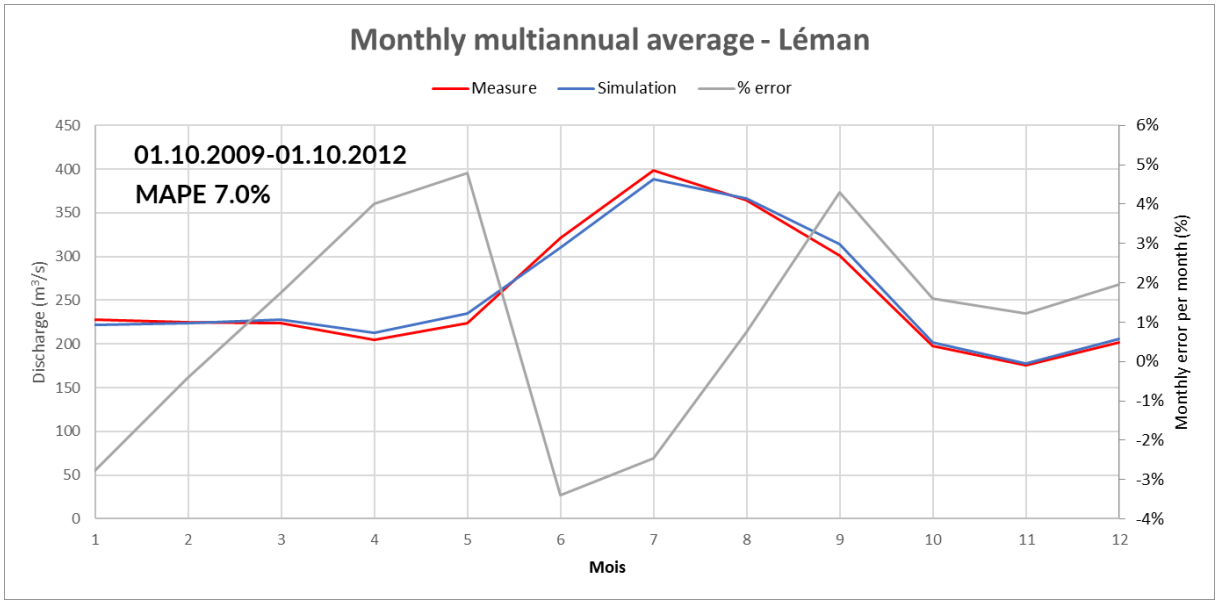


Figure C-16 Measured and simulated monthly multiannual average discharge for the Léman basin.

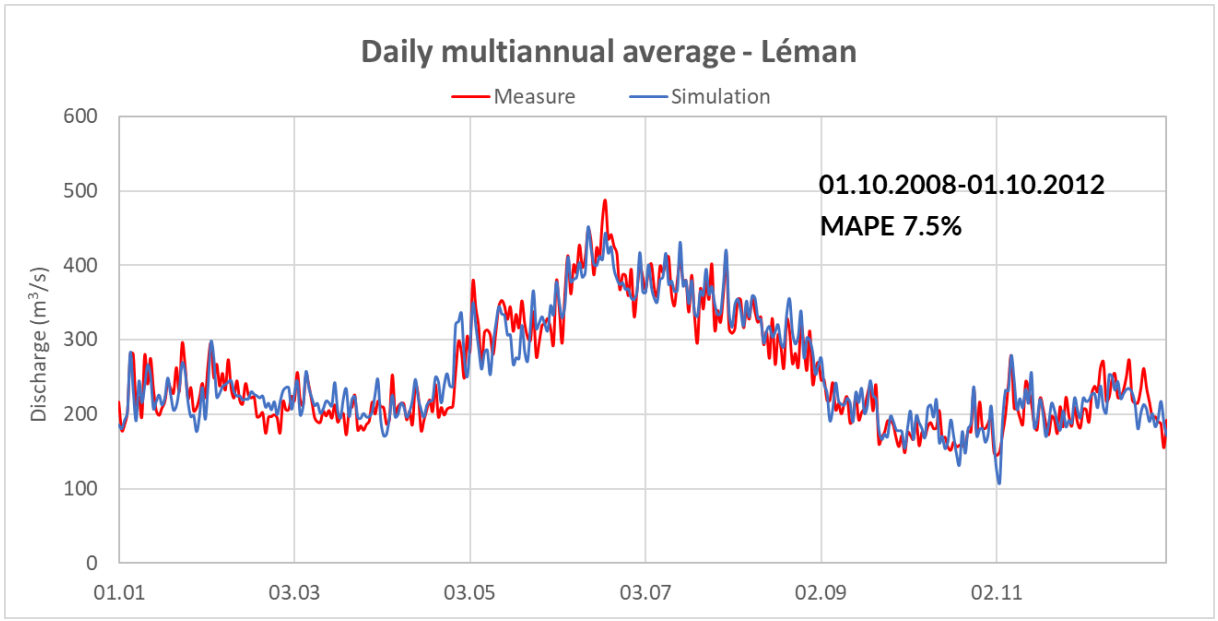


Figure C-17 Measured and simulated daily multiannual average discharge for the Léman basin.

ii. Seasonal forecasts using linear regressions

The performance of seasonal forecasts based on the RS simulation SWE and with the introduction of satellite SWE data are presented in this chapter, in comparison with the performance of the "benchmark" represented by the multiannual average. The training performances are evaluated first, then the cross-validation performances.

Training

Table C-2 and Table C-3 present the differences in monthly MAPE between the seasonal "Hydrique" forecast and the multiannual, based on the training scores. February and September are represented and correspond to the months of the forecast date (e.g., a 90-day forecast made in March is counted in March, although it forecasts volumes over March, April and May). A negative value (green) indicates a reduction of the MAPE with the "Hydrique" forecast, corresponding to an improved performance compared to the benchmark.

The performance of the seasonal Hydrique forecast is almost systematically better than that of the multiannual training forecast (benchmark). The improvements reach a maximum of 22% over one month (Hongrin, April, 30 days). The degradation of performance does not exceed 1% over a month (Gletsch, June, 60-90 days). On average, for all catchments, an improvement of at least 10% is achieved in April for a 30-day horizon. For a 180-day horizon, an improvement of at least 5% is achieved in June.

For shorter lead times (30-60 days), the improvements are mainly obtained at the beginning of the season, during the rise of the flow in spring (March, April, May). Bortelsee and Kummenbord are exceptions, with higher improvements in June-July.

On the longer lead times (150-180 days), the improvements are more consistent, with June showing the largest increases of skills. The June forecast volumes for the months of June through October-November are thus improved by 5% with the "Hydrique"-based linear regression.

Hydrique vs Multiannual - Training									
		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
30	Arve	-0.01	-0.05	-0.10	-0.07	-0.05	-0.04	-0.03	-0.02
	Bortelsee	+0.00	-0.01	-0.06	-0.02	-0.04	-0.14	-0.08	-0.02
	Emosson	-0.02	-0.05	-0.11	-0.03	-0.04	-0.01	-0.00	-0.05
	Ferden	-0.01	-0.06	-0.08	-0.00	-0.04	-0.01	-0.04	-0.01
	Gletsch	-0.03	-0.01	-0.01	-0.00	-0.00	-0.00	-0.01	-0.01
	Godet	-0.12	-0.11	-0.12	-0.01	-0.00	-0.01	-0.00	-0.01
	Gruyère	-0.05	-0.08	-0.14	-0.19	-0.06	-0.01	-0.01	-0.04
	Hongrin	-0.06	-0.09	-0.22	-0.09	-0.04	+0.00	-0.02	-0.07
	Joux	-0.10	-0.12	-0.09	-0.15	-0.02	0.00	0.00	-0.03
	Kummenbord	+0.00	-0.02	-0.04	-0.03	-0.08	-0.15	-0.02	-0.04
	Léman	-0.00	-0.01	-0.07	-0.05	-0.03	-0.03	-0.00	-0.02
	Zeuzier	-0.01	-0.02	-0.15	-0.00	-0.08	-0.06	-0.02	-0.02
	Average	**-0.03**	**-0.05**	**-0.10**	**-0.05**	**-0.04**	**-0.04**	**-0.02**	**-0.03**
60	Arve	-0.02	-0.07	-0.06	-0.06	-0.03	-0.03	-0.02	-0.01
	Bortelsee	-0.00	-0.05	-0.06	-0.05	-0.08	-0.13	-0.03	-0.02
	Emosson	-0.03	-0.12	-0.05	-0.04	-0.04	-0.01	-0.00	-0.06
	Ferden	-0.03	-0.03	-0.01	-0.03	-0.04	-0.01	-0.01	-0.01
	Gletsch	-0.00	-0.01	+0.00	-0.01	+0.01	+0.00	-0.01	-0.01
	Godet	-0.11	-0.04	-0.04	-0.01	-0.00	-0.01	-0.01	-0.02
	Gruyère	-0.01	-0.08	-0.09	-0.14	-0.02	-0.00	-0.01	-0.02
	Hongrin	-0.05	-0.11	-0.10	-0.07	-0.00	-0.00	-0.02	-0.05
	Joux	-0.02	-0.09	-0.07	-0.09	-0.01	0.00	0.00	-0.00
	Kummenbord	-0.01	-0.00	-0.01	-0.03	-0.13	-0.11	-0.04	-0.04
	Léman	-0.01	-0.04	-0.07	-0.07	-0.04	-0.02	-0.01	-0.00
	Zeuzier	-0.03	-0.09	-0.04	-0.04	-0.07	-0.03	-0.03	-0.03
	Average	**-0.03**	**-0.06**	**-0.05**	**-0.05**	**-0.04**	**-0.03**	**-0.02**	**-0.02**
90	Arve	-0.04	-0.05	-0.05	-0.04	-0.03	-0.04	-0.01	-0.01
	Bortelsee	-0.03	-0.04	-0.07	-0.07	-0.09	-0.12	-0.09	-0.02
	Emosson	-0.14	-0.07	-0.06	-0.03	-0.04	-0.02	-0.00	-0.06
	Ferden	-0.02	-0.00	-0.03	-0.05	-0.04	-0.01	-0.01	-0.02
	Gletsch	-0.02	+0.00	-0.02	-0.01	+0.01	-0.00	-0.02	-0.01
	Godet	-0.01	-0.03	-0.03	-0.01	-0.01	-0.01	-0.02	-0.01
	Gruyère	-0.03	-0.06	-0.06	-0.07	-0.01	-0.00	-0.05	-0.01
	Hongrin	-0.04	-0.05	-0.05	-0.03	-0.00	-0.03	-0.02	-0.03
	Joux	-0.02	-0.07	-0.07	-0.04	-0.00	0.00	0.00	-0.00
	Kummenbord	-0.00	-0.01	-0.03	-0.06	-0.12	-0.12	-0.04	-0.04
	Léman	-0.03	-0.05	-0.04	-0.05	-0.03	-0.02	-0.00	-0.00
	Zeuzier	-0.06	-0.04	-0.03	-0.05	-0.06	-0.04	-0.04	-0.03
	Average	**-0.04**	**-0.04**	**-0.04**	**-0.04**	**-0.03**	**-0.03**	**-0.03**	**-0.02**

Table C-2 Difference between Multiannual MAPE and “Hydrique” MAPE (Training score). A negative value (green) indicates an improvement in the forecasting performance. Lead times from 30 to 90 days.

Hydrique vs Multiannual - Training									
		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
120	Arve	-0.03	-0.03	-0.03	-0.03	-0.05	-0.07	-0.02	-0.00
	Bortelsee	-0.02	-0.05	-0.05	-0.08	-0.09	-0.16	-0.10	-0.02
	Emosson	-0.06	-0.06	-0.05	-0.03	-0.04	-0.01	-0.01	-0.06
	Ferden	+0.01	-0.02	-0.05	-0.04	-0.03	-0.01	-0.01	-0.01
	Gletsch	+0.01	-0.02	-0.03	-0.01	+0.01	-0.00	-0.02	-0.00
	Godet	-0.00	-0.03	-0.02	-0.01	-0.01	-0.02	-0.02	-0.01
	Gruyère	-0.03	-0.03	-0.02	-0.05	-0.03	-0.03	-0.04	-0.01
	Hongrin	-0.03	-0.02	-0.02	-0.03	-0.03	-0.07	-0.01	-0.02
	Joux	-0.03	-0.06	-0.04	-0.03	-0.02	0.00	0.00	-0.00
	Kummenbord	-0.01	-0.01	-0.03	-0.06	-0.12	-0.15	-0.05	-0.04
	Léman	-0.04	-0.02	-0.03	-0.05	-0.04	-0.04	-0.00	+0.00
	Zeuzier	-0.01	-0.01	-0.03	-0.04	-0.06	-0.05	-0.03	-0.02
	Average	**-0.02**	**-0.03**	**-0.03**	**-0.04**	**-0.04**	**-0.05**	**-0.02**	**-0.02**
150	Arve	-0.04	-0.03	-0.02	-0.04	-0.06	-0.06	-0.01	-0.01
	Bortelsee	-0.04	-0.04	-0.05	-0.07	-0.10	-0.16	-0.09	-0.02
	Emosson	-0.05	-0.05	-0.04	-0.03	-0.03	-0.01	-0.01	-0.05
	Ferden	-0.01	-0.03	-0.04	-0.04	-0.03	-0.00	-0.01	-0.01
	Gletsch	-0.02	-0.03	-0.03	-0.01	+0.01	-0.00	-0.03	-0.00
	Godet	-0.01	-0.02	-0.02	-0.01	-0.02	-0.02	-0.02	-0.01
	Gruyère	-0.03	-0.02	-0.01	-0.05	-0.04	-0.02	-0.01	-0.02
	Hongrin	-0.02	-0.01	-0.01	-0.04	-0.05	-0.06	-0.01	-0.03
	Joux	-0.02	-0.04	-0.04	-0.03	-0.03	0.00	0.00	-0.00
	Kummenbord	-0.01	-0.02	-0.03	-0.07	-0.14	-0.14	-0.05	-0.03
	Léman	-0.02	-0.01	-0.03	-0.03	-0.05	-0.04	-0.01	-0.00
	Zeuzier	-0.02	-0.02	-0.02	-0.04	-0.06	-0.05	-0.03	-0.02
	Average	**-0.02**	**-0.03**	**-0.03**	**-0.04**	**-0.05**	**-0.05**	**-0.02**	**-0.02**
180	Arve	-0.03	-0.02	-0.02	-0.04	-0.07	-0.02	-0.01	-0.01
	Bortelsee	-0.05	-0.04	-0.06	-0.08	-0.10	-0.15	-0.08	-0.02
	Emosson	-0.05	-0.04	-0.04	-0.03	-0.03	-0.02	-0.00	-0.05
	Ferden	-0.03	-0.03	-0.04	-0.03	-0.02	-0.00	-0.01	-0.01
	Gletsch	-0.03	-0.03	-0.03	-0.01	+0.01	-0.00	-0.03	-0.00
	Godet	-0.01	-0.02	-0.03	-0.02	-0.03	-0.02	-0.01	-0.01
	Gruyère	-0.02	-0.02	-0.01	-0.05	-0.04	-0.01	-0.02	-0.02
	Hongrin	+0.00	+0.00	-0.02	-0.06	-0.05	-0.03	-0.01	-0.03
	Joux	-0.01	-0.05	-0.04	-0.03	-0.03	0.00	0.00	-0.00
	Kummenbord	-0.02	-0.02	-0.03	-0.08	-0.14	-0.14	-0.05	-0.03
	Léman	-0.02	-0.01	-0.03	-0.03	-0.05	-0.03	+0.00	-0.00
	Zeuzier	-0.02	-0.02	-0.03	-0.04	-0.06	-0.04	-0.03	-0.02
	Average	**-0.02**	**-0.03**	**-0.03**	**-0.04**	**-0.05**	**-0.04**	**-0.02**	**-0.02**

Table C-3 Difference between Multiannual MAPE and “Hydrique” MAPE (Training score). A negative value (green) indicates an improvement in the forecasting performance. Lead times from 120 to 180 days.

Table C-4 and Table C-5 show the differences in monthly MAPE between the seasonal satellite-based "Wegaw" forecast and the multiannual average, based on the training scores. February and September are represented and correspond to the months of the forecast date (e.g., a 90-day forecast made in March is counted in March, although it forecasts volumes over March, April and May). A negative value (green) indicates a reduction of the MAPE with the "Wegaw" forecast, corresponding to an improved performance compared to the benchmark.

Wegaw Training

		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
30	Arve	-0.02	-0.05	-0.08	-0.06	-0.09	-0.09	-0.02	-0.02
	Bortelsee	-0.02	-0.01	-0.03	-0.01	-0.03	-0.12	-0.07	-0.02
	Emosson	-0.04	-0.03	-0.07	-0.01	-0.04	-0.00	-0.00	-0.06
	Ferden	-0.01	-0.04	-0.08	-0.00	-0.05	-0.01	-0.02	-0.01
	Gletsch	-0.03	-0.01	-0.03	-0.00	-0.00	-0.02	-0.01	-0.01
	Godet	-0.11	-0.12	-0.02	-0.02	-0.00	-0.00	-0.00	-0.01
	Gruyère	-0.05	-0.08	-0.16	-0.16	-0.04	+0.00	-0.02	-0.02
	Hongrin	-0.10	-0.11	-0.17	-0.06	-0.03	-0.00	-0.02	-0.07
	Joux	-0.09	-0.11	-0.08	-0.03	-0.04	0.00	0.00	-0.02
	Kummenbord	-0.01	-0.05	-0.02	-0.02	-0.07	-0.13	-0.03	-0.04
	Léman	+0.00	-0.01	-0.06	-0.03	-0.06	-0.03	-0.00	-0.02
	Zeuzier	-0.01	-0.03	-0.09	-0.03	-0.05	-0.05	-0.02	-0.01
	Average	**-0.04**	**-0.05**	**-0.08**	**-0.04**	**-0.04**	**-0.04**	**-0.02**	**-0.03**
60	Arve	-0.01	-0.05	-0.06	-0.08	-0.06	-0.05	-0.00	-0.02
	Bortelsee	-0.01	-0.06	-0.04	-0.02	-0.08	-0.13	-0.04	-0.03
	Emosson	-0.05	-0.08	-0.03	-0.03	-0.03	-0.00	-0.00	-0.06
	Ferden	-0.03	-0.04	-0.01	-0.04	-0.05	-0.01	-0.01	-0.01
	Gletsch	-0.01	-0.05	-0.03	-0.04	+0.00	-0.01	-0.01	-0.01
	Godet	-0.08	-0.00	-0.00	-0.00	+0.00	-0.01	-0.01	-0.02
	Gruyère	-0.02	-0.10	-0.15	-0.12	-0.02	-0.00	-0.00	-0.01
	Hongrin	-0.08	-0.11	-0.11	-0.06	-0.01	-0.01	-0.02	-0.05
	Joux	-0.02	-0.09	-0.08	-0.03	-0.03	0.00	0.00	-0.00
	Kummenbord	-0.03	-0.00	-0.01	-0.04	-0.12	-0.13	-0.04	-0.02
	Léman	-0.01	-0.05	-0.07	-0.07	-0.06	-0.02	-0.01	-0.01
	Zeuzier	-0.03	-0.05	-0.01	-0.04	-0.07	-0.03	-0.02	-0.02
	Average	**-0.03**	**-0.05**	**-0.05**	**-0.05**	**-0.04**	**-0.03**	**-0.01**	**-0.02**
90	Arve	-0.03	-0.06	-0.07	-0.07	-0.05	-0.03	-0.00	-0.01
	Bortelsee	-0.05	-0.04	-0.04	-0.04	-0.09	-0.14	-0.06	-0.03
	Emosson	-0.07	-0.05	-0.04	-0.02	-0.02	-0.01	-0.00	-0.06
	Ferden	-0.02	-0.01	-0.03	-0.05	-0.04	-0.02	-0.01	-0.01
	Gletsch	-0.07	-0.06	-0.04	-0.04	+0.00	-0.02	-0.02	-0.01
	Godet	+0.00	-0.00	-0.00	-0.00	-0.00	-0.01	-0.02	-0.01
	Gruyère	-0.03	-0.08	-0.10	-0.07	-0.01	-0.02	-0.01	+0.00
	Hongrin	-0.03	-0.07	-0.08	-0.03	-0.01	-0.03	-0.02	-0.03
	Joux	-0.02	-0.07	-0.08	-0.01	-0.01	0.00	0.00	-0.00
	Kummenbord	-0.00	-0.01	-0.04	-0.06	-0.11	-0.12	-0.05	-0.02
	Léman	-0.03	-0.05	-0.06	-0.07	-0.06	-0.01	-0.00	-0.00
	Zeuzier	-0.04	-0.03	-0.03	-0.05	-0.05	-0.04	-0.02	-0.02
	Average	**-0.03**	**-0.04**	**-0.05**	**-0.04**	**-0.04**	**-0.04**	**-0.02**	**-0.02**

Table C-4 Difference between Multiannual MAPE and "Wegaw" MAPE (Training score). A negative value (green) indicates an improvement in the forecasting performance. Lead times from 30 to 90 days.

Wegaw Training									
		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
120	Arve	-0.02	-0.05	-0.06	-0.06	-0.04	-0.07	-0.00	-0.01
	Bortelsee	-0.03	-0.03	-0.03	-0.04	-0.10	-0.14	-0.05	-0.03
	Emosson	-0.01	-0.04	-0.03	-0.02	-0.03	-0.01	-0.00	-0.06
	Ferden	+0.01	-0.02	-0.04	-0.03	-0.04	-0.01	-0.01	-0.01
	Gletsch	-0.02	-0.06	-0.05	-0.04	+0.00	-0.02	-0.02	-0.00
	Godet	+0.00	-0.01	-0.00	-0.00	-0.01	-0.02	-0.02	-0.01
	Gruyère	-0.04	-0.05	-0.05	-0.06	-0.04	-0.04	-0.02	-0.01
	Hongrin	-0.02	-0.04	-0.03	-0.03	-0.03	-0.07	-0.01	-0.02
	Joux	-0.02	-0.06	-0.05	-0.00	-0.02	0.00	0.00	-0.00
	Kummenbord	-0.00	-0.03	-0.03	-0.05	-0.12	-0.13	-0.05	-0.02
	Léman	-0.04	-0.04	-0.05	-0.06	-0.04	-0.02	-0.00	+0.00
	Zeuzier	+0.00	-0.02	-0.04	-0.05	-0.06	-0.05	-0.02	-0.02
	Average	**-0.02**	**-0.04**	**-0.04**	**-0.04**	**-0.04**	**-0.05**	**-0.02**	**-0.02**
150	Arve	-0.04	-0.06	-0.05	-0.06	-0.07	-0.07	-0.01	-0.02
	Bortelsee	-0.03	-0.02	-0.04	-0.04	-0.10	-0.13	-0.05	-0.02
	Emosson	-0.02	-0.02	-0.03	-0.03	-0.02	-0.00	-0.00	-0.06
	Ferden	-0.01	-0.03	-0.04	-0.04	-0.04	-0.01	-0.01	-0.01
	Gletsch	-0.05	-0.06	-0.05	-0.03	+0.00	-0.02	-0.03	-0.00
	Godet	-0.00	-0.00	-0.00	-0.00	-0.01	-0.02	-0.02	-0.01
	Gruyère	-0.03	-0.04	-0.04	-0.09	-0.06	-0.03	-0.00	-0.01
	Hongrin	-0.02	-0.02	-0.03	-0.04	-0.05	-0.06	-0.01	-0.03
	Joux	-0.02	-0.04	-0.05	-0.02	-0.03	0.00	0.00	-0.00
	Kummenbord	-0.03	-0.03	-0.03	-0.05	-0.13	-0.12	-0.06	-0.02
	Léman	-0.04	-0.03	-0.05	-0.04	-0.05	-0.03	-0.00	-0.00
	Zeuzier	-0.02	-0.03	-0.03	-0.05	-0.07	-0.05	-0.02	-0.02
	Average	**-0.02**	**-0.03**	**-0.03**	**-0.04**	**-0.05**	**-0.05**	**-0.02**	**-0.02**
180	Arve	-0.04	-0.05	-0.05	-0.08	-0.08	-0.04	-0.03	-0.03
	Bortelsee	-0.03	-0.03	-0.03	-0.04	-0.10	-0.13	-0.05	-0.02
	Emosson	-0.02	-0.02	-0.04	-0.03	-0.02	-0.00	-0.00	-0.06
	Ferden	-0.02	-0.02	-0.04	-0.04	-0.03	-0.01	-0.01	-0.01
	Gletsch	-0.05	-0.06	-0.04	-0.03	+0.00	-0.02	-0.03	-0.00
	Godet	-0.00	-0.01	-0.01	-0.00	-0.01	-0.02	-0.01	-0.01
	Gruyère	-0.02	-0.04	-0.06	-0.09	-0.06	-0.01	-0.01	-0.01
	Hongrin	+0.00	-0.01	-0.04	-0.07	-0.05	-0.03	-0.01	-0.03
	Joux	-0.02	-0.04	-0.04	-0.03	-0.03	0.00	0.00	-0.00
	Kummenbord	-0.03	-0.03	-0.02	-0.06	-0.13	-0.12	-0.06	-0.02
	Léman	-0.04	-0.02	-0.04	-0.03	-0.05	-0.03	-0.00	-0.00
	Zeuzier	-0.03	-0.02	-0.04	-0.05	-0.07	-0.05	-0.02	-0.02
	Average	**-0.03**	**-0.03**	**-0.04**	**-0.05**	**-0.05**	**-0.04**	**-0.02**	**-0.02**

Table C-5 Difference between Multiannual MAPE and “Wegaw” MAPE (Training score). A negative value (green) indicates an improvement in the forecasting performance. Lead times from 120 to 180 days.

Table C-6 and Table C-7 show the differences in monthly MAPEs between the satellite SWE-based “Wegaw” seasonal forecast and the RS simulation-based “Hydrique” seasonal forecasts (training scores). The months of February and September are represented and correspond to the months of the forecast date (e.g., a 90-day forecast made in March is counted in March, although it forecasts volume over the months of March, April and May). A negative value indicates a decrease in MAPE with the “Wegaw” forecast and thus an improvement of the performance by the “Wegaw” forecast.

On average, over all the catchments, the “Wegaw” forecasts with the satellite SWE data produce performances (monthly MAPE) that are similar to the “Hydrique” forecasts. However, the performances are not homogeneous on all the catchments. Moreover, for a given catchment, the differences are not homogeneous on the different months. For example, an improvement of 2 to 6% is observed in the Gletsch catchment between February and May. On the contrary, a loss of performance of almost 12% is possible (Lac de Joux, May, 30 days). Overall, the improvements by using “Wegaw” forecasts are slightly higher for longer time frames (150-180 days).

Wegaw vs Hydrique - Training

		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
30	Arve	-0.01	+0.00	+0.02	+0.01	-0.03	-0.05	+0.01	+0.01
	Bortelsee	-0.02	+0.00	+0.03	+0.01	+0.01	+0.02	+0.01	-0.00
	Emosson	-0.02	+0.02	+0.04	+0.02	+0.00	+0.01	-0.00	-0.01
	Ferden	+0.00	+0.02	-0.00	-0.00	-0.01	-0.00	+0.02	+0.00
	Gletsch	-0.00	-0.01	-0.02	-0.00	-0.00	-0.02	-0.01	-0.00
	Godet	+0.01	-0.02	+0.09	-0.01	+0.00	+0.00	-0.00	-0.00
	Gruyère	-0.01	-0.01	-0.02	+0.03	+0.03	+0.01	-0.01	+0.02
	Hongrin	-0.03	-0.02	+0.04	+0.03	+0.01	-0.01	-0.00	-0.00
	Joux	+0.01	+0.02	+0.01	+0.12	-0.01	0.00	0.00	+0.01
	Kummenbord	-0.01	-0.03	+0.02	+0.01	+0.01	+0.02	-0.01	+0.00
	Léman	+0.00	-0.00	+0.01	+0.01	-0.03	-0.01	+0.00	+0.00
	Zeuzier	-0.00	-0.01	+0.06	-0.03	+0.03	+0.01	-0.00	+0.00
	Average	**-0.01**	**-0.00**	**+0.02**	**+0.02**	**-0.00**	**-0.00**	**+0.00**	**+0.00**
60	Arve	+0.01	+0.02	+0.01	-0.02	-0.03	-0.03	+0.02	-0.00
	Bortelsee	-0.01	-0.00	+0.02	+0.03	+0.00	-0.00	-0.02	-0.01
	Emosson	-0.02	+0.04	+0.03	+0.01	+0.01	+0.01	+0.00	-0.00
	Ferden	-0.00	-0.00	+0.00	-0.01	-0.01	-0.00	+0.00	+0.00
	Gletsch	-0.01	-0.04	-0.03	-0.03	-0.00	-0.01	+0.00	-0.00
	Godet	+0.02	+0.03	+0.04	+0.01	+0.01	+0.00	+0.00	-0.00
	Gruyère	-0.01	-0.02	-0.05	+0.01	+0.00	+0.00	+0.01	+0.01
	Hongrin	-0.03	+0.00	-0.01	+0.01	-0.00	-0.00	-0.00	-0.00
	Joux	-0.00	+0.00	-0.01	+0.06	-0.02	0.00	0.00	+0.00
	Kummenbord	-0.02	+0.00	-0.00	-0.01	+0.00	-0.01	-0.00	+0.02
	Léman	-0.00	-0.00	-0.00	-0.01	-0.02	-0.00	-0.00	-0.00
	Zeuzier	-0.00	+0.04	+0.03	+0.00	+0.01	+0.01	+0.01	+0.01
	Average	**-0.01**	**+0.01**	**+0.00**	**+0.01**	**-0.00**	**-0.00**	**+0.00**	**+0.00**
90	Arve	+0.01	-0.01	-0.02	-0.03	-0.02	+0.01	+0.01	-0.00
	Bortelsee	-0.03	+0.00	+0.03	+0.03	+0.00	-0.02	+0.04	-0.01
	Emosson	+0.06	+0.02	+0.01	+0.01	+0.01	+0.01	+0.00	-0.00
	Ferden	-0.00	-0.01	+0.00	-0.00	-0.00	-0.00	+0.00	+0.00
	Gletsch	-0.05	-0.06	-0.02	-0.03	-0.00	-0.02	+0.00	-0.00
	Godet	+0.01	+0.02	+0.03	+0.00	+0.00	+0.00	+0.00	-0.00
	Gruyère	-0.00	-0.02	-0.04	-0.00	+0.00	-0.02	+0.03	+0.01
	Hongrin	+0.01	-0.02	-0.03	+0.01	-0.00	-0.00	-0.00	-0.00
	Joux	+0.00	-0.00	-0.01	+0.03	-0.01	0.00	0.00	+0.00
	Kummenbord	-0.00	-0.00	-0.01	+0.00	+0.00	+0.00	-0.01	+0.01
	Léman	-0.00	-0.00	-0.03	-0.01	-0.02	+0.01	+0.00	+0.00
	Zeuzier	+0.02	+0.01	+0.00	-0.01	+0.01	-0.00	+0.01	+0.01
	Average	**+0.00**	**-0.01**	**-0.01**	**+0.00**	**-0.00**	**-0.00**	**+0.01**	**+0.00**

Table C-6 Difference between “Wegaw” and “Hydrique” MAPE (Training score). A negative value (green) indicates an improvement in the forecasting performance “Wegaw”. Lead times from 30 to 90 days.

Wegaw vs Hydrique - Training

		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
120	Arve	+0.01	-0.02	-0.03	-0.03	+0.01	+0.00	+0.01	-0.01
	Bortelsee	-0.01	+0.02	+0.02	+0.03	-0.00	+0.02	+0.04	-0.01
	Emosson	+0.04	+0.02	+0.02	+0.02	+0.01	+0.01	+0.00	-0.00
	Ferden	-0.00	+0.00	+0.00	+0.00	-0.01	-0.01	+0.00	+0.00
	Gletsch	-0.03	-0.03	-0.02	-0.03	-0.00	-0.02	+0.00	-0.00
	Godet	+0.00	+0.01	+0.02	+0.01	+0.01	+0.00	-0.00	-0.00
	Gruyère	-0.01	-0.02	-0.03	-0.01	-0.01	-0.01	+0.02	+0.01
	Hongrin	+0.01	-0.02	-0.01	+0.00	-0.00	-0.00	-0.00	-0.00
	Joux	+0.01	+0.00	-0.01	+0.03	-0.00	0.00	0.00	+0.00
	Kummenbord	+0.01	-0.02	-0.00	+0.01	+0.00	+0.02	-0.01	+0.01
	Léman	+0.00	-0.02	-0.02	-0.01	-0.00	+0.01	+0.00	+0.00
	Zeuzier	+0.01	-0.01	-0.01	-0.01	-0.00	-0.01	+0.01	+0.01
	Average	**+0.00**	**-0.01**	**-0.01**	**+0.00**	**-0.00**	**+0.00**	**+0.01**	**+0.00**
150	Arve	+0.00	-0.03	-0.03	-0.02	-0.01	-0.01	+0.00	-0.01
	Bortelsee	+0.01	+0.02	+0.02	+0.03	-0.00	+0.02	+0.04	-0.00
	Emosson	+0.03	+0.02	+0.01	+0.00	+0.00	+0.01	+0.00	-0.00
	Ferden	+0.00	+0.00	+0.00	-0.00	-0.01	-0.00	-0.00	+0.00
	Gletsch	-0.03	-0.03	-0.02	-0.02	-0.00	-0.02	-0.00	-0.00
	Godet	+0.01	+0.01	+0.02	+0.01	+0.01	+0.00	+0.00	-0.00
	Gruyère	-0.00	-0.02	-0.03	-0.04	-0.02	-0.01	+0.01	+0.01
	Hongrin	-0.00	-0.01	-0.01	-0.01	-0.00	-0.00	-0.00	-0.00
	Joux	+0.00	+0.00	-0.01	+0.02	+0.00	0.00	0.00	+0.00
	Kummenbord	-0.01	-0.01	+0.00	+0.02	+0.01	+0.02	-0.01	+0.01
	Léman	-0.01	-0.01	-0.02	-0.00	+0.00	+0.01	+0.00	+0.00
	Zeuzier	-0.00	-0.01	-0.01	-0.01	-0.00	-0.01	+0.01	+0.00
	Average	**-0.00**	**-0.00**	**-0.01**	**-0.00**	**-0.00**	**+0.00**	**+0.01**	**+0.00**
180	Arve	-0.01	-0.03	-0.04	-0.04	-0.02	-0.03	-0.02	-0.02
	Bortelsee	+0.02	+0.02	+0.02	+0.03	-0.00	+0.02	+0.04	-0.00
	Emosson	+0.02	+0.02	+0.01	-0.00	+0.01	+0.01	+0.00	-0.00
	Ferden	+0.00	+0.01	+0.00	-0.01	-0.01	-0.00	-0.00	+0.00
	Gletsch	-0.03	-0.03	-0.02	-0.02	-0.00	-0.02	-0.00	-0.00
	Godet	+0.01	+0.01	+0.02	+0.01	+0.01	+0.00	+0.00	-0.00
	Gruyère	-0.01	-0.02	-0.05	-0.05	-0.01	-0.01	+0.01	+0.01
	Hongrin	-0.00	-0.01	-0.02	-0.00	-0.00	+0.00	-0.00	+0.00
	Joux	-0.00	+0.00	+0.00	-0.00	+0.00	0.00	0.00	+0.00
	Kummenbord	-0.01	-0.00	+0.01	+0.03	+0.01	+0.02	-0.01	+0.01
	Léman	-0.02	-0.01	-0.01	-0.00	+0.00	+0.00	-0.00	+0.00
	Zeuzier	-0.00	-0.00	-0.01	-0.01	-0.00	-0.01	+0.01	+0.00
	Average	**-0.00**	**-0.00**	**-0.01**	**-0.01**	**-0.00**	**-0.00**	**+0.00**	**+0.00**

Table C-7 Difference between “Wegaw” and “Hydrique” MAPE (Training score). A negative value (green) indicates an improvement in the forecasting performance “Wegaw”. Lead times from 90 to 180 days.

Cross-validation scores

Table C-8 and Table C-9 present the differences in monthly MAPE between the seasonal “Hydrique” forecast and the multiannual “benchmark” forecasts, based on the cross-validation. The months of February and September are represented and correspond to the months of the forecast date (e.g., a 90-day forecast made in March is counted in the month of March, although it forecasts volume over the months of March, April, and May). A negative value indicates a decrease in MAPE with the “Hydrique” forecasts and thus an improvement in performance compared to the benchmark.

The cross-validation results show more contrasting differences in monthly MAPE between the seasonal Hydrique forecast and the multiannual “benchmark” forecast. The periods for which the Hydrique forecasts are better are shorter than observed with the training scores.

Overall, the cross-validation performance of the “Hydrique” forecasts is worse at the end of the snow melt season, when there is very little snow left on the catchment. They are much worse than the multiannual in September, when there is no more, or very little, snow. Similarly, in August, only Bortelsee shows a significant improvement on all time frames, except for 60 days.

However, the “Hydrique” forecasts are still better overall than the March-May multiannual. The improvements made with the seasonal forecasts depend on the catchment areas, the lead times and the month. Some catchment areas such as Kummenbord and Bortelsee show more errors than the multiannual from February to May for a 30-day horizon, but less for a 180-day horizon. On the contrary, the “Hydrique” forecast is better for the “Lac de Gruyère” basin at the beginning of the year for a 30-day horizon but not for a 180-day horizon.

Hydrique vs Multiannual - Cross-Validation									
		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
30	Arve	+0.03	-0.04	-0.08	-0.06	-0.01	-0.01	-0.00	+0.06
	Bortelsee	+0.07	+0.04	+0.14	+0.11	-0.02	-0.13	-0.04	+0.10
	Emosson	+0.01	+0.14	-0.06	-0.00	-0.04	-0.00	+0.03	+0.02
	Ferden	+0.02	-0.04	-0.07	+0.04	-0.02	-0.00	+0.10	+0.05
	Gletsch	-0.00	+0.04	+0.09	+0.08	+0.03	+0.01	+0.02	+0.04
	Godet	-0.08	-0.09	-0.12	+0.04	+0.02	+0.02	NA	+1.34
	Gruyère	-0.03	-0.07	-0.14	-0.18	+0.06	+0.12	+0.05	+0.25
	Hongrin	-0.00	-0.07	-0.21	+0.00	+0.11	+0.58	-0.01	NA
	Joux	-0.08	-0.09	+0.09	+0.03	+0.41	0.00	0.00	-0.02
	Kummenbord	+0.02	+0.01	+0.21	+0.05	-0.07	-0.15	+0.02	+0.04
	Léman	+0.02	+0.00	-0.05	-0.03	-0.01	-0.02	+0.02	+0.02
	Zeuzier	+0.04	+0.09	-0.14	+0.05	-0.06	-0.02	+0.01	+0.05
	Average	**+0.00**	**-0.01**	**-0.03**	**+0.01**	**+0.03**	**+0.03**	**+0.02**	**+0.18**
60	Arve	-0.00	-0.06	-0.05	-0.04	-0.00	-0.01	+0.02	+0.12
	Bortelsee	+0.06	+0.05	+0.03	-0.05	-0.08	-0.12	+0.02	+0.14
	Emosson	+0.02	-0.10	-0.02	-0.03	-0.04	-0.01	+0.01	+0.02
	Ferden	-0.02	-0.01	+0.02	-0.02	-0.03	+0.01	+0.04	+0.04
	Gletsch	+0.03	+0.07	+0.07	+0.02	+0.03	+0.02	+0.02	+0.04
	Godet	-0.09	-0.03	-0.02	+0.02	+0.01	+0.00	NA	+1.40
	Gruyère	-0.00	-0.07	-0.07	-0.11	+0.08	+0.06	+0.05	+0.31
	Hongrin	-0.02	-0.11	-0.07	+0.01	+0.08	+0.50	-0.00	NA
	Joux	+0.01	-0.08	+0.09	+0.07	+0.10	0.00	0.00	+0.00
	Kummenbord	+0.01	+0.10	+0.07	-0.02	-0.14	-0.11	-0.02	+0.04
	Léman	+0.00	-0.02	-0.07	-0.06	-0.02	-0.01	+0.04	+0.04
	Zeuzier	+0.02	-0.07	-0.00	-0.02	-0.06	+0.01	-0.00	+0.04
	Average	**+0.00**	**-0.03**	**-0.00**	**-0.02**	**-0.01**	**+0.03**	**+0.02**	**+0.20**
90	Arve	-0.03	-0.04	-0.03	-0.02	-0.00	-0.04	+0.08	+0.06
	Bortelsee	+0.08	+0.03	-0.07	-0.08	-0.09	-0.11	-0.07	+0.13
	Emosson	-0.14	-0.05	-0.06	-0.03	-0.04	-0.01	+0.02	+0.02
	Ferden	+0.00	+0.03	-0.02	-0.04	-0.03	-0.00	+0.05	+0.04
	Gletsch	+0.03	+0.07	+0.01	+0.00	+0.03	+0.02	+0.00	+0.04
	Godet	+0.00	-0.01	-0.02	+0.01	+0.00	+0.00	NA	+1.12
	Gruyère	-0.02	-0.04	-0.02	-0.03	+0.07	+0.06	+0.01	+0.18
	Hongrin	-0.03	-0.04	-0.02	+0.03	+0.07	+0.83	-0.00	NA
	Joux	-0.01	-0.06	+0.03	+0.07	+0.31	0.00	0.00	+0.00
	Kummenbord	+0.08	+0.04	-0.01	-0.06	-0.12	-0.12	-0.01	+0.03
	Léman	-0.01	-0.04	-0.02	-0.05	-0.02	-0.01	+0.06	+0.03
	Zeuzier	-0.04	-0.01	-0.02	-0.05	-0.04	+0.00	-0.02	+0.04
	Average	**-0.01**	**-0.01**	**-0.02**	**-0.02**	**+0.01**	**+0.05**	**+0.01**	**+0.15**

Table C-8 Difference between “Hydrique” and multiannual “benchmark” MAPE (cross-validation score). A negative value (green) indicates an improvement in the forecasting performance “Wegaw”. Lead times from 30 to 90 days.

Hydrique vs Multiannual - Cross-Validation									
		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
120	Arve	-0.03	-0.02	-0.01	-0.01	-0.04	-0.05	+0.04	+0.07
	Bortelsee	+0.05	-0.04	-0.05	-0.08	-0.10	-0.17	-0.08	+0.12
	Emosson	-0.04	-0.06	-0.05	-0.03	-0.04	+0.00	+0.02	+0.01
	Ferden	+0.05	-0.00	-0.05	-0.03	-0.02	+0.00	+0.04	+0.04
	Gletsch	+0.07	+0.01	-0.01	-0.00	+0.04	+0.02	-0.00	+0.04
	Godet	+0.03	-0.02	-0.01	+0.00	-0.01	-0.01	NA	+1.02
	Gruyère	-0.02	+0.00	+0.03	-0.01	+0.01	+0.04	+0.00	+0.19
	Hongrin	-0.01	+0.00	+0.01	+0.03	+0.04	+0.47	-0.00	NA
	Joux	-0.02	-0.04	+0.07	+0.06	+0.38	0.00	0.00	+0.00
	Kummenbord	+0.04	-0.00	-0.02	-0.05	-0.13	-0.14	-0.02	+0.03
	Léman	-0.03	-0.00	-0.01	-0.05	-0.03	-0.03	+0.05	+0.03
	Zeuzier	+0.04	-0.00	-0.03	-0.04	-0.05	-0.02	-0.01	+0.03
	Average	**+0.01**	**-0.01**	**-0.01**	**-0.02**	**+0.00**	**+0.01**	**+0.00**	**+0.14**
150	Arve	-0.02	-0.01	+0.01	-0.03	-0.06	-0.04	+0.03	+0.06
	Bortelsee	-0.04	-0.04	-0.05	-0.08	-0.11	-0.17	-0.08	+0.10
	Emosson	-0.05	-0.05	-0.05	-0.03	-0.02	-0.00	+0.02	+0.01
	Ferden	+0.01	-0.02	-0.04	-0.04	-0.02	+0.01	+0.04	+0.04
	Gletsch	+0.01	-0.02	-0.02	+0.01	+0.04	+0.02	-0.01	+0.04
	Godet	+0.01	-0.01	-0.01	-0.00	-0.02	-0.02	NA	+0.74
	Gruyère	-0.01	+0.02	+0.04	-0.02	-0.01	+0.03	+0.04	+0.21
	Hongrin	+0.00	+0.02	+0.01	-0.01	-0.00	+0.33	-0.00	NA
	Joux	+0.00	-0.02	+0.09	+0.08	+0.63	0.00	0.00	+0.00
	Kummenbord	-0.00	-0.02	-0.01	-0.06	-0.16	-0.14	-0.02	+0.03
	Léman	-0.01	+0.01	-0.01	-0.03	-0.05	-0.04	+0.04	+0.02
	Zeuzier	-0.00	-0.02	-0.02	-0.03	-0.05	-0.02	-0.01	+0.03
	Average	**-0.01**	**-0.01**	**-0.00**	**-0.02**	**+0.01**	**-0.00**	**+0.01**	**+0.12**
180	Arve	-0.01	+0.00	+0.01	-0.02	-0.06	+0.02	+0.02	+0.06
	Bortelsee	-0.05	-0.04	-0.05	-0.08	-0.10	-0.16	-0.07	+0.08
	Emosson	-0.05	-0.04	-0.04	-0.02	-0.02	-0.00	+0.02	+0.01
	Ferden	-0.02	-0.02	-0.04	-0.03	-0.02	+0.01	+0.05	+0.03
	Gletsch	-0.01	-0.02	-0.01	+0.01	+0.04	+0.02	-0.01	+0.04
	Godet	+0.00	-0.01	-0.03	-0.01	-0.02	-0.01	NA	+0.96
	Gruyère	+0.01	+0.03	+0.05	-0.00	-0.02	+0.06	+0.06	+0.14
	Hongrin	+0.02	+0.03	+0.01	-0.05	-0.01	+0.51	-0.00	NA
	Joux	+0.00	-0.03	+0.12	+0.13	+0.66	0.00	0.00	+0.00
	Kummenbord	-0.02	-0.02	-0.01	-0.08	-0.16	-0.14	-0.02	+0.03
	Léman	-0.00	+0.01	-0.01	-0.01	-0.05	-0.02	+0.03	+0.02
	Zeuzier	-0.02	-0.02	-0.03	-0.03	-0.05	-0.02	-0.01	+0.03
	Average	**-0.01**	**-0.01**	**-0.00**	**-0.02**	**+0.02**	**+0.02**	**+0.01**	**+0.13**

Table C-9 Difference between “Hydrique” and multiannual “benchmark” MAPE (cross-validation score). A negative value (green) indicates an improvement in the forecasting performance “Wegaw”. Lead times from 120 to 180 days.

Table C-10 and Table C-11 present the differences in monthly MAPE between the seasonal “Wegaw” forecast and the multiannual average “benchmark” (cross-validation score). February and September are represented and correspond to the months of the forecast date (e.g., a 90-day forecast made in March is counted in March, although it forecasts volume over March, April, and May). A negative value indicates a decrease in MAPE with the “Wegaw” forecast and thus an improvement in performance compared to the benchmark.

Like the “Hydrique” forecast, the improvements with the “Wegaw” forecast over the benchmark forecast are heterogeneous and depend on the catchment, month, and lead times. Longer lead times profit from better improvements, but the multiannual average is better in August and September.

Wegaw vs Multiannual - Cross-Validation									
		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
30	Arve	+0.02	-0.04	-0.06	-0.04	-0.06	-0.07	+0.06	+0.06
	Bortelsee	+0.02	+0.05	+0.10	+0.07	-0.00	-0.11	+0.07	NA
	Emosson	+0.01	+0.32	-0.02	+0.03	-0.04	+0.01	+0.01	+0.01
	Ferden	+0.02	-0.01	-0.07	+0.04	-0.04	-0.00	+0.17	+0.15
	Gletsch	+0.01	+0.05	+0.09	+0.10	+0.02	-0.00	+0.03	+0.03
	Godet	-0.08	-0.11	+0.02	+0.03	+0.03	+0.08	NA	+3.67
	Gruyère	-0.02	-0.07	-0.15	-0.15	+0.07	+0.10	+0.04	+0.07
	Hongrin	-0.04	-0.09	-0.15	+0.05	+0.15	+1.06	-0.01	NA
	Joux	-0.03	-0.07	-0.04	+0.05	+0.14	0.00	0.00	-0.01
	Kummenbord	+0.01	-0.04	+0.29	+0.12	-0.06	-0.12	-0.01	+0.01
	Léman	+0.03	+0.00	-0.04	-0.01	-0.05	-0.01	+0.03	+0.02
	Zeuzier	+0.03	+0.05	-0.06	+0.01	-0.02	-0.01	+0.00	+0.04
	Average	**-0.00**	**+0.00**	**-0.01**	**+0.03**	**+0.01**	**+0.08**	**+0.04**	**+0.41**
60	Arve	+0.01	-0.03	-0.04	-0.06	-0.04	-0.02	+0.04	+0.08
	Bortelsee	+0.03	+0.03	+0.00	-0.01	-0.07	-0.10	+0.13	+10.70
	Emosson	+0.02	-0.03	+0.00	-0.01	-0.03	+0.01	+0.01	+0.00
	Ferden	-0.01	-0.01	+0.02	-0.02	-0.05	+0.01	+0.06	+0.12
	Gletsch	+0.03	-0.00	+0.04	-0.02	+0.03	+0.00	+0.04	+0.05
	Godet	-0.06	+0.03	+0.04	+0.03	+0.01	+0.00	NA	+4.59
	Gruyère	-0.01	-0.10	-0.13	-0.09	+0.09	+0.06	+0.06	+0.10
	Hongrin	-0.06	-0.10	-0.06	+0.03	+0.12	+1.08	-0.00	NA
	Joux	+0.00	-0.08	-0.05	+0.07	+0.18	0.00	0.00	+0.00
	Kummenbord	-0.02	+0.10	+0.09	-0.02	-0.13	-0.11	-0.02	+0.07
	Léman	+0.01	-0.03	-0.07	-0.07	-0.06	-0.00	+0.03	+0.04
	Zeuzier	+0.01	-0.01	+0.04	-0.02	-0.04	+0.03	-0.00	+0.04
	Average	**-0.00**	**-0.02**	**-0.01**	**-0.02**	**+0.00**	**+0.08**	**+0.03**	**+1.43**
90	Arve	-0.01	-0.05	-0.04	-0.05	-0.03	-0.02	+0.04	+0.07
	Bortelsee	-0.00	+0.00	-0.04	-0.04	-0.09	-0.13	+0.13	NA
	Emosson	-0.03	-0.04	-0.03	-0.01	-0.02	+0.01	+0.03	+0.01
	Ferden	-0.00	+0.02	-0.01	-0.04	-0.03	-0.01	+0.07	+0.12
	Gletsch	-0.05	-0.02	-0.02	-0.03	+0.02	-0.00	+0.02	+0.05
	Godet	+0.03	+0.03	+0.02	+0.02	+0.01	+0.02	NA	+2.45
	Gruyère	-0.02	-0.07	-0.07	-0.03	+0.08	+0.03	+0.07	+0.07
	Hongrin	-0.01	-0.05	-0.03	+0.05	+0.09	+0.80	-0.00	+15.36
	Joux	-0.01	-0.06	-0.05	+0.10	+0.14	0.00	0.00	+0.00
	Kummenbord	+0.09	+0.06	-0.03	-0.05	-0.12	-0.10	-0.02	+0.06
	Léman	-0.02	-0.05	-0.06	-0.06	-0.06	+0.01	+0.05	+0.03
	Zeuzier	-0.02	+0.01	-0.01	-0.05	-0.03	-0.01	-0.01	+0.03
	Average	**0.00**	**-0.02**	**-0.03**	**-0.02**	**0.00**	**0.05**	**0.03**	**1.66**

Table C-10 Difference between “Wegaw” and multiannual “benchmark” MAPE (cross-validation score). A negative value (green) indicates an improvement in the forecasting performance “Wegaw”. Lead times from 30 to 90 days.

Wegaw vs Multiannual - Cross-Validation									
		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
120	Arve	-0.01	-0.05	-0.04	-0.04	-0.03	-0.05	+0.04	+0.04
	Bortelsee	+0.01	-0.02	-0.02	-0.04	-0.10	-0.14	+0.08	NA
	Emosson	+0.03	-0.03	-0.03	-0.01	-0.03	+0.02	+0.03	+0.00
	Ferden	+0.04	-0.00	-0.04	-0.03	-0.04	-0.00	+0.07	+0.12
	Gletsch	+0.03	-0.04	-0.04	-0.03	+0.03	-0.01	+0.01	+0.05
	Godet	+0.04	+0.01	+0.01	+0.01	+0.00	-0.00	NA	+2.60
	Gruyère	-0.03	-0.03	-0.01	-0.02	+0.01	-0.00	+0.03	+0.03
	Hongrin	+0.01	-0.01	+0.01	+0.03	+0.05	+0.45	-0.00	+9.06
	Joux	-0.00	-0.03	-0.01	+0.08	+0.03	0.00	0.00	+0.00
	Kummenbord	+0.05	-0.02	-0.02	-0.04	-0.13	-0.10	-0.02	+0.06
	Léman	-0.03	-0.03	-0.04	-0.06	-0.04	-0.01	+0.04	+0.03
	Zeuzier	+0.05	-0.01	-0.04	-0.05	-0.04	-0.02	-0.01	+0.03
	Average	**+0.02**	**-0.02**	**-0.02**	**-0.02**	**-0.02**	**+0.01**	**+0.02**	**+1.09**
150	Arve	-0.02	-0.05	-0.03	-0.06	-0.07	-0.06	+0.04	+0.02
	Bortelsee	-0.03	-0.01	-0.03	-0.04	-0.11	-0.13	+0.09	NA
	Emosson	-0.00	-0.01	-0.03	-0.02	-0.02	+0.02	+0.03	+0.00
	Ferden	+0.01	-0.02	-0.03	-0.04	-0.04	+0.00	+0.06	+0.10
	Gletsch	-0.02	-0.06	-0.04	-0.01	+0.03	-0.01	-0.00	+0.05
	Godet	+0.02	+0.01	+0.01	+0.02	-0.01	-0.00	NA	+1.95
	Gruyère	-0.02	-0.02	-0.00	-0.07	-0.04	-0.01	+0.05	+0.04
	Hongrin	+0.01	+0.01	+0.01	-0.02	-0.01	+0.32	-0.00	+5.36
	Joux	+0.01	-0.01	-0.00	+0.52	+0.06	0.00	0.00	+0.00
	Kummenbord	-0.02	-0.03	-0.01	-0.03	-0.14	-0.10	-0.03	+0.05
	Léman	-0.03	-0.01	-0.04	-0.03	-0.04	-0.01	+0.03	+0.02
	Zeuzier	-0.01	-0.02	-0.03	-0.04	-0.05	-0.03	-0.01	+0.02
	Average	**-0.01**	**-0.02**	**-0.02**	**+0.01**	**-0.03**	**+0.00**	**+0.02**	**+0.69**
180	Arve	-0.03	-0.05	-0.05	-0.09	-0.08	-0.03	+0.03	+0.01
	Bortelsee	-0.02	-0.01	-0.02	-0.03	-0.10	-0.13	+0.11	NA
	Emosson	-0.01	-0.01	-0.02	-0.02	-0.01	+0.02	+0.03	-0.00
	Ferden	-0.02	-0.01	-0.04	-0.04	-0.03	+0.00	+0.07	+0.09
	Gletsch	-0.04	-0.05	-0.03	-0.02	+0.04	-0.01	-0.01	+0.05
	Godet	+0.01	+0.01	+0.01	+0.01	-0.01	+0.00	NA	+1.79
	Gruyère	-0.00	-0.01	-0.05	-0.08	-0.04	+0.02	+0.04	+0.03
	Hongrin	+0.03	+0.02	-0.01	-0.06	-0.01	+0.50	+0.00	+3.67
	Joux	-0.00	-0.02	+0.01	+0.94	+0.05	0.00	0.00	+0.00
	Kummenbord	-0.03	-0.02	+0.00	-0.05	-0.14	-0.09	-0.02	+0.05
	Léman	-0.03	-0.01	-0.03	-0.02	-0.04	-0.01	+0.03	+0.02
	Zeuzier	-0.03	-0.02	-0.03	-0.05	-0.05	-0.03	-0.00	+0.02
	Average	**-0.01**	**-0.02**	**-0.02**	**0.04**	**-0.04**	**0.02**	**0.02**	**0.52**

Table C-11 Difference between “Wegaw” and multiannual “benchmark” MAPE (cross-validation score). A negative value (green) indicates an improvement in the forecasting performance “Wegaw”. Lead times from 120 to 180 days.

Summary

As a conclusion, the analysis of the different forecasts allows us to determine which method is the best for each catchment, month and time frame. Table C-3 to Table C-16 summarize the performance improvements (MAPE) achieved by month if the best forecasting method is used, compared to the systematic use of the multiannual average (benchmark). Training and cross-validation scores are presented. Table C-12 provides a generalised overview on the performance of each methodology in comparison per basin.

In training, the best results are distributed between the “Hydrique” and “Wegaw” forecast. For shorter time frames (30 and 60 days), the “Hydrique” forecasts are slightly dominant while “Wegaw” method is slightly better for longer time frames (150 and 180 days). In practice this means that the “Wegaw” method is preferably used for longer lead times since it can identify long-term trends reflected in the snow dynamics in a more accurate manner. Once the lead time is shortened, the “Hydrique” method, which calculates and calibrates its SWE value based on the past inflow measurements, is able to reflect the inflow more accurately due to the nature of the model. This indicates that a hybrid approach of these two methods would be most beneficial to minimize inflow errors.

In cross-validation, for the shorter time frames of 30 and 60 days, the multiannual and the “Hydrique” forecasts provide overall better results. For longer time frames of 150 and 180 days, the “Wegaw” forecast is better, followed by the “Hydrique” forecast. These results support the assumption in the paragraph above.

In the end, an average improvement of 4% of MAPE is achieved on average in cross-validation on the forecasts made during the months of March to June included. This improvement rises to 5% in training. To put this into a statistical context, the MAPE of the benchmark approach ranges between 10% and 25%, depending on the season and the lead time.

This means for shorter lead times, the error is reduced by 25%, and for longer lead times between 35% and 50%. This presents a significant error reduction that creates potential to be leveraged in hydropower operations through better timely forecasts, therefore improving decision making.

Catchment	Wegaw	RS	Similar
Arve	✓		
Emosson		✓	
Bortelsee		✓	
Ferden			✓
Gletsch	✓		
Godet		✓	
Gruyère	✓		
Hongrin	✓		
Kummenbord	✓		
Lac de Joux		✓	
Léman	✓		
Zeuzier	✓		

Table C-12 Overall identification of the best performance for seasonal inflow forecast by methodology

Best MAPE - Training

		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
30	Arve	-0.02	-0.05	-0.10	-0.07	-0.09	-0.09	-0.03	-0.02
	Bortelsee	-0.02	-0.01	-0.06	-0.02	-0.04	-0.14	-0.08	-0.02
	Emosson	-0.04	-0.05	-0.11	-0.03	-0.04	-0.01	-0.00	-0.06
	Ferden	-0.01	-0.06	-0.08	-0.00	-0.05	-0.01	-0.04	-0.01
	Gletsch	-0.03	-0.01	-0.03	-0.00	-0.00	-0.02	-0.01	-0.01
	Godet	-0.12	-0.12	-0.12	-0.02	-0.00	-0.01	-0.00	-0.01
	Gruyère	-0.05	-0.08	-0.16	-0.19	-0.06	-0.01	-0.02	-0.04
	Hongrin	-0.10	-0.11	-0.22	-0.09	-0.04	-0.00	-0.02	-0.07
	Joux	-0.10	-0.12	-0.09	-0.15	-0.04	0.00	0.00	-0.03
	Kummenbord	-0.01	-0.05	-0.04	-0.03	-0.08	-0.15	-0.03	-0.04
	Léman	-0.00	-0.01	-0.07	-0.05	-0.06	-0.03	-0.00	-0.02
	Zeuzier	-0.01	-0.03	-0.15	-0.03	-0.08	-0.06	-0.02	-0.02
		-0.04	**-0.06**	**-0.10**	**-0.06**	**-0.05**	**-0.04**	**-0.02**	**-0.03**
60	Arve	-0.02	-0.07	-0.06	-0.08	-0.06	-0.05	-0.02	-0.02
	Bortelsee	-0.01	-0.06	-0.06	-0.05	-0.08	-0.13	-0.04	-0.03
	Emosson	-0.05	-0.12	-0.05	-0.04	-0.04	-0.01	-0.00	-0.06
	Ferden	-0.03	-0.04	-0.01	-0.04	-0.05	-0.01	-0.01	-0.01
	Gletsch	-0.01	-0.05	-0.03	-0.04	0.00	-0.01	-0.01	-0.01
	Godet	-0.11	-0.04	-0.04	-0.01	-0.00	-0.01	-0.01	-0.02
	Gruyère	-0.02	-0.10	-0.15	-0.14	-0.02	-0.00	-0.01	-0.02
	Hongrin	-0.08	-0.11	-0.11	-0.07	-0.01	-0.01	-0.02	-0.05
	Joux	-0.02	-0.09	-0.08	-0.09	-0.03	0.00	0.00	-0.00
	Kummenbord	-0.03	-0.00	-0.01	-0.04	-0.13	-0.13	-0.04	-0.04
	Léman	-0.01	-0.05	-0.07	-0.07	-0.06	-0.02	-0.01	-0.01
	Zeuzier	-0.03	-0.09	-0.04	-0.04	-0.07	-0.03	-0.03	-0.03
		-0.03	**-0.07**	**-0.06**	**-0.06**	**-0.05**	**-0.03**	**-0.02**	**-0.03**
90	Arve	-0.04	-0.06	-0.07	-0.07	-0.05	-0.04	-0.01	-0.01
	Bortelsee	-0.05	-0.04	-0.07	-0.07	-0.09	-0.14	-0.09	-0.03
	Emosson	-0.14	-0.07	-0.06	-0.03	-0.04	-0.02	-0.00	-0.06
	Ferden	-0.02	-0.01	-0.03	-0.05	-0.04	-0.02	-0.01	-0.02
	Gletsch	-0.07	-0.06	-0.04	-0.04	0.00	-0.02	-0.02	-0.01
	Godet	-0.01	-0.03	-0.03	-0.01	-0.01	-0.01	-0.02	-0.01
	Gruyère	-0.03	-0.08	-0.10	-0.07	-0.01	-0.02	-0.05	-0.01
	Hongrin	-0.04	-0.07	-0.08	-0.03	-0.01	-0.03	-0.02	-0.03
	Joux	-0.02	-0.07	-0.08	-0.04	-0.01	0.00	0.00	-0.00
	Kummenbord	-0.00	-0.01	-0.04	-0.06	-0.12	-0.12	-0.05	-0.04
	Léman	-0.03	-0.05	-0.06	-0.07	-0.06	-0.02	-0.00	-0.00
	Zeuzier	-0.06	-0.04	-0.03	-0.05	-0.06	-0.04	-0.04	-0.03
		-0.04	**-0.05**	**-0.06**	**-0.05**	**-0.04**	**-0.04**	**-0.03**	**-0.02**

Multiannual
Hydrique
Wegaw

Table C-13 Realized improvements (Training) on MAPE if the best forecasting method is used, compared to the multiannual average. Colors indicate the best method (Multiannual in gray, Hydrique in blue and Wegaw in green). Lead times from 30 to 90 days.

Best MAPE - Training

		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
120	Arve	-0.03	-0.05	-0.06	-0.06	-0.05	-0.07	-0.02	-0.01
	Bortelsee	-0.03	-0.05	-0.05	-0.08	-0.10	-0.16	-0.10	-0.03
	Emosson	-0.06	-0.06	-0.05	-0.03	-0.04	-0.01	-0.01	-0.06
	Ferden	0.00	-0.02	-0.05	-0.04	-0.04	-0.01	-0.01	-0.01
	Gletsch	-0.02	-0.06	-0.05	-0.04	0.00	-0.02	-0.02	-0.00
	Godet	-0.00	-0.03	-0.02	-0.01	-0.01	-0.02	-0.02	-0.01
	Gruyère	-0.04	-0.05	-0.05	-0.06	-0.04	-0.04	-0.04	-0.01
	Hongrin	-0.03	-0.04	-0.03	-0.03	-0.03	-0.07	-0.01	-0.02
	Joux	-0.03	-0.06	-0.05	-0.03	-0.02	0.00	0.00	-0.00
	Kummenbord	-0.01	-0.03	-0.03	-0.06	-0.12	-0.15	-0.05	-0.04
	Léman	-0.04	-0.04	-0.05	-0.06	-0.04	-0.04	-0.00	0.00
	Zeuzier	-0.01	-0.02	-0.04	-0.05	-0.06	-0.05	-0.03	-0.02
		-0.02	**-0.04**	**-0.04**	**-0.05**	**-0.05**	**-0.05**	**-0.03**	**-0.02**
150	Arve	-0.04	-0.06	-0.05	-0.06	-0.07	-0.07	-0.01	-0.02
	Bortelsee	-0.04	-0.04	-0.05	-0.07	-0.10	-0.16	-0.09	-0.02
	Emosson	-0.05	-0.05	-0.04	-0.03	-0.03	-0.01	-0.01	-0.06
	Ferden	-0.01	-0.03	-0.04	-0.04	-0.04	-0.01	-0.01	-0.01
	Gletsch	-0.05	-0.06	-0.05	-0.03	0.00	-0.02	-0.03	-0.00
	Godet	-0.01	-0.02	-0.02	-0.01	-0.02	-0.02	-0.02	-0.01
	Gruyère	-0.03	-0.04	-0.04	-0.09	-0.06	-0.03	-0.01	-0.02
	Hongrin	-0.02	-0.02	-0.03	-0.04	-0.05	-0.06	-0.01	-0.03
	Joux	-0.02	-0.04	-0.05	-0.03	-0.03	0.00	0.00	-0.00
	Kummenbord	-0.03	-0.03	-0.03	-0.07	-0.14	-0.14	-0.06	-0.03
	Léman	-0.04	-0.03	-0.05	-0.04	-0.05	-0.04	-0.01	-0.00
	Zeuzier	-0.02	-0.03	-0.03	-0.05	-0.07	-0.05	-0.03	-0.02
		-0.03	**-0.04**	**-0.04**	**-0.05**	**-0.06**	**-0.05**	**-0.02**	**-0.02**
180	Arve	-0.04	-0.05	-0.05	-0.08	-0.08	-0.04	-0.03	-0.03
	Bortelsee	-0.05	-0.04	-0.06	-0.08	-0.10	-0.15	-0.08	-0.02
	Emosson	-0.05	-0.04	-0.04	-0.03	-0.03	-0.02	-0.00	-0.06
	Ferden	-0.03	-0.03	-0.04	-0.04	-0.03	-0.01	-0.01	-0.01
	Gletsch	-0.05	-0.06	-0.04	-0.03	0.00	-0.02	-0.03	-0.00
	Godet	-0.01	-0.02	-0.03	-0.02	-0.03	-0.02	-0.01	-0.01
	Gruyère	-0.02	-0.04	-0.06	-0.09	-0.06	-0.01	-0.02	-0.02
	Hongrin	0.00	-0.01	-0.04	-0.07	-0.05	-0.03	-0.01	-0.03
	Joux	-0.02	-0.05	-0.04	-0.03	-0.03	0.00	0.00	-0.00
	Kummenbord	-0.03	-0.03	-0.03	-0.08	-0.14	-0.14	-0.06	-0.03
	Léman	-0.04	-0.02	-0.04	-0.03	-0.05	-0.03	-0.00	-0.00
	Zeuzier	-0.03	-0.02	-0.04	-0.05	-0.07	-0.05	-0.03	-0.02
		-0.03	**-0.03**	**-0.04**	**-0.05**	**-0.06**	**-0.04**	**-0.02**	**-0.02**
	Multiannual								
	Hydrique								
	Wegaw								

Table C-14 Realized improvements (Training) on MAPE if the best forecasting method is used, compared to the multiannual average. Colors indicate the best method (Multiannual in gray, Hydrique in blue and Wegaw in green). Lead times from 120 to 180 days.

Best MAPE - Cross-Validation

		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
30	Arve	0.00	-0.04	-0.08	-0.06	-0.06	-0.07	-0.00	0.00
	Bortelsee	0.00	0.00	0.00	0.00	-0.02	-0.13	-0.04	0.00
	Emosson	0.00	0.00	-0.06	-0.00	-0.04	-0.00	0.00	0.00
	Ferden	0.00	-0.04	-0.07	0.00	-0.04	-0.00	0.00	0.00
	Gletsch	-0.00	0.00	0.00	0.00	0.00	-0.00	0.00	0.00
	Godet	-0.08	-0.11	-0.12	0.00	0.00	0.00	0.00	0.00
	Gruyère	-0.03	-0.07	-0.15	-0.18	0.00	0.00	0.00	0.00
	Hongrin	-0.04	-0.09	-0.21	0.00	0.00	0.00	-0.01	0.00
	Joux	-0.08	-0.09	-0.04	0.00	0.00	0.00	0.00	-0.02
	Kummenbord	0.00	-0.04	0.00	0.00	-0.07	-0.15	-0.01	0.00
	Léman	0.00	0.00	-0.05	-0.03	-0.05	-0.02	0.00	0.00
	Zeuzier	0.00	0.00	-0.14	0.00	-0.06	-0.02	0.00	0.00
		-0.02	**-0.04**	**-0.08**	**-0.02**	**-0.03**	**-0.03**	**-0.01**	**-0.00**
60	Arve	-0.00	-0.06	-0.05	-0.06	-0.04	-0.02	0.00	0.00
	Bortelsee	0.00	0.00	0.00	-0.05	-0.08	-0.12	0.00	0.00
	Emosson	0.00	-0.10	-0.02	-0.03	-0.04	-0.01	0.00	0.00
	Ferden	-0.02	-0.01	0.00	-0.02	-0.05	0.00	0.00	0.00
	Gletsch	0.00	-0.00	0.00	-0.02	0.00	0.00	0.00	0.00
	Godet	-0.09	-0.03	-0.02	0.00	0.00	0.00	0.00	0.00
	Gruyère	-0.01	-0.10	-0.13	-0.11	0.00	0.00	0.00	0.00
	Hongrin	-0.06	-0.11	-0.07	0.00	0.00	0.00	-0.00	0.00
	Joux	0.00	-0.08	-0.05	0.00	0.00	0.00	0.00	0.00
	Kummenbord	-0.02	0.00	0.00	-0.02	-0.14	-0.11	-0.02	0.00
	Léman	0.00	-0.03	-0.07	-0.07	-0.06	-0.01	0.00	0.00
	Zeuzier	0.00	-0.07	-0.00	-0.02	-0.06	0.00	-0.00	0.00
		-0.02	**-0.05**	**-0.03**	**-0.03**	**-0.04**	**-0.02**	**-0.00**	**0.00**
90	Arve	-0.03	-0.05	-0.04	-0.05	-0.03	-0.04	0.00	0.00
	Bortelsee	-0.00	0.00	-0.07	-0.08	-0.09	-0.13	-0.07	0.00
	Emosson	-0.14	-0.05	-0.06	-0.03	-0.04	-0.01	0.00	0.00
	Ferden	-0.00	0.00	-0.02	-0.04	-0.03	-0.01	0.00	0.00
	Gletsch	-0.05	-0.02	-0.02	-0.03	0.00	-0.00	0.00	0.00
	Godet	0.00	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00
	Gruyère	-0.02	-0.07	-0.07	-0.03	0.00	0.00	0.00	0.00
	Hongrin	-0.03	-0.05	-0.03	0.00	0.00	0.00	-0.00	0.00
	Joux	-0.01	-0.06	-0.05	0.00	0.00	0.00	0.00	0.00
	Kummenbord	0.00	0.00	-0.03	-0.06	-0.12	-0.12	-0.02	0.00
	Léman	-0.02	-0.05	-0.06	-0.06	-0.06	-0.01	0.00	0.00
	Zeuzier	-0.04	-0.01	-0.02	-0.05	-0.04	-0.01	-0.02	0.00
		-0.03	**-0.03**	**-0.04**	**-0.04**	**-0.03**	**-0.03**	**-0.01**	**0.00**

Multiannual
Hydrique
Wegaw

Table C-15 Realized improvements (Cross-validation) on MAPE if the best forecasting method is used, compared to the multiannual average. Colors indicate the best method (Multiannual in gray, Hydrique in blue and Wegaw in green). Lead times from 30 to 90 days.

Best MAPE - Cross-Validation

		Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre
120	Arve	-0.03	-0.05	-0.04	-0.04	-0.04	-0.05	0.00	0.00
	Bortelsee	0.00	-0.04	-0.05	-0.08	-0.10	-0.17	-0.08	0.00
	Emosson	-0.04	-0.06	-0.05	-0.03	-0.04	0.00	0.00	0.00
	Ferden	0.00	-0.00	-0.05	-0.03	-0.04	-0.00	0.00	0.00
	Gletsch	0.00	-0.04	-0.04	-0.03	0.00	-0.01	-0.00	0.00
	Godet	0.00	-0.02	-0.01	0.00	-0.01	-0.01	0.00	0.00
	Gruyère	-0.03	-0.03	-0.01	-0.02	0.00	-0.00	0.00	0.00
	Hongrin	-0.01	-0.01	0.00	0.00	0.00	0.00	-0.00	0.00
	Joux	-0.02	-0.04	-0.01	0.00	0.00	0.00	0.00	0.00
	Kummenbord	0.00	-0.02	-0.02	-0.05	-0.13	-0.14	-0.02	0.00
	Léman	-0.03	-0.03	-0.04	-0.06	-0.04	-0.03	0.00	0.00
	Zeuzier	0.00	-0.01	-0.04	-0.05	-0.05	-0.02	-0.01	0.00
		-0.01	**-0.03**	**-0.03**	**-0.03**	**-0.04**	**-0.04**	**-0.01**	**0.00**
150	Arve	-0.02	-0.05	-0.03	-0.06	-0.07	-0.06	0.00	0.00
	Bortelsee	-0.04	-0.04	-0.05	-0.08	-0.11	-0.17	-0.08	0.00
	Emosson	-0.05	-0.05	-0.05	-0.03	-0.02	-0.00	0.00	0.00
	Ferden	0.00	-0.02	-0.04	-0.04	-0.04	0.00	0.00	0.00
	Gletsch	-0.02	-0.06	-0.04	-0.01	0.00	-0.01	-0.01	0.00
	Godet	0.00	-0.01	-0.01	-0.00	-0.02	-0.02	0.00	0.00
	Gruyère	-0.02	-0.02	-0.00	-0.07	-0.04	-0.01	0.00	0.00
	Hongrin	0.00	0.00	0.00	-0.02	-0.01	0.00	-0.00	0.00
	Joux	0.00	-0.02	-0.00	0.00	0.00	0.00	0.00	0.00
	Kummenbord	-0.02	-0.03	-0.01	-0.06	-0.16	-0.14	-0.03	0.00
	Léman	-0.03	-0.01	-0.04	-0.03	-0.05	-0.04	0.00	0.00
	Zeuzier	-0.01	-0.02	-0.03	-0.04	-0.05	-0.03	-0.01	0.00
		-0.02	**-0.03**	**-0.03**	**-0.04**	**-0.05**	**-0.04**	**-0.01**	**0.00**
180	Arve	-0.03	-0.05	-0.05	-0.09	-0.08	-0.03	0.00	0.00
	Bortelsee	-0.05	-0.04	-0.05	-0.08	-0.10	-0.16	-0.07	0.00
	Emosson	-0.05	-0.04	-0.04	-0.02	-0.02	-0.00	0.00	-0.00
	Ferden	-0.02	-0.02	-0.04	-0.04	-0.03	0.00	0.00	0.00
	Gletsch	-0.04	-0.05	-0.03	-0.02	0.00	-0.01	-0.01	0.00
	Godet	0.00	-0.01	-0.03	-0.01	-0.02	-0.01	0.00	0.00
	Gruyère	-0.00	-0.01	-0.05	-0.08	-0.04	0.00	0.00	0.00
	Hongrin	0.00	0.00	-0.01	-0.06	-0.01	0.00	-0.00	0.00
	Joux	-0.00	-0.03	0.00	0.00	0.00	0.00	0.00	0.00
	Kummenbord	-0.03	-0.02	-0.01	-0.08	-0.16	-0.14	-0.02	0.00
	Léman	-0.03	-0.01	-0.03	-0.02	-0.05	-0.02	0.00	0.00
	Zeuzier	-0.03	-0.02	-0.03	-0.05	-0.05	-0.03	-0.01	0.00
		-0.02	**-0.03**	**-0.03**	**-0.05**	**-0.05**	**-0.03**	**-0.01**	**-0.00**

Multiannual
Hydrique
Wegaw

Table C-16 Realized improvements (Cross-validation) on MAPE if the best forecasting method is used, compared to the multiannual average. Colors indicate the best method (Multiannual in gray, Hydrique in blue and Wegaw in green). Lead times from 120 to 180 days.

iii. Seasonal forecasts using machine learning models

Preliminary tests are realized, in order to evaluate the potential to improve the linear regression models by adding other data. Machine learning (ML) is appropriate to assimilate this external independent data and was tested in the hope of improving forecasts.

In this chapter, ML is used to provide seasonal forecasts for a 30 days lead time for the Ferden and Lac de Gruyère catchments.

Table C-17 summarizes the results of seasonal forecasts with ML at Ferden. The linear regression results are presented to determine if ML is better than the linear regression. Unfortunately, the ML model for seasonal forecasting did not beat the linear regression method for the Ferden catchment. This is probably due to the fact that the flows are very similar each year since the snowmelt period does not vary much, making the forecasting by regression simpler. The only model that comes close to the regression model is the Hybrid ML model, which uses the results of the regression forecasts as input.

Case study : Ferden catchment

		Ferden				
Month	Qmoy m^3/s	Q Sim > 0 m3/s MAPE 30 days				
		Linear regression SWE RS	**benchmark ML (without SWE)**	**ML SWE Wegaw**	**Hybrid ML (SWE RS)**	**Persistance**
January	1.2	16.2 %	40.7 %	43.6 %	17.1 %	20.4 %
February	1.3	22.0 %	49.4 %	53.0 %	22.9 %	15.5 %
March	2.2	32.0 %	48.6 %	47.0 %	29.6 %	36.9 %
April	5.7	28.4 %	37.4 %	37.6 %	27.3 %	57.2 %
May	13.0	24.7 %	25.2 %	24.4 %	26.6 %	53.5 %
June	18.4	13.6 %	17.2 %	17.4 %	15.5 %	30.6 %
July	16.0	11.0 %	11.5 %	12.6 %	12.9 %	21.3 %
August	11.2	9.8 %	17.3 %	17.7 %	10.5 %	45.7 %
September	5.9	16.4 %	38.5 %	36.5 %	20.3 %	96.4 %
October	3.2	22.3 %	23.7 %	26.0 %	28.8 %	90.0 %
November	2.3	19.7 %	21.6 %	20.1 %	23.6 %	67.9 %
December	1.3	16.9 %	37.5 %	34.2 %	15.9 %	37.2 %
AVERAGE	Summer	17.3 %	24.5 %	24.4 %	18.8 %	50.8 %

Table C-17 Perfomance (MAPE) of the seasonal forecast ML at the Ferden catchment, 30 days lead time.

Furthermore, incorporating the satellite SWE into the model does not appear to change the model; it is slightly worse than the model using the RS simulation SWE. Thus, incorporating the satellite SWE into seasonal forecasts with ML does not add any skill to the forecast. This is confirmed in Figure C-18, which shows that the differences between the two forecasts are very slight.

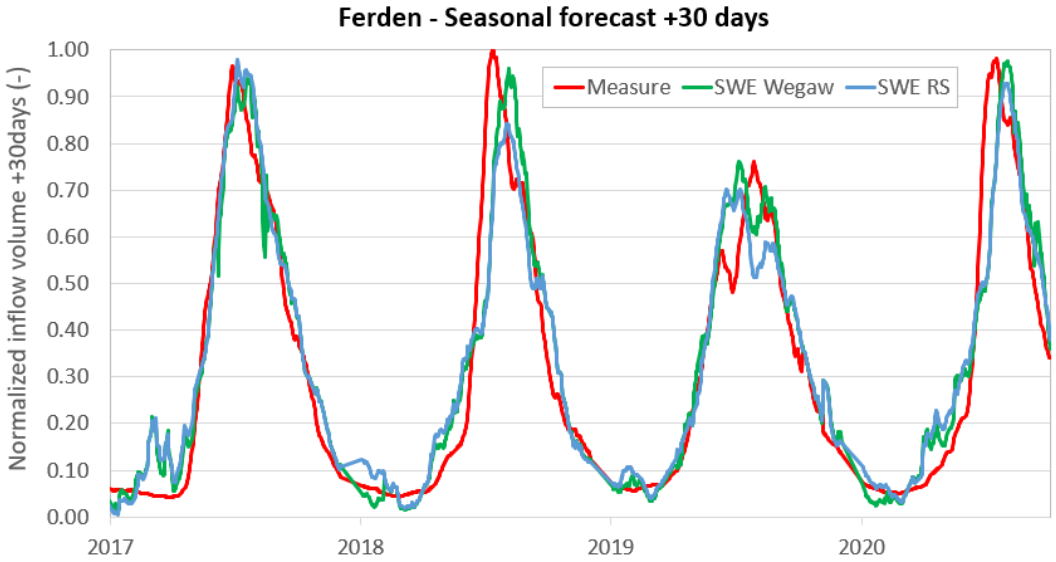


Figure C-18 Time series of seasonal forecasts by ML at Ferden, 30 days lead time. The green curve represents the SWE Wegaw model results, the blue curve represents the SWE RS model and the red curve represents the measured cumulative flow measurement.

Case study : Lac de Gruyère catchment

Table C-18 shows the results of ML as well as linear regression by inputs other than SWE. As with the linear regression, SWE is a good predictor for the months of March, April, and May. The Wegaw SWE does not appear to be the optimal predictor at all for this catchment: the MAPE is 54.6% over the entire year, compared to 49.5% for the RS model.

An overview of the forecast in Figure C-19 shows that many events are not predicted by the ML forecasting model. This is probably due to the fact that there is a high uncertainty related to the future meteorology. Still, for this catchment, the hybrid ML model performs better than the linear regression alone (particularly the spring season). Notably, among the ML models, the models that use the linear regression forecast results as input are the best.

Month	Qmoy m^3/s	Lac de Gruyère				
		Q Sim > 0 m3/s MAPE 30 days				
		PERS	Benchmark	SWE RS ML	WE WEGAW M	Hybrid ML
January	25.6	65.2 %	77.6 %	68.7 %	73.4 %	59.7 %
February	28.0	47.4 %	46.4 %	53.0 %	52.0 %	38.1 %
March	38.1	37.4 %	22.5 %	22.2 %	22.4 %	21.9 %
April	49.6	27.4 %	27.0 %	24.8 %	28.8 %	22.9 %
May	47.8	33.5 %	24.7 %	24.2 %	27.6 %	22.3 %
June	36.5	57.0 %	43.4 %	32.5 %	29.7 %	35.2 %
July	29.0	58.2 %	61.1 %	38.2 %	42.3 %	46.3 %
August	20.9	60.8 %	39.9 %	45.1 %	51.7 %	48.2 %
September	19.1	102.2 %	166.1 %	127.2 %	154.1 %	142.0 %
October	22.7	65.6 %	146.4 %	37.3 %	43.3 %	41.1 %
November	21.9	59.9 %	64.8 %	67.2 %	69.2 %	62.4 %
December	26.9	66.0 %	74.5 %	53.7 %	61.3 %	54.8 %
AVERAGE		56.7 %	66.2 %	49.5 %	54.6 %	49.6 %

Table C-18 Performance (MAPE) of the seasonal forecast ML at the Lac de Gruyère catchment, 30 days lead time.

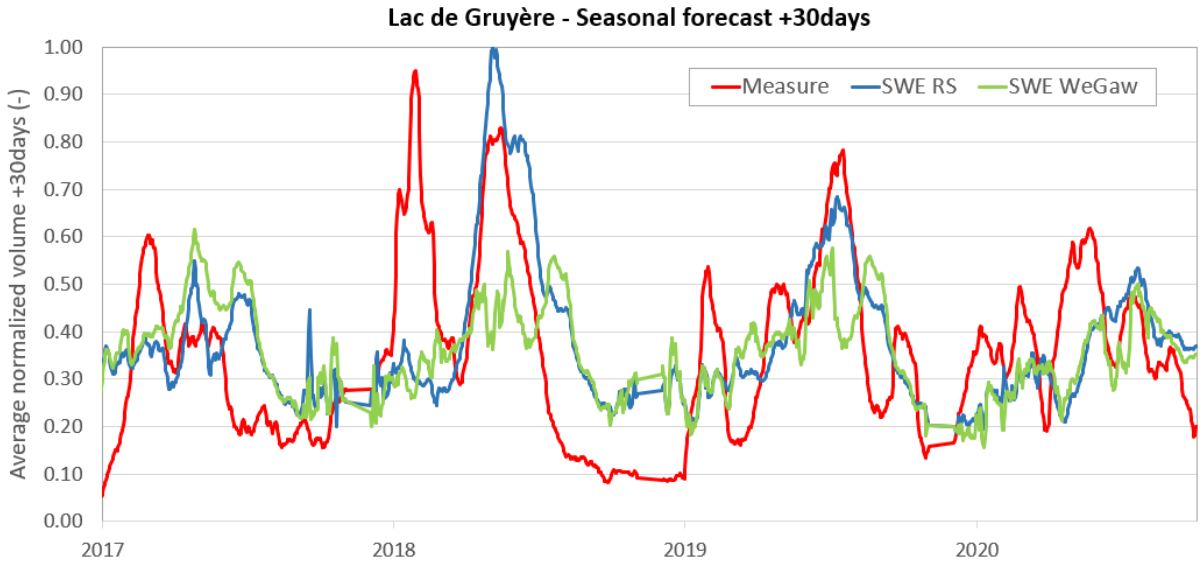


Figure C-19 Time series of seasonal forecasts by ML at Gruyère, 30 days lead time. The green curve represents the results of the SWE Wegaw model, the blue curve represents the SWE RS model and the red curve represents the cumulative flow measurement.

Summary

Incorporated into the ML models, the satellite SWE in the Lac de Gruyère and Ferden catchments do not improve performance. For the Lac de Gruyère case, the satellite data reduces performance by 4% during the snowmelt period, and by 6% throughout the year compared to the model containing the RS SWE. In the Ferden case, the model that incorporates the Wegaw SWE is tied with the RS model.

The results also show that there is potential for improvement for ML in 30-day seasonal forecasts, especially outside the snowmelt period, which are not well predicted by the linear regression alone.

c. Short-term forecasts

Short-term forecasts are made using rainfall-runoff simulation with Routing System RS with Machine Learning models. SWE and MSC “Melting-snow” Satellite data are integrated to these two models and the performances with the benchmark models are compared. Following on the assumption from the previous section, that Wegaw data does not bring as much improvement for shorter forecast lead times, this chapter will give a more depth analysis on potential additional value.

i. Integration of the satellite SWE into the Routing System simulation

Several rainfall-runoff models developed with Routing System are calibrated: a “benchmark” model and a “Wegaw” model using satellite SWE data. In the benchmark model case, the SWE is modeled by the RS snow model, while for the Wegaw SWE models, the SWE is updated once a day by the measured SWE Wegaw values. Table C-19 summarizes the performance of the tested models. “Nash” is the Nash-Sutcliffe model efficiency coefficient, a measure of the predictive skill of hydrological models.

Catchment	MAPE (%)		Nash (-)	
	Benchmark	SWE Wegaw	Benchmark	SWE Wegaw
Kummenbord	31.58	30.9	0.91	0.92
Bortelsee	53.12	56.45	0.85	0.81
Hongrin	42.52	39.93	0.69	0.73
Lac de Joux (Orbe le chenit)	39.56	42.74	0.77	0.8
Lac de Joux (Orbe le sentier)	36.6	40.1	0.76	0.77
Lac de Gruyère (Louibach)	26.62	26.71	0.65	0.65
Lac de Gruyère (Rossinière)	26.5	28.23	0.82	0.68

Table C-19 Performance of several rainfall-runoff simulation models for the Benchmark (SWE modeled by RS) and SWE-assimilated simulation model (Wegaw).

For Kummenbord, the performance of the model is slightly better with the Wegaw SWE.

For the Lac de Joux, although the Nash coefficient is higher, the MAPE is lower with the Wegaw SWE, so there is no significant improvement for this basin. This basin was particularly complicated to calibrate, as the flow created in the model by the melt of the assimilated SWE did not seem to match the measurements.

The Hongrin catchment shows the most positive results with respect to the use of the satellite SWE, with a better MAPE (40% instead of 42.5%), and an improved Nash coefficient (0.73 instead of 0.68). Furthermore, the simulation model using satellite SWE was easier to calibrate, and the snowmelt periods seem to correspond well to the measured flows.

In the Bortelsee and Lac de Gruyère cases, the assimilation of the satellite SWE in the simulation model does not improve the performance, the indicators being similar for both models.

These examples show that the results are very variable depending on the catchment area, depending on altitude and basin size, and if forests or glaciers are located in the basin. In Kummenbord and Hongrin, the models with satellite SWE (Wegaw) perform as well or better. Hongrin, as a large basin where calibration data for the “Wegaw” method was available performed significantly better than the benchmark. In Lac de Joux, Bortelsee and Lac de Gruyère, the results are not improved. Overall, the

integration of SWE from satellite measurements (instead of the SWE issued from the simulation model) does not significantly improve the MAPE and Nash coefficient indicators of the calibrations. However, some catchments show potential for improvements with the satellite SWE from Wegaw. These findings show that for short-term forecast, the use of Wegaw data is limited if the model is not highly trained for the specific basin based on ground truth, as it has been done for Hongrin. The need for this calibration data does limit the scalability of Wegaw data for short-term forecast since the data collection through stations and drones in a basin present an investment not necessarily attractive for each hydropower provider. However, if this specific data is available and the model can be calibrated, a significant improvement can be achieved.

Furthermore, it is noticed that the rainfall-runoff model calibration using satellite SWE is easier to achieve than a calibration without this information. This may be because in the RS snow model, the variation in melt intensity impacts the distribution of the snowpack throughout the season; it may be that there is insufficient snowpack to meet certain peak flows, or that there is not enough snowpack to meet flows at the end of the season. This is not the case when the calibration is performed with satellite SWE from Wegaw: the snowpack is updated once a day, its value does not change according to the calibration parameters. It is possible that the calibration is more robust on models calibrated with longer time series of Wegaw SWE.

ii. Machine learning models for short-term forecast

The potential of integrating the satellite SWE for short-term forecasts is tested in ML models for the case of Ferden, for 24-hours lead time forecasts at hourly time step.

Table C-20 shows that the snowmelt period (April to August) is the best performing (MAPE around 10%) for all models. The model containing the satellite SWE (Wegaw) is the only one that comes close to the benchmark model, beating it by less than 1% in May, July and August. This means that, in general, the satellite SWE data does not help improving the ML short-term forecasting models at Ferden.

Month	Qmoy m³/s	Ferden					
		Q Sim day > 4 m3/s MAPE 1h					
		PERS24h	Benchmark	SWE RS	SWE WeGaw	MSC WeGaw	SWE+MSC WeGaw
January	6.2	80.5 %	68.6 %	80.4 %	70.4 %	75.6 %	81.7 %
February							
March	4.4	42.4 %	27.8 %	26.7 %	30.1 %	28.4 %	30.0 %
April	7.0	10.5 %	11.0 %	11.8 %	12.9 %	13.3 %	13.3 %
May	10.5	11.9 %	10.0 %	10.6 %	9.9 %	11.0 %	11.5 %
June	20.0	12.0 %	9.4 %	9.8 %	9.7 %	10.1 %	9.9 %
July	19.0	14.1 %	10.5 %	11.0 %	10.2 %	10.5 %	10.7 %
August	14.2	17.0 %	12.4 %	13.4 %	12.2 %	12.3 %	13.0 %
September	8.2	16.4 %	15.9 %	16.5 %	16.0 %	16.1 %	16.3 %
October	5.3	22.8 %	19.3 %	20.5 %	20.1 %	20.6 %	20.6 %
November	5.4	30.3 %	22.0 %	21.9 %	23.6 %	23.2 %	21.9 %
December							
AVERAGE	13.4	14.8 %	12.2 %	12.9 %	12.4 %	12.8 %	13.0 %

Table C-20 Performance (expressed by MAPE for flows above 4 m3/s) of the different ML models developed to predict the flow at Ferden, at a 24h lead time, according to the month of the year.

* PERS24h : ML persistance model ; SWE RS : ML model using SWE from RS as input ; MSC Wgaw : ML model using melting snow (not detailed here) ; SWE+MSC WeGaw : ML model using SWE and melting snow.

Moreover, by observing the MAPE by flow class in Figure C-20, it turns out that the hybrid “SWE WeGaw” model (red curve) achieves less error than the Benchmark model (black line) for flows above 9 m^3/s.

The comparison of the forecasts in Figure C-21 (red for the Benchmark, blue for the model with SWE Wegaw data) in September shows that the Benchmark model is indeed able to better represent the daily oscillations due to snowmelt during the day. The results during the rest of the year are very similar, with the two models often overlapping.

The benchmark model contains variables from RS simulation forecasts (Qsimulated, Qsnow, precipitation, temperature). The results show that the addition of supplementary external variables from satellite measurements only improves the model very slightly for the months of May, July and August, as well as for flows greater than 9 m^3/s. Although this improvement is not significant, the results are encouraging. Indeed, the addition of the satellite SWE improves the model while the addition of the RS SWE reduces its performance. Satellite SWE has better predictive power in this case than the SWE modeled by RS. Satellite SWE shows exploitable potential, in several models tested, as it is the only variable that improves the benchmark instead of deteriorating it.

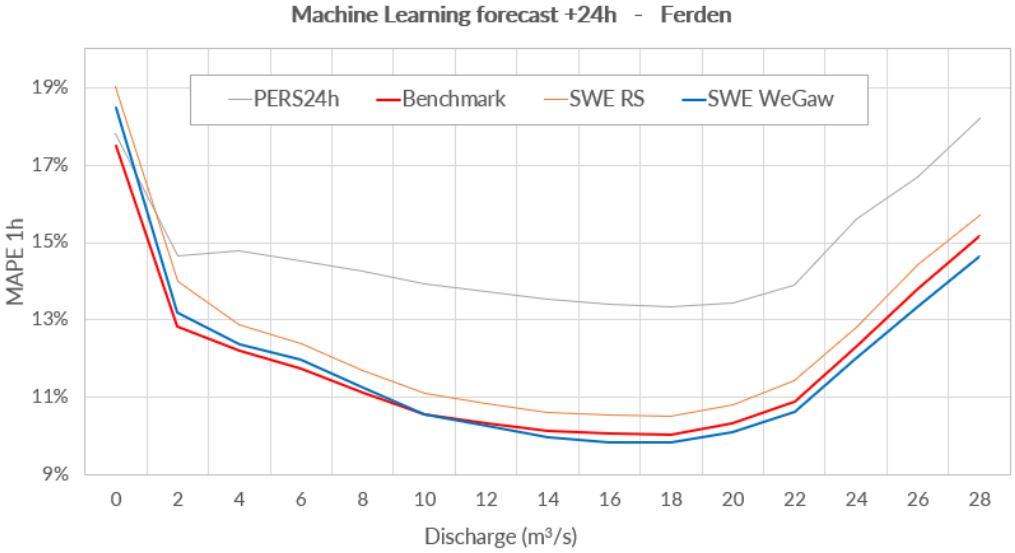


Figure C-20 Performance of the tested models for 24-hour forecasts for Ferden (MAPE) for different flow classes.

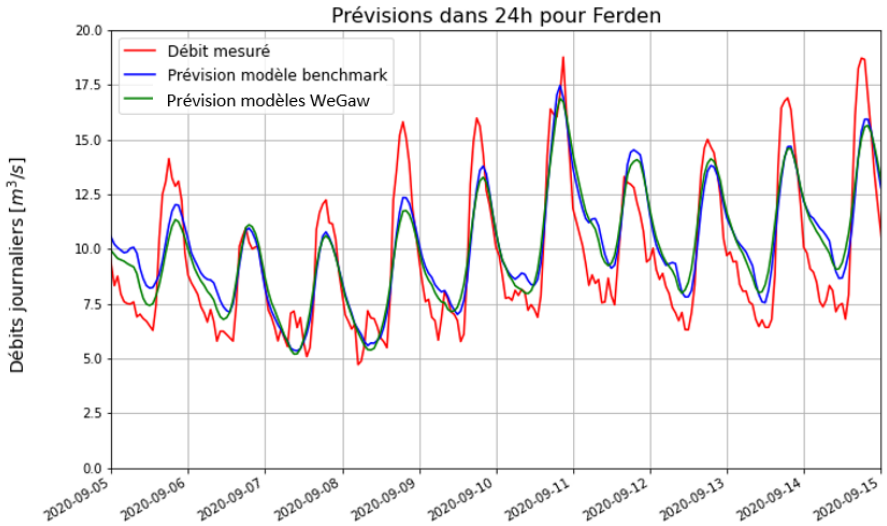


Figure C-21 Forecasts from the ML benchmark models and the hybrid Wegaw SWE model for Ferden, 24h lead time, hourly time step.

d. Economic assessment

An economic evaluation of the improvements achieved by seasonal forecasts is proposed. The difficulties in assessing the revenues of the facility operators are very significant and present a limitation of this project to reach a trustworthy number. Some explanations are described below:

- The marketing of electricity is possible on many markets (short term, medium term, regulation, guarantees, etc.). Thus, depending on the situation, each operator adapts its strategy according to the opportunities.
- As the different existing markets are linked to different time frames, it is always possible to adapt a bad medium-term strategy by a new short-term strategy.
- There are also possibilities to adapt for a given market. For example, a forecast deviation can be compensated for by updating the marketing strategy.
- In configurations with flexible arrangements, revenues are further optimised by the water storage strategy. Thus, a medium-term forecast deviation can always be compensated by a possible destocking / restocking
- Human decision-making is still very prominent for generation and trading strategies. This “human factor” is impossible to predict and adds significant uncertainty in the simulation.

Thus, revenue optimisation through better seasonal forecasting is difficult to demonstrate perfectly and in an ultra-realistic methodology.

However, it is obvious that any adaptation of the strategy has a cost, which can be called "adjustment cost". Indeed, renegotiating an existing contract involves a penalty. It can thus be shown that better forecasts imply a reduction in adjustment needs, and therefore a reduction in penalties. A visualisation of “adjustment costs” is shown below in Figure C-22 along with a text example how the economic analysis is calculated:

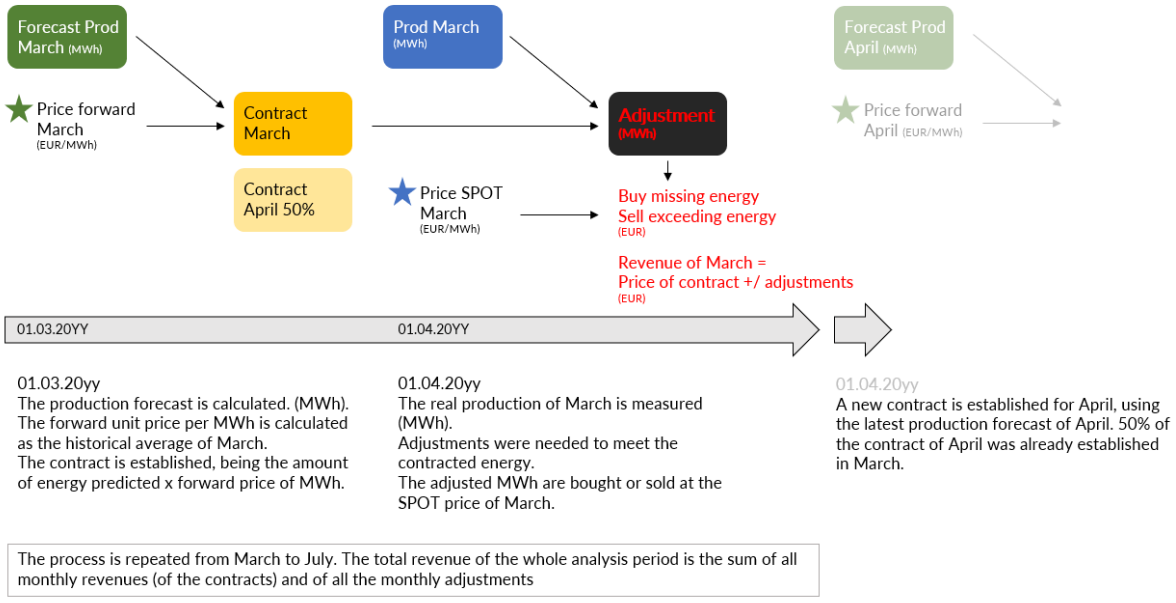


Figure C-22 Example of the adjustment process over the time of 2 months.

1. The analysis starts on 1st of March 2011. The seasonal flow forecast is converted into a monthly production volume (MWh). The entire volume forecast for March is contracted, at a fixed price corresponding to the historical average of March. The 50% of the volume forecast for April is contracted for April, the 33% of the volume forecast for May is contracted, etc.

2. On 1st of April 2011, the balance for the month of March is calculated since the actual production possible in March is known. To fulfil the contract, the operator agrees to adjustments during the month of March. If there is a shortage of energy, he buys it at the SPOT price for March. If there is exceeding energy, he sells it at the March SPOT price. The total revenue for March is the contract revenue + the adjustment revenue (or loss).

3. The contract for April must be established. 50% of the volume for April has already been contracted on 1st of March. The remaining 50% is contracted based on the new seasonal forecast of 1 April for April. 33% of the volume for May is contracted, 25% of the volume for June, etc.

4. On 1st of May 2011, the assessment for April is carried out, and the cycle continues.

The assessment ends on 31 July 2011, and starts again on 1 March 2012, and so on until 31 July 2021.

i. Methodology for analyzing adjustments in MWh

The objective of this assessment is to compare the required adjustment differences, in MWh, according to the forecasts used. The methodology is as follows:

- Electricity is sold from 1 March to 31 July. For the rest of the year, it is assumed that seasonal forecasts do not produce any added value.
- At the beginning of each month, production forecasts are made for each of the following 6 months. E.g., on 1 April 2021, production forecasts (in MWh) are provided for the periods 1st April to 1st May, 1st May to 1st June, ..., 1st July to 1st August.
- On 1 March, the electricity is sold as follows:
  - 100% of the expected quantity for the month of March
  - 50% of the forecast quantity for April
  - 33% of the forecast quantity for May
  - 25% of the forecast quantity for June
  - 20% of the forecast quantity for July
- On 1 April, the electricity is sold as follows:
  - 50% of the forecast quantity for April
  - 33% of the planned quantity for May
  - ...
- At the beginning of each month, the differences are calculated between the sum of the previous month's contracts and the potential production (the inflows) actually measured.
- According to this methodology, electricity is only sold once, which is consistent with rational marketing.
- The final indicator is the sum of the necessary adjustments, in absolute.
- All forecasts are derived from the cross-validation, and correspond to the forecasts that will be possible in 2023.

ii. Methodology for analyzing total income differences

The objective of this assessment is to analyse the total income differences. The following assumptions are made:

- Electricity is sold, at the beginning of each month, as per the adjustment gap method: from 1st March to 31st July; allocating contracts according to available maturities.
- The selling **price of the contract** is the **average SPOT price of the month**, based on the period 2013-2020 (2021 is deleted due to the change in price behaviour)
- The **purchase/sale price** of the balancing electricity corresponds to the **current SPOT price** (e.g. price of May 2019)
- Excess contracted energy has to be purchased on the market to fulfil the contract.
- Energy in excess of the contract must be sold on the market.
- The total revenue for the season is the contract revenue plus the revenue from the sale of excess electricity, minus the costs of the deviation from the contract (penalties) and the buy-back of electricity missing from the contract.
- All forecasts are derived from cross-validation, and correspond to the forecasts that will be achievable in 2023.

In this methodology, forecast errors sometimes have favourable consequences (if electricity has to be bought back cheaper than contracted, or if surplus electricity has to be sold more expensive than contracted), and sometimes unfavourable consequences.

iii. Results of the economic evaluation

Four seasonal forecasting models are compared:

- Perfect Forecast (PF): theoretical scenario where it is assumed that the inflows are perfectly known in advance.
- Multiannual forecast: average of historical inflows. This is the benchmark.
- Wegaw forecast: linear regression with SWE satellite data.
- Hydrique forecast: linear regression without SWE satellite data.

Table C-21 shows the energy balancing (adjustments) differences and total revenues for eight schemes. The following can be observed:

- In all cases, the total adjustment deviations are lower with the seasonal forecast than with the multi-annual average. The reduction in forecast errors is between 15% and 25%.
- As noticed during the analysis of forecast errors on volumes at +30d, +60d, etc., the Hydrique and Wegaw forecasts are quite close. In particular, the Wegaw forecasts are better for Ferden and Leman.
- The revenues are often better than with the multi-annual average. Compared to the multi-annual forecast, the use of seasonal forecasts yields between CHF 100'000 and 1'000'000 over the period 2013-2021 (9 years).
- Surprisingly, the perfect forecast does not always produce the best revenues. This is mainly due to the year 2021, when prices rose sharply, while the forecast was somewhat underestimated. Thus, the compensations by resale of electricity were very favourable.
- Table C-22 shows the same summary for the period 2013-2020, which confirms the superiority of the seasonal forecast models.

In the context of this project it is important to again mention the limited data availability of the satellite-based SWE used for the “Wegaw method”. With currently only 4 years available (and a minimum of 8 years needed), 4 SWE years were replaced by calibrated Hydrique SWE to complete the necessary 8 years. Considering the methodology used, the results are close as expected.

2013-2021	Adjustment (MWh)			Revenue (CHF)			
HPP - catchment	Multiannual	WeGaw	Hydrique	Perfect forecast	Multiannual	WeGaw	Hydrique
Kummenbord	139 212	117 711	113 188	22 899 847	22 952 386	22 801 732	22 677 352
Ferden	302 297	262 875	267 460	65 390 011	65 652 431	65 145 842	65 110 872
Emosson	446 828	388 846	375 024	86 587 524	86 258 174	85 109 428	86 425 578
Hongrin	464 016	420 543	412 877	49 569 251	48 925 997	49 315 181	49 394 376
Léman	810 967	629 335	686 952	172 705 954	174 379 007	173 384 333	174 698 218
Gruyère	698 394	590 766	576 916	71 348 630	72 996 505	73 861 915	73 290 067
Zeuzier	274 822	244 928	249 182	42 452 669	42 532 720	42 548 396	42 426 110
Godet	43 550	45 156	42 087	8 648 161	8 575 443	8 575 509	8 601 273
Bortelsee	34 928	33 683	32 259	5 256 640	5 265 140	5 285 946	5 285 751
Lac de Joux	174 369	175 497	168 459	21 212 966	20 530 169	20 637 462	20 699 033
Gletsch	25 891	22 382	25 366	9 118 596	9 063 766	9 040 513	9 050 180

Table C-21 Adjustment differences in MWh and total revenues of the forecast season (CHF) for eight hydropower schemes and four forecast scenarios. Period 2013-2021.

2013-2020	Adjustment (MWh)			Revenue (CHF)			
HPP - catchment	Multiannual	WeGaw	Hydrique	Perfect forecast	Multiannual	WeGaw	Hydrique
Kummenbord	126 552	103 947	104 649	20 371 998	20 323 960	20 128 021	20 196 524
Ferden	261 488	228 797	232 254	57 660 223	57 307 641	57 072 247	57 047 724
Emosson	406 241	334 314	334 878	76 947 010	76 477 492	76 526 100	76 171 283
Hongrin	426 097	378 607	373 744	43 943 445	43 138 218	43 222 293	43 279 263
Léman	682 933	514 729	558 720	152 048 664	151 211 282	150 276 036	150 690 123
Gruyère	596 727	467 253	473 690	61 156 590	60 004 986	60 085 771	60 137 289
Zeuzier	236 531	206 913	213 495	37 263 320	36 711 743	36 600 424	36 578 077
Godet	37 087	38 451	35 572	7 674 336	7 545 198	7 524 555	7 541 576
Bortelsee	33 287	31 195	29 477	4 706 136	4 692 500	4 682 365	4 670 243
Lac de Joux	153 846	154 372	147 139	19 125 075	18 691 105	18 795 204	18 832 540
Gletsch	24 202	20 467	23 533	8 116 432	8 096 500	8 078 812	8 086 745

Table C-22 Adjustment differences in MWh and total revenues of the forecast season (CHF) for eight hydropower schemes and four forecast scenarios. Period 2013-2020.

iv. Economical evaluation of FMV for the Gletsch hydropower plant

According to the discussions with the trading team, the following are also the gains that FMV could achieve with the use of the SWE forecast:

- ✓ Improve risk management
- ✓ Anticipate market actions
- ✓ Obtain better market prices
- ✓ Establish an annual budget closer to reality
- ✓ Improve rolling budget

Examples of beneficial situations:

- ✓ Deciding not to buy more energy from the market because we can anticipate an increase in production compared to the initial budget.
- ✓ Deciding to buy more energy from the market because we can anticipate a decrease in production compared to the initial budget.
- ✓ Deciding not to sell more energy to the market because we anticipate a decrease in production compared to the original budget.
- ✓ Deciding to sell more energy to the market because we anticipate an increase in production compared to the original budget.

When comparing the current strategy of FMV, using their annual forecast (based on the observed last year), the additional revenue due to the seasonal forecast is EUR 100'000 based on the methodology described in Section d. This additional revenue does not take into account eventual bonus through sell in advance, or penalties for energy adjustments.

The most interesting result is the reduction of the energy deviations through seasonal forecasts (Table C-23). This improvement ranges from 38% to 44%, which is a very important result.

Wegaw's high performance in comparison with the FMV and Hydrique methodology can be explained by the high data quality of the SWE produced. Gletsch being a forest-free and high-altitude basin, it provided excellent conditions for the Wegaw method to perform well. This high performance appears to have translated into a solid seasonal forecast and therefore increased total revenues in this simulation.

	Energy adjustments (MWh)			
	PERFECT	FMV	WeGaw	Hydrique
2013-2020	0	33 082	20 241	22 880
2017-2020	0	19 821	11 822	12 300
2013-2021	0	39 978	22 034	24 592

	Total revenues			
	PERFECT	FMV	WeGaw	Hydrique
2013-2020	8 116 432	7 949 335	8 075 810	8 073 671
2017-2020	4 351 171	4 193 730	4 272 386	4 254 333
2013-2021	9 118 596	8 947 325	9 041 033	9 039 990

Table C-23 Adjustments and total revenues of the forecast season (EUR) for the Gletsch Hydropower installation. Period 2013D-2021.

v. Economical evaluation of Romande Energie for the Lac de Joux hydropower installation

The trading strategy of Romande Energie is to try to sell as much energy in February and March (to lower the lake) but ensure the filling of the lake at the beginning of July. The idea behind is that the price of electricity if the highest during the winter and early spring.

Based on this general strategy, the economic evaluation is based on a simulation similar to the one presented in the general economic evaluation. The main assumptions are :

- Years 2013-2021 are considered in the analysis
- The energy is sold monthly in advance, on the first of each month, for the coming month
- The price of the energy is the following :

  February : SPOT + 15 EUR/MWh
  March : SPOT + 10 EUR/MWh
  April : SPOT + 5 EUR/MWh
  May, June : SPOT

- On 1st of February, the lake level is considered at the historical measured level.
- In February and March, the lake level is lowered to the minimum (122 Mio m^3)
- From April to July, the lake level is slowly increased to reach the maximum on 1st ot July (140 Mio m^3)
- In order to take into account for uncertainties, starting from April, only the half of the incoming volume is sold in advance, the rest being sold at the SPOT price
- The adjustments are realized as follows:
  - If exceeding water is coming, it is sold at the SPOT price
  - If the contracted energy cannot be produced, then the balancing energy is bought at the contract price + a penalty (5 EUR / MWh)
  - On 1st of July, if the lake is not filled at the maximum, then the missing water energy is calculated at the cost of SPOT + 75 EUR / MWh

According to this methodology the final results are presented in Table C-24. The results indicate the following information:

- ✓ The perfect forecast always produces the best total revenue, as expected. This is due to the assumptions which do not allow any additional revenue when a deviation occurs.
- ✓ The use of real forecasts shows that the seasonal forecasts (Wegaw = with satellite data; Hydrique = without satellite data) always outperform the multiannual inflow forecasting model.
- ✓ The additional revenue, through to the seasonal forecasts, is over 450’000 EUR over the 9 years period. This corresponds to an additional yearly revenue of 50’000 EUR/year.
- ✓ In this case, Hydrique’s method outperformed Wegaw’s for the total costs of adjustment and the total revenue. The cause for this is the inferior performance of the Wegaw SWE data in Lac du Joux, whose errors (primarily caused by the dense and extensive forest in the basin and lack of ground reference) are carried into the total seasonal forecast (where Hydrique’s method also performed better) and then into the economic assessment results. These results confirm a base assumption of this project, which is that a poor SWE measurement does indeed cause a poor forecast and a suboptimal economic performance.

	Total costs of adjustments (EUR)			
	PF	Multiannual	Wegaw	Hydrique
2013-2020	0	2 044 226	1 485 860	1 458 768
2017-2020	0	1 276 626	1 386 983	1 202 632
2013-2021	0	1 813 901	1 299 582	1 193 000

	Revenues of the contract (EUR)			
	PF	Multiannual	WeGaw	Hydrique
2013-2020	25 099 927	24 380 557	24 229 183	24 268 783
2017-2020	11 270 294	11 258 374	11 663 204	11 505 145
2013-2021	29 728 557	28 799 930	28 681 985	28 614 164

	TOTAL REVENUES (EUR)			
	PF	Multiannual	WeGaw	Hydrique
2013-2020	25 099 927	22 336 330	22 743 323	22 810 014
2017-2020	11 270 294	9 981 748	10 276 221	10 302 513
2013-2021	29 728 557	26 986 029	27 382 403	27 421 164

Table C-24 Adjustments, revenues of the contracts and total revenues of the forecast season (CHF) for the Lac de Joux Hydropower installation (La Dernier + Le Day). Period 2013-2021.

vi. Synthesis of the economical assessment

The most relevant indicator of the economical assessment is the sum of the adjustments (or deviations) in MWh. The goal is to minimize this indicator, as deviations represent a risk for the hydroelectricity trading. In general, the economic evaluation shows that the adjustment differences are smaller, about 10%-30%, due to the use of seasonal flow forecasts. Depending on the catchment area, satellite information allows a clear improvement, especially on the Lake Geneva, Gletsch or Zeuzier rivers.

With the methodology above, we attempted to create a realistic simulation to extract a relevant economic assessment highlighting current and future limitations and potential. As mentioned before, the economical assessment has proven to be a challenging part of the project due to several reasons.

- Firstly, trading and generation data and strategies are considered highly sensitive and confidential data for the energy generators. This data does normally not leave the hands of the company, making it impossible to run an independent assessment.

- Secondly, each generator follows a slightly to considerably different market strategy. This means they market their electricity on different markets (short term, medium term, regulation, guarantees, etc.) and adapt between and within their markets differently depending on their status quo and opportunities. Their water storage strategy and capabilities also play a role for some, since the storage can be used for medium-term adjustments.

- Thirdly, their decision-making process not only regarding adaptations but in the day-to-day operations differs. This depends on the existing technology and capabilities (e.g. if they have a seasonal forecast model and if yes, how it operates), how digitalized their operations are and how much the human factor comes into play. All these variables add uncertainty and make the trading and generation strategy something of a highly individualised “black box”.

Particularly, the indicator of total income over the period includes an element of chance and is calculated as an indication. If a forecast scenario produces a lower total income, this does not mean that the forecast should be abandoned. However, this indicator does help to understand the mechanics of how the seasonal forecast influences the valuation of hydroelectricity. Both the examples of Gletsch and Lac du Joux highlight how the (high or low) quality of the SWE measurements are reflected in the quality of the seasonal inflow forecast, and therefore the economic performance, further highlighting the importance of high-quality SWE data for a sustainable future for Swiss hydropower.

Based on these experiments, it is recommended to develop the use of seasonal forecasts in the hydroelectricity trading. Moreover, satellite information has a clear potential to improve the forecasts. If today’s results do not always show an improvement using satellite date, it is likely that in the future with a full dataset of 8+ years available by 2025, this additional information will help improving the forecasts, as the currently short historical period will naturally grow and allow a better calibration of the models.

D. Conclusion (English)

The objective of the DeFROST4Hydropower project was to develop an improved seasonal forecast using high-resolution satellite snow cover data to derive snow-water equivalent (SWE) and snow moisture to improve production and trading capabilities of the Swiss hydropower sector.

These seasonal forecasts allow for better prediction of spring runoff and hydropower production compared to the average of historical inflows. Improved forecasts should therefore lead to better water use, reduced balancing in hydropower production, and better marketing of electricity. These are therefore very favourable effects for the hydropower industry.

Several watersheds and hydropower facilities were tested in this project, which correspond to the main interests of the 9 industry project partners. These catchments are located in the Alps, the Pre-Alps or the Jura.

The conclusions are structured to answer the three main questions derived from the project:

1. Can a reliable snow water equivalent be extracted from satellite data to accurately represent the snow status?
2. Can this accurate snow data improve hydrological forecasting capabilities and therefore improve the final forecast?
3. Can the improved forecast be translated into better trading and generation results for the hydropower providers and what is the potential impact for Switzerland?

i. Can a reliable snow water equivalent be extracted from satellite data to accurately represent the snow status?

Satellite-based data extraction is a novel approach, with currently no known industry usage on the Swiss market. Current systems often consist of using point data from measurement stations or collecting information through yearly to bi-yearly field work. Both of these approaches only deliver information for one specific point, generally failing to give insights over larger areas or whole basins, whose nature tends to be highly heterogeneous and variable (e.g. different types of land cover, altitude, geomorphology). Alternatively, models are used which either interpolate between measured points (again, failing to reflect the local heterogeneity) or simulations based on multi-annual averages, which have shown to be not flexible enough to be accurate, as also shown in this project.

Snowpack information based on satellite data is uniquely positioned as a potential solution, offering large-scale, frequent snowpack observations over large areas. This premise and benefit are known and understood within the scientific community, and is slowly moving towards being accepted in a commercial context too, yet remained untested within the Swiss industry until now.

For this project, we therefore aimed to answer the question if we can produce a reliable, integrable Snow Water Equivalent from satellite, which can then be integrated into a hydrological model for commercial hydropower use.

For that, Wegaw developed a methodology that allows to produce of snow cover, an estimation of the snow height at high resolution, as well as an estimation of the SWE at high resolution from satellite data using Machine Learning algorithms. For that, SAR data from Sentinel-1 is combined with

available station data, the pre-existing Wegaw Snow Cover Extent product, and a geomorphological profile layer.

After a successful data production, this data was validated based on Ultracam photogrammetry Snow Height (HS) data collected by the SLF during four drone flights in two Swiss basins, namely Lauchernalp und Salfischpass. For the validation, a variety of statistical measurements were run both comparing satellite HS and drone data HS pixel-by-pixel at 100m resolution and over the entire measurement extent, with the latter being more significant for the final product, namely the inflow for a whole basin. Results show that the pixel-by-pixel RMSE is 57cm with an R-value of 0.65. These errors are most likely due to wind-driven snow redistribution and snow trapping. Comparing the catchment-scale HS values produced very solid results, with an R-value of 0.86 and an RMSE of 27cm. This stark improvement is most likely due to pixels with overestimations and pixels with underestimations balancing each other out.

Since no comparable product is currently being used within the Swiss hydropower industry, the validation against the drone measurements is currently the best option for a quality assessment. This work was done iteratively and helped identify limitations in the technology, particularly the fact that forests create significant data disturbances and make the creation of reliable data more difficult. Another factor we identified which reduces the accuracy of the product, is if the basins are small, presumably since the balancing of over-and underestimations does not work as well.

Basins with glaciers also present an introduction of uncertainty, yet do not necessarily cause low accuracy.

The methodology also demonstrates that the SWE, derived from satellite data, performs better if calibrated on the basis of ground measurements or global data from rainfall-runoff modelling. Indeed, very important error factors can otherwise appear, in particular if the share of forest is important in the catchment area.

All in all, the question above can be answered positively. We have proven that the extraction of snowpack information of such a product is possible and performs particularly well in basins at high-altitude, with low forest cover, consistent snowpack and over large areas. Since many of the basins in this project meet these criteria, the overall result can be considered positive.

In addition, Wegaw has created an R&D roadmap that aims to tackle the limitations discovered in the project.

ii. Can this accurate snow data improve hydrological forecasting capabilities and therefore improve the final forecast?

Seasonal forecasts are developed for the spring season until August of each year. These forecasts are based on a linear regression approach, which relates the SWE for a given date to the subsequent 30-180 days historical flow inputs. The SWE is either derived from rainfall-runoff modelling (Hydrique) or from calibrated satellite data (Wegaw).

The results show that the seasonal forecasts considerably improve those obtained by simple averaging of historical inflows, the method currently used by the project partners. Depending on the catchment, the forecast period and the forecast horizon, the best forecast is obtained from the rainfall-runoff model or from the satellite. In general, the improvement is significant in the months of March to

June and the errors are reduced between 15% (30 days ahead) and 40% (120 days ahead). It is thus assumed that this better predictability leads to a better valuation of the water.

Table d-1 presents a summary of the best choice of seasonal forecasting model for the different catchments. In most situations, the satellite data provides an improved forecast, usually after calibration with the rainfall-runoff simulation model. To date, it is not possible to determine in advance which model will be the best choice for a given catchment, but the methodology developed makes it possible to easily evaluate the model variants and make a choice.

In training, the best results are distributed between the “Hydrique” and “Wegaw” forecast. For shorter time frames (30 and 60 days), the “Hydrique” forecasts are slightly dominant while “Wegaw” method is slightly better for longer time frames (150 and 180 days).
In cross-validation, for the shorter time frames of 30 and 60 days, the multiannual and the “Hydrique” forecasts provide overall better results. For longer time frames of 150 and 180 days, the “Wegaw” forecast is better, followed by the “Hydrique” forecast.

Different factors influence the potential for improving forecasts with satellite data. An important factor is the presence of extensive forest, which complicates the interpretation of the satellite signal, and leads to a decrease in its value. The presence of large glaciers also seems to reduce the impact of the satellite information, because of the snowmelt/ice melt compensation effect making the snow stock estimate slightly less relevant.

Catchment	Wegaw	RS	Similar
Arve	✓		
Emosson		✓	
Bortelsee		✓	
Ferden			✓
Gletsch	✓		
Godet		✓	
Gruyère	✓		
Hongrin	✓		
Kummenbord	✓		
Lac de Joux		✓	
Léman	✓		
Zeuzier	✓		

Table D-1 Evaluation of the best seasonal forecast model

iii. Can the improved forecast be translated into better trading and generation results for the hydropower providers and what is the potential impact for Switzerland?

Finally, an economic analysis was carried out, based on the study of adjustment deviations and total revenues of medium-term contracts (per month, up to 5 months in advance), for several partner schemes of the project. The results show that the adjustment deviations are always smaller than the ones obtained by using the average of historical inflows. The difference, evaluated over the period 2013-2021, is generally 15-30% depending on the scheme. Total revenues are also systematically higher than with the average of historical inflows. In this case, the differences are sometimes due to luck, since depending on SPOT price variations, some forecasting errors can lead to higher revenues.

This study clearly demonstrates the value of using seasonal linear regression forecasts for hydro marketing from late winter until early summer. Revenue increases of between EUR 50,000 and 500,000 per year on average are envisaged depending on the facilities. The value of using satellite data has been demonstrated in certain situations, even if the history available is currently limited (4 years). It is certain that with time and the increase in the historical data, these data will allow a more significant improvement in the predictability of melt flows.

Hydropower companies in Switzerland are forced to use financial tools, like substantial credit lines, to support the fact that the vast majority of the revenues are obtained during spring-melt. This causes them to be dependent on financial tools to honour their commitments during late summer and winter times, when their energy generation capabilities are very low[10]. It is essential, to have a healthy financial status, to be able to sell the energy produced during spring-melt as early as possible, in order to have a manageable cash flow and not be dependent on additional financial tools or credit lines. The only sustainable way to do this, is by having a long-term forecast as unbiased as possible that is resilient to climate anomalies. Traders will use this forecast to sell the energy in long-term contracts several months in advance, ensuring the income of their companies as early as in January/February.

Market volatility has a substantial impact on these companies' bottom lines, making it very unreliable to do solid financial forecasts when economic market conditions are so unreliable. When the long-term forecasts are not reliable and energy companies need to sell on the spot market, they are at the mercy of the volatility of the market, which can turn their revenues up or down depending on the current market conditions, increasing their downside risk.

Additionally, the energy companies in Switzerland are currently relying on these trading forecasts in 20-year averages, which makes them very vulnerable to climate anomalies, which are being more common with the recent climate change scenarios.

During the project, the consortium has demonstrated there is a substantial improvement for satellite enhanced SWE based long term forecasting, and therefore, a reasonable financial risk reduction opportunity for the energy companies using it, and indirectly for the Swiss State. The long term forecast provided to the 9 companies during the project has demonstrated that can reduce the need of trading adjusting by an average of 10%, which translated to a reduction of the financial risk of energy

[10] https://www.reuters.com/markets/europe/swiss-utility-axpo-increases-syndicated-credit-lines-53-bln-euros-2022-10-11/

companies. In addition, the satellite-based forecast seems to work even better in years with heavier climate anomalies, making the forecast even more essential in these climate conditions.

From a qualitative standpoint, the project has been able to demonstrate how an effective long term forecast calibrated with Satellite extracted Snow Water Equivalent datasets can help energy companies in Switzerland be more resilient to climate change anomalies and market volatility, which are of essential importance for the Swiss Confederation and the renewable energy ecosystem.

Furthermore, the consortium has identified several opportunities to continue enhancing the forecast to ensure the financial risk of the Swiss energy companies is as diminished as possible.

For an overview of the main findings, please check the summary.

Conclusion (Français)

L'objectif du projet DeFROST4Hydropower était de développer une prévision saisonnière améliorée en utilisant des données satellitaires à haute résolution sur la couverture neigeuse pour dériver l'équivalent en eau de la neige (SWE) et l'humidité de la neige afin d'améliorer la production et les capacités commerciales du secteur hydroélectrique suisse.

Ces prévisions saisonnières permettent de mieux prévoir le ruissellement printanier et la production hydroélectrique par rapport à la moyenne des apports historiques. L'amélioration des prévisions devrait donc conduire à une meilleure utilisation de l'eau, à une réduction de l'équilibrage de la production hydroélectrique et à une meilleure commercialisation de l'électricité. Il s'agit donc d'effets très favorables pour l'industrie hydroélectrique.

Plusieurs bassins versants et installations hydroélectriques ont été testés dans ce projet, qui correspondent aux principaux intérêts des 9 partenaires industriels du projet. Ces bassins versants sont situés dans les Alpes, les Préalpes ou le Jura.

Les conclusions sont structurées de manière à répondre aux trois questions principales dérivées du projet :

1. Peut-on extraire un équivalent en eau de la neige fiable à partir de données satellitaires pour représenter avec précision l'état de la neige ?
2. Ces données nivologiques précises peuvent-elles améliorer les capacités de prévision hydrologique et donc améliorer la prévision finale ?
3. L'amélioration des prévisions peut-elle se traduire par de meilleurs résultats commerciaux et de production pour les fournisseurs d'énergie hydroélectrique et quel est l'impact potentiel pour la Suisse ?

iv. Peut-on extraire un équivalent en eau de la neige fiable à partir de données satellitaires pour représenter avec précision l'état de la neige ?

L'extraction de données par satellite est une approche nouvelle, qui n'est actuellement pas utilisée par l'industrie sur le marché suisse. Les systèmes actuels consistent souvent à utiliser des données

ponctuelles provenant de stations de mesure ou à collecter des informations par le biais d'un travail de terrain annuel ou bisannuel. Ces deux approches ne fournissent des informations que pour un point spécifique, et ne donnent généralement pas d'indications sur des zones plus vastes ou des bassins entiers, dont la nature tend à être très hétérogène et variable (par exemple, différents types de couverture du sol, altitude, géomorphologie). On utilise également des modèles qui interpolent entre les points mesurés (là encore, ils ne reflètent pas l'hétérogénéité locale) ou des simulations basées sur des moyennes pluriannuelles, qui se sont avérées insuffisamment flexibles pour être précises, comme le montre également ce projet.

Les informations sur le manteau neigeux basées sur les données satellitaires occupent une position unique en tant que solution potentielle, offrant des observations fréquentes et à grande échelle du manteau neigeux sur de vastes zones. Ce principe et cet avantage sont connus et compris au sein de la communauté scientifique, et sont en passe d'être acceptés dans un contexte commercial également, mais n'ont pas encore été testés par l'industrie suisse jusqu'à présent.

Pour ce projet, nous avons donc cherché à répondre à la question de savoir si nous pouvons produire un équivalent en eau de la neige fiable et intégrable à partir du satellite, qui peut ensuite être intégré dans un modèle hydrologique pour l'utilisation commerciale de l'hydroélectricité.

Pour cela, Wegaw a développé une méthodologie qui permet de produire une couverture de neige, une estimation de la hauteur de neige à haute résolution, ainsi qu'une estimation de l'EEN à haute résolution à partir de données satellites en utilisant des algorithmes d'apprentissage automatique. Pour cela, les données SAR de Sentinel-1 sont combinées avec les données de stations disponibles, le produit Wegaw préexistant sur l'étendue de la couverture neigeuse, et une couche de profil géomorphologique.

Après avoir été produites avec succès, ces données ont été validées sur la base des données de photogrammétrie Ultracam sur la hauteur de neige (HS) recueillies par le SLF au cours de quatre vols de drone dans deux bassins suisses, à savoir Lauchernalp et Salfischpass. Pour la validation, une variété de mesures statistiques ont été effectuées en comparant les données satellite HS et les données drone HS pixel par pixel à une résolution de 100m et sur toute l'étendue de la mesure, cette dernière étant plus significative pour le produit final, à savoir le débit entrant pour un bassin entier. Les résultats montrent que la RMSE pixel par pixel est de 57 cm avec une valeur R de 0,65. Ces erreurs sont très probablement dues à la redistribution de la neige par le vent et au piégeage de la neige. La comparaison des valeurs HS à l'échelle du bassin versant a donné des résultats très solides, avec une valeur R de 0,86 et une EQM de 27 cm. Cette nette amélioration est très probablement due au fait que les pixels surestimés et les pixels sous-estimés s'équilibrent.

Comme aucun produit comparable n'est actuellement utilisé dans l'industrie hydroélectrique suisse, la validation par rapport aux mesures effectuées par les drones est actuellement la meilleure option pour une évaluation de la qualité. Ce travail a été effectué de manière itérative et a permis d'identifier les limites de la technologie, notamment le fait que les forêts créent des perturbations importantes des données et rendent plus difficile la création de données fiables. Un autre facteur que nous avons identifié et qui réduit la précision du produit, est si les bassins sont petits, vraisemblablement parce que l'équilibrage des sur- et sous-estimations ne fonctionne pas aussi bien.

Les bassins avec des glaciers présentent également une introduction d'incertitude, mais ne causent pas nécessairement une faible précision.

La méthodologie démontre également que l'ESO, dérivé des données satellitaires, est plus performant s'il est calibré sur la base de mesures au sol ou de données globales issues de la modélisation pluie-

débit. En effet, des facteurs d'erreur très importants peuvent sinon apparaître, en particulier si la part de la forêt est importante dans le bassin versant.

Dans l'ensemble, on peut répondre positivement à la question ci-dessus. Nous avons prouvé que l'extraction d'informations sur l'enneigement d'un tel produit est possible et qu'elle est particulièrement performante dans les bassins à haute altitude, avec une faible couverture forestière, un enneigement constant et sur de grandes surfaces. Comme de nombreux bassins de ce projet répondent à ces critères, le résultat global peut être considéré comme positif.

En outre, Wegaw a créé une feuille de route de R&D qui vise à s'attaquer aux limites découvertes dans le projet.

v. Ces données nivologiques précises peuvent-elles améliorer les capacités de prévision hydrologique et donc améliorer la prévision finale ?

Les prévisions saisonnières sont développées pour la saison du printemps jusqu'au mois d'août de chaque année. Ces prévisions sont basées sur une approche de régression linéaire, qui met en relation le SWE pour une date donnée avec les données historiques de débit des 30 à 180 jours suivants. Le SWE est soit dérivé de la modélisation pluie-débit (Hydrique), soit de données satellites calibrées (Wegaw).

Les résultats montrent que les prévisions saisonnières améliorent considérablement celles obtenues par la simple moyenne des débits historiques, la méthode actuellement utilisée par les partenaires du projet. Selon le bassin versant, la période de prévision et l'horizon de prévision, la meilleure prévision est obtenue à partir du modèle pluie-débit ou du satellite. En général, l'amélioration est significative dans les mois de mars à juin et les erreurs sont réduites entre 15% (30 jours d'avance) et 40% (120 jours d'avance). On suppose donc que cette meilleure prévisibilité conduit à une meilleure valorisation de l'eau.

Le tableau d-1 présente un résumé du meilleur choix de modèle de prévision saisonnière pour les différents bassins versants. Dans la plupart des situations, les données satellitaires fournissent une meilleure prévision, généralement après calibration avec le modèle de simulation pluie-débit. A ce jour, il n'est pas possible de déterminer à l'avance quel modèle sera le meilleur choix pour un bassin versant donné, mais la méthodologie développée permet d'évaluer facilement les variantes du modèle et de faire un choix.

En formation, les meilleurs résultats sont répartis entre les prévisions "Hydrique" et "Wegaw". Pour des

Pour les échéances courtes (30 et 60 jours), les prévisions "Hydrique" sont légèrement dominantes alors que la méthode "Wegaw" est légèrement meilleure pour les échéances plus longues (150 et 150 jours). En validation croisée, pour les périodes plus courtes de 30 et 60 jours, les prévisions pluriannuelles et la méthode "Hydrique" donnent de meilleurs résultats.

Pour les périodes plus longues de 150 et 180 jours, la prévision "Wegaw" est meilleure, suivie de la prévision "Hydrique".

Différents facteurs influencent le potentiel d'amélioration des prévisions grâce aux données satellitaires. Un facteur important est la présence de forêts étendues, qui complique l'interprétation du signal satellite et entraîne une diminution de sa valeur. La présence de grands glaciers semble

également réduire l'impact des informations satellitaires, en raison de l'effet de compensation entre la fonte des neiges et la fonte des glaces qui rend l'estimation du stock de neige légèrement moins pertinente.

Catchment	Wegaw	RS	Similar
Arve	✓		
Emosson		✓	
Bortelsee		✓	
Ferden			✓
Gletsch	✓		
Godet		✓	
Gruyère	✓		
Hongrin	✓		
Kummenbord	✓		
Lac de Joux		✓	
Léman	✓		
Zeuzier	✓		

Table D-2 Evaluation du meilleur choix de modèle de prévision par bassin versant

vi. L'amélioration des prévisions peut-elle se traduire par de meilleurs résultats commerciaux et de production pour les fournisseurs d'énergie hydroélectrique et quel est l'impact potentiel pour la Suisse ?

Enfin, une analyse économique a été réalisée, basée sur l'étude des écarts d'ajustement et des recettes totales des contrats à moyen terme (par mois, jusqu'à 5 mois d'avance), pour plusieurs régimes partenaires du projet. Les résultats montrent que les écarts d'ajustement sont toujours plus faibles que ceux obtenus en utilisant la moyenne des entrées historiques. L'écart, évalué sur la période 2013-2021, est généralement de 15 à 30 % selon les régimes. Les recettes totales sont également systématiquement plus élevées qu'avec la moyenne des entrées historiques. Dans ce cas, les différences sont parfois dues à la chance, car en fonction des variations de prix SPOT, certaines erreurs de prévision peuvent conduire à des revenus plus élevés.

Cette étude démontre clairement l'intérêt d'utiliser des prévisions saisonnières par régression linéaire pour la commercialisation de l'hydroélectricité de la fin de l'hiver au début de l'été. Des augmentations de revenus de 50 000 à 500 000 euros par an en moyenne sont envisagées en fonction des installations. L'intérêt de l'utilisation des données satellitaires a été démontré dans certaines situations, même si l'historique disponible est actuellement limité (4 ans). Il est certain qu'avec le temps et l'augmentation de l'historique, ces données permettront une amélioration plus significative de la prévisibilité des débits de fonte.

Les sociétés hydroélectriques en Suisse sont obligées d'utiliser des outils financiers, comme des lignes de crédit importantes, pour soutenir le fait que la grande majorité des revenus sont obtenus

pendant la fonte de printemps. Il est essentiel, pour avoir une situation financière saine, de pouvoir vendre l'énergie produite pendant la fonte de printemps le plus tôt possible, afin d'avoir un flux de trésorerie gérable et de ne pas être dépendant d'outils financiers ou de lignes de crédit supplémentaires. La seule façon durable d'y parvenir est de disposer de prévisions à long terme aussi impartiales que possible et résistantes aux anomalies climatiques. Les négociants utiliseront ces prévisions pour vendre l'énergie dans des contrats à long terme plusieurs mois à l'avance, assurant ainsi les revenus de leurs entreprises dès janvier/février.

La volatilité du marché a un impact considérable sur les résultats de ces entreprises. Il est donc très difficile de faire des prévisions financières solides lorsque les conditions économiques du marché sont si peu fiables. Lorsque les prévisions à long terme ne sont pas fiables et que les entreprises énergétiques doivent vendre sur le marché au comptant, elles sont à la merci de la volatilité du marché, qui peut faire monter ou descendre leurs revenus en fonction des conditions actuelles du marché, augmentant ainsi leur risque de perte.

De plus, les compagnies d'énergie en Suisse se basent actuellement sur ces prévisions commerciales en moyennes sur 20 ans, ce qui les rend très vulnérables aux anomalies climatiques, qui sont de plus en plus fréquentes avec les récents scénarios de changement climatique.

Au cours du projet, le consortium a démontré qu'il existe une amélioration substantielle des prévisions à long terme basées sur le SWE amélioré par satellite, et donc une opportunité raisonnable de réduction des risques financiers pour les sociétés d'énergie qui l'utilisent, et indirectement pour l'État suisse. Les prévisions à long terme fournies aux 9 entreprises au cours du projet ont démontré qu'elles pouvaient réduire le besoin d'ajustement des échanges de 10% en moyenne, ce qui s'est traduit par une réduction du risque financier des entreprises énergétiques. En outre, la prévision par satellite semble fonctionner encore mieux les années où les anomalies climatiques sont plus importantes, ce qui rend la prévision encore plus essentielle dans ces conditions climatiques.

D'un point de vue qualitatif, le projet a pu démontrer comment une prévision efficace à long terme calibrée avec des ensembles de données d'équivalent en eau de la neige extraites par satellite peut aider les entreprises énergétiques en Suisse à être plus résistantes aux anomalies du changement climatique et à la volatilité du marché, qui sont d'une importance essentielle pour la Confédération suisse et l'écosystème des énergies renouvelables.

En outre, le consortium a identifié plusieurs opportunités pour continuer à améliorer les prévisions afin de s'assurer que le risque financier des entreprises énergétiques suisses est aussi réduit que possible.

Pour un aperçu des principaux résultats, veuillez consulter le résumé.

E. Outlook and next steps (ENG and FR)

During this project various approaches were tested with a view to improving the methodology based on linear regressions. Some of these approaches have potential and should be further developed:

- The combination of linear regression and machine learning (hybrid models) can sometimes improve the predictive performance of models. One of the most important input variables is the prediction from linear regression. However, other variables derived from historical values may also improve the prediction. These tests were only carried out for two catchments and for a 30-day horizon. It is therefore necessary to extend the catalogue of catchment areas and forecasting periods to better understand the potential for improving the method.
- Multiple regressions, using forecast model data and historical data, produce extremely good results. However, the very high scores obtained in training could not be maintained in cross-validation. It is therefore necessary to better understand the reasons for this situation and to try to improve this methodology, as the potential for improvement in seasonal forecasting is very large.
- Short-term flow forecasts (up to +3 days) are a very important tool for hydropower producers. Preliminary tests have been carried out to analyse the interest of assimilating the satellite SWE in hybrid rainfall-flow simulation and machine learning models. The results are not yet as good as expected, but only one catchment area has been studied. It is therefore necessary to develop the analysis on other catchment areas in order to better evaluate the potential for improving these forecasts.
- Glacier melt forecasting seems a line of evidence to include in both short-term and long-term forecasts improvement. Currently glacier melts are becoming difficult to quantify additional discharge in very hot summers, creating a higher spread in the error when forecasting short and long term.
- Snow Density model improvement will help to increase the accuracy of SWE later in the season, allowing to improve short term and midterm forecasts (<30 days)
- More in-depth R&D on SWE in forested areas is another area where improvement will help with the SWE accuracy in certain basins and with the general scalability of the technology.

For a proper, quantifiable economic assessment in the future, the consortium suggest an in-depth project with a selected hydropower generator. In this setup, the intricacies of the operation of the generator can be explored understood and optimally considered in the project. An option would be to create a live stream of the inflow forecast improved with Wegaw SWE for the generator, which connects to a digital twin of the generator's trading and generation systems. The data could then be used to make real decisions in a simulated environment, and the results of those decisions could be economically evaluated after a certain timeframe, such as one or two years.

This idea presents a challenging technological setup that would require substantial investments in digital infrastructure, yet it is the most close-to-reality option to assess the potential economic impact we can currently imagine.

Durant ce projet, d'autres approches ont été testées, en vue d'améliorer la méthodologie basée sur les régressions linéaires. Certaines de ces approches présentent un potentiel et devraient être approfondies :

- *La combinaison entre régression linéaire et machine learning (modèles hybrides) permet parfois d'améliorer la performance prédictive des modèles. L'une des variables d'entrée les plus importantes est la prévision issue de la régression linéaire. Cependant, d'autres variables issues de valeurs historiques permettent éventuellement d'améliorer la prévision. Ces tests n'ont été effectués que pour deux bassins versants et pour un horizon de 30 jours. Il s'agit donc d'étendre le catalogue des bassins versants et échéances de prévision pour mieux connaître le potentiel d'amélioration de la méthode.*
- *Les régressions multiples, utilisant des données de modèles de prévision et des données historiques, produisent des résultats extrêmement bons. Toutefois, les scores très élevés obtenus en apprentissage n'ont pas pu être conservés en cross-validation. Il s'agit donc de mieux comprendre les raisons de cette situation et d'essayer d'améliorer cette méthodologie, car le potentiel d'amélioration de la prévision saisonnière est très important.*
- *Les prévisions court-terme de débit (échéance jusqu'à +3 jours) sont un outil très important pour les producteurs d'hydro-électricité. Des tests préliminaires ont été effectués pour analyser l'intérêt d'assimiler le SWE satellite dans les modèles hybrides simulation pluie-débit et machine learning. Les résultats ne sont pour le moment pas à la heuteur des attentes, mais seul un bassin versant a été étudié. Il s'agit donc de développer l'analyse sur d'autres bassins versants afin de mieux évaluer le potentiel d'amélioration de ces prévisions.*
- *La prévision de la fonte des glaciers semble une ligne d'évidence à inclure dans l'amélioration des prévisions à court et à long terme. Actuellement, les fontes de glaciers deviennent difficiles à quantifier la décharge supplémentaire dans les étés très chauds, créant une plus grande propagation de l'erreur lors de la prévision à court et à long terme.*
- *L'amélioration du modèle de densité de la neige aidera à augmenter la précision de l'ETS plus tard dans la saison, permettant d'améliorer les prévisions à court et moyen terme (<30 jours).*
- *Une R&D plus approfondie sur le SWE dans les zones forestières est un autre domaine où l'amélioration contribuera à la précision du SWE dans certains bassins et à l'évolutivité générale de la technologie.*

Pour une évaluation économique correcte et quantifiable à l'avenir, le consortium suggère un projet approfondi avec un générateur hydroélectrique sélectionné. Dans cette configuration, les subtilités du fonctionnement du générateur peuvent être explorées, comprises et prises en compte de manière optimale dans le projet. Une option serait de créer un flux en direct des prévisions de débit améliorées avec Wegaw SWE pour le générateur, qui se connecte à un jumeau numérique des systèmes de commerce et de production du générateur. Les données pourraient alors être utilisées pour prendre des décisions réelles dans un environnement simulé, et les résultats de ces décisions pourraient être évalués économiquement après un certain délai, par exemple un ou deux ans.

Cette idée présente une configuration technologique difficile qui nécessiterait des investissements substantiels dans l'infrastructure numérique, mais c'est l'option la plus proche de la réalité pour évaluer l'impact économique potentiel que nous pouvons actuellement imaginer.

F. National and international cooperation

Table F-1 shows the partners involved in the project.

Partner Type	Partner Name	Project involvement	Background and experience	Role in project implementation
Prime Operator EO System Operator	Wegaw SA https://www.wegaw.com/	Prime	Near real-time high-resolution snow and water information from Earth Observation.	EO System Design and Implementation to produce SWE
Forecasting System Operator	Hydrique Ingénieurs https://www.hydrique.ch/fr	Project Partner	Hydrology, real-time and forecasting information as well as watershed management.	Forecasting System Design and Implementation to produce seasonal inflow forecast
Ground Truth and Validation Operator	WSL Institute for Snow and Avalanche Research (SLF) https://www.slf.ch/en/index.html	Project Partner	Switzerland's leading research institute on snow and avalanches.	Provision of validation data
Industry partner & manager	FMV SA https://www.fmv.ch/	Project steering committee member & manager, early adopter	Hydroelectric generation, transmission and trading. Umbrella organisation for Valais energy policy.	Industry partner coordination and communication Data provision and internal impact assessment
Industry partner	Alpiq Holding AG https://www.alpiq.com/	Project steering committee member & early adopter	Leading Swiss energy services provider and electricity producer in Europe.	Data provision and internal impact assessment

Industry partner	Canton Geneva https://www.ge.ch/en/welcome-geneva	Project steering committee member & early adopter	Hydropower provider for the Canton of Geneva.	Internal impact assessment
Industry partner	EnAlpin https://www.enalpin.com/	Project steering committee member & early adopter	Hydropower & clean energy company providing 10% of hydroelectricity in Valais.	Data provision and internal impact assessment
Industry partner	EnBAG http://www.enbag.ch/	Project steering committee member & early adopter	Energy provider and producer in Valais.	Data provision and internal impact assessment
Industry partner & manager	FMV SA https://www.fmv.ch/	Project steering committee member & early adopter	Energy company in Valais with a portfolio of 1 billion kWh annually.	Industry partner coordination and communication Data provision and internal impact assessment
Industry partner	Groupe E https://www.groupe-e.ch/fr	Project steering committee member & early adopter	Energy company with focus on renewables, producing 3TWWh annually	Data provision and internal impact assessment
Industry partner	OIKEN https://www.oiken.ch	Project steering committee member & early adopter	Primary energy producer in Valais.	Data provision and internal impact assessment
Industry partner	Romande Energie	Project steering committee	Vaud-based energy producer and provider using 100%	Data provision and internal impact assessment

	https://www.romande-energie.ch/	member & early adopter	renewable energy.	
Industry partner	Services Industriels de Genève (SIG) https://ww2.sig-ge.ch/	Project steering committee member & early adopter	Geneva-based electricity company providing 100% renewable energy.	Internal impact assessment

Table F-1 Partners and collaborators.

G. Publications

Le Stock De Neige Sur Les Sommets – SIG

Snow Height Product Quality Assessment - Wegaw

Intégration De Données Satellite De Neige Pour La Prévision À Court Terme Et La Prévision Saisonnière Des Apports En Eau Dans Les Barrages Alpins – Raphael Renevy (Project de Master avec Hydrique and EPFL)

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Vasco Conde , Giovanni Nico, Pedro Mateus , João Catalão , Anna Kontu , Maria Gritsevich (2017) “On the estimation of temporal changes of snow water equivalent by spaceborne SAR interferometry: a new application for the Sentinel-1 mission”, J. Hydrol. Hydromech., 67, 2019, 1, 93–100, DOI: 10.2478/johh-2018-0003

I. Appendix

a. User needs collection results

We identified three key areas of user needs:

a) Seasonal Water Inflow

- 60-90 days-ahead forecast was identified as the most relevant
- Daily or weekly updates are requested
- Most relevant time frame during the year is March to June
- Benchmark with SWE-free model or other inhouse models required to assess accuracies
- SWE data can be helpful for qualitative analysis during the year(Lake height in March or operations/maintenance planning)
- Impact on trading unclear but insights are highly requested (Executed in Feb-March)

b) Short-term Water Inflow

- Up to 10 days forecast as the desired time frame
- To confirm impact, a backtest with in-house model, Hydrique model and Hydrique SWE powered model in comparison is needed
- If the generator has an optimizer, a back-test with the optimizer (such as Time Step) needs to be executed

c) Snow Water Equivalent

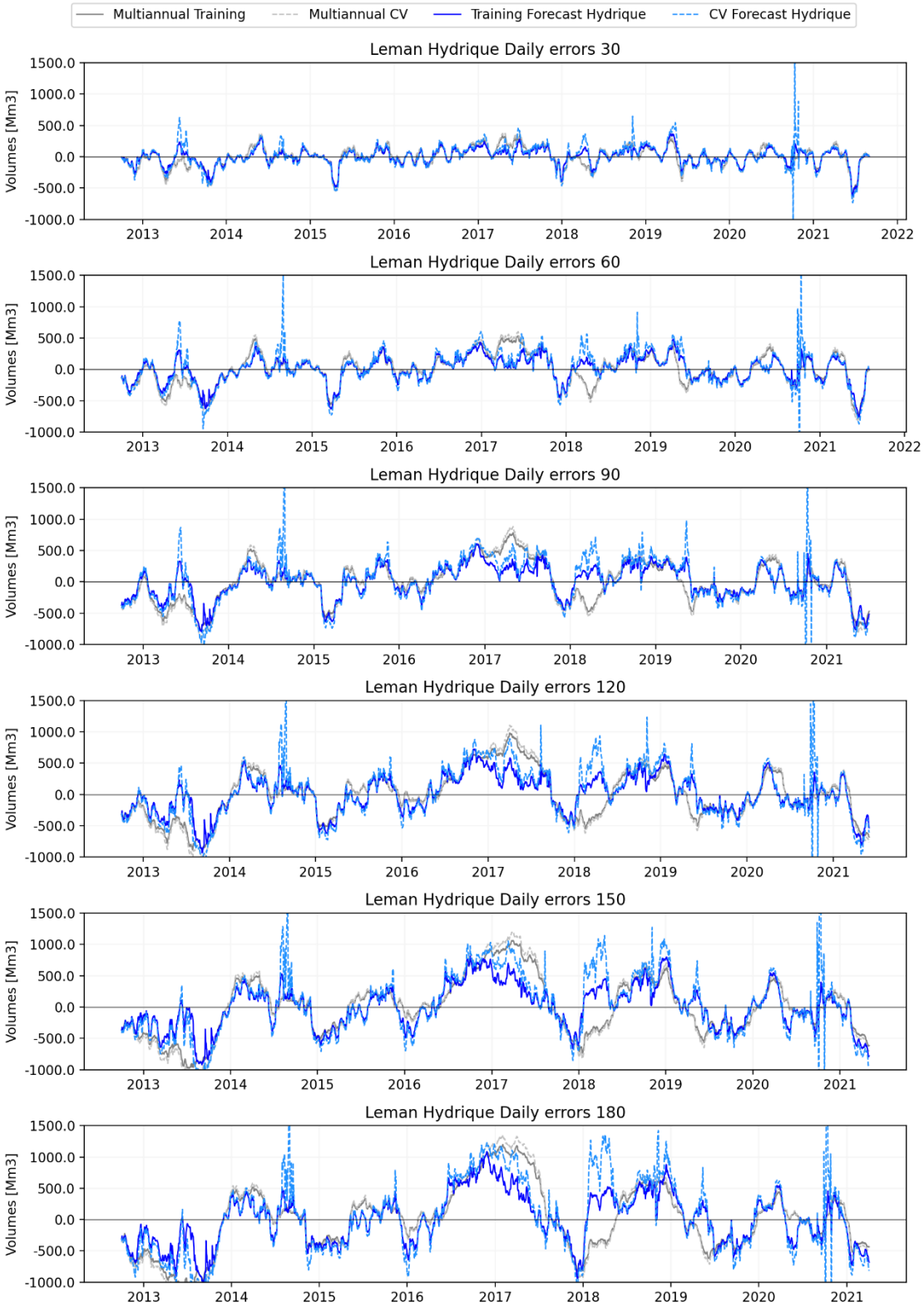
- SWE data as an additional input into existing optimizers
- SWE raw data visualizer and downloader

b. Forecasting errors for the pilot catchments of the DeFROST project

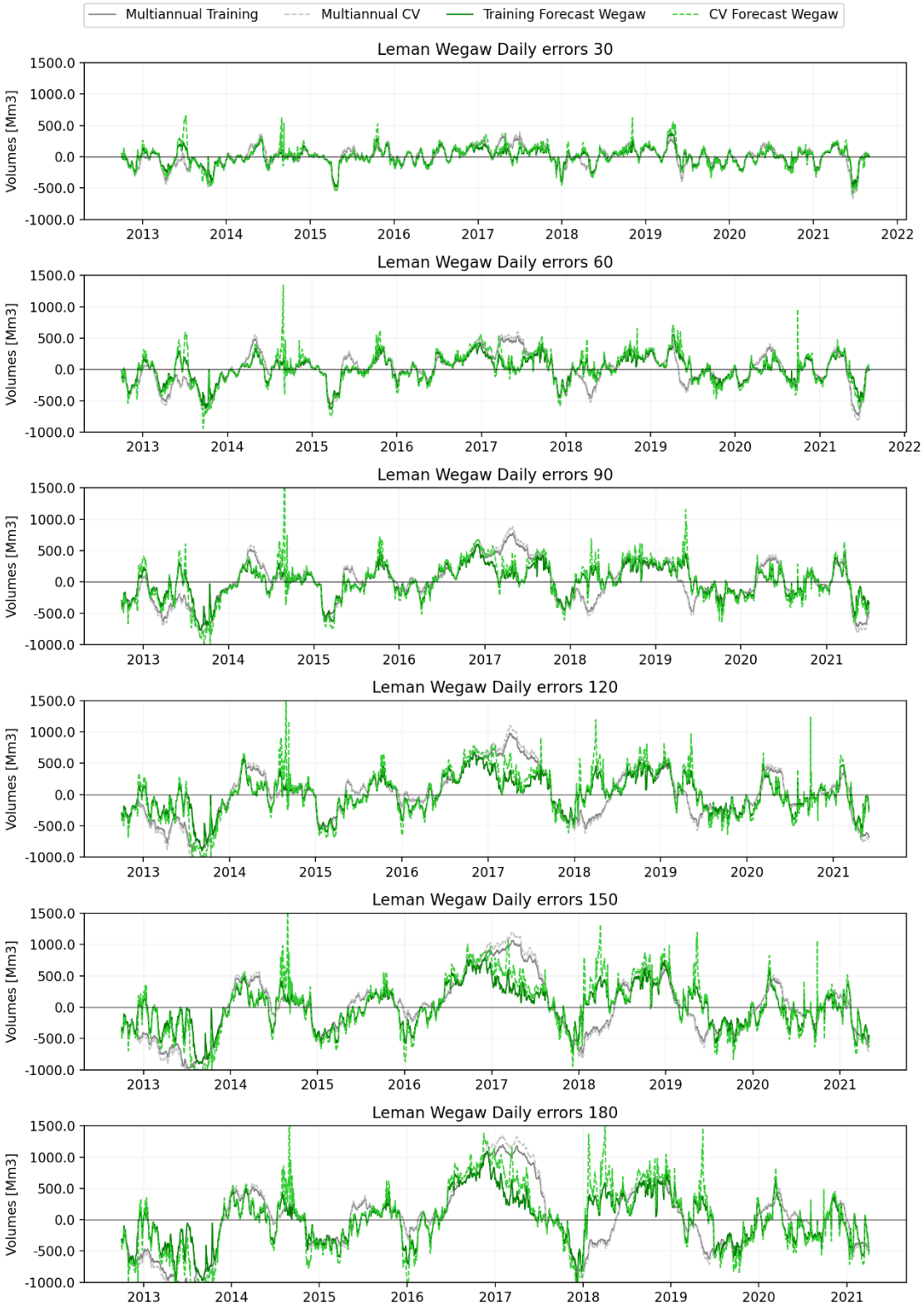
The following appenedix presents the forecasting errors of the linear regression method

- Forecast lead times : 30, 60, 90, 120, 150, 180 days
- Errors in daily MAE (Mm^3, if not confidential) or in daily MAPE (%)
- Evolution of the daily errors over the forecasting season (in general from February to August)
- Comparison between training and cross-validation scores
- Comparison between “Hydrique” SWE (from rainfall-runoff simulation) and “Wegaw” SWE (from satellite data)

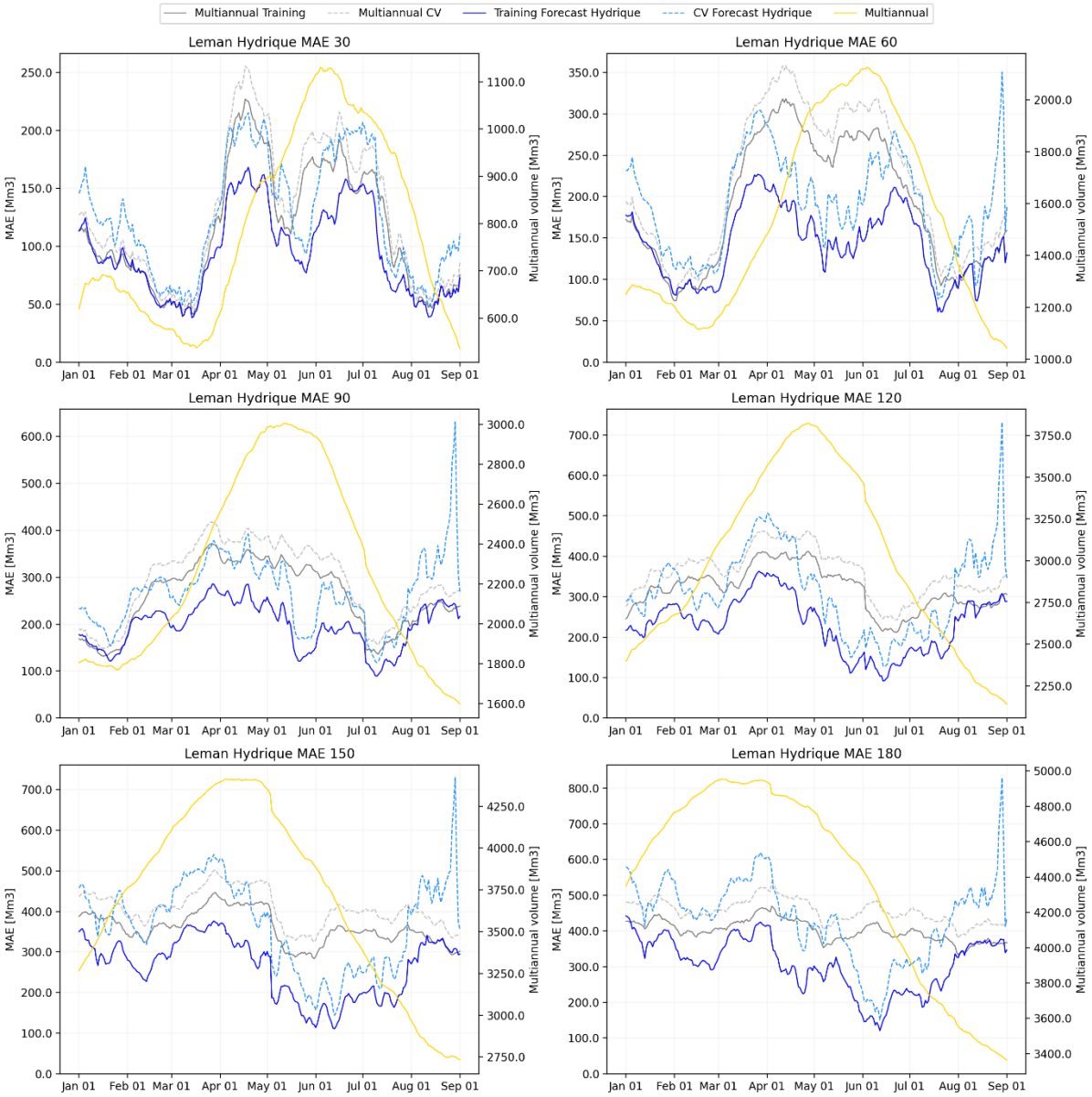
c. Léman, daily errors, Hydrique SWE, training+cross-validation



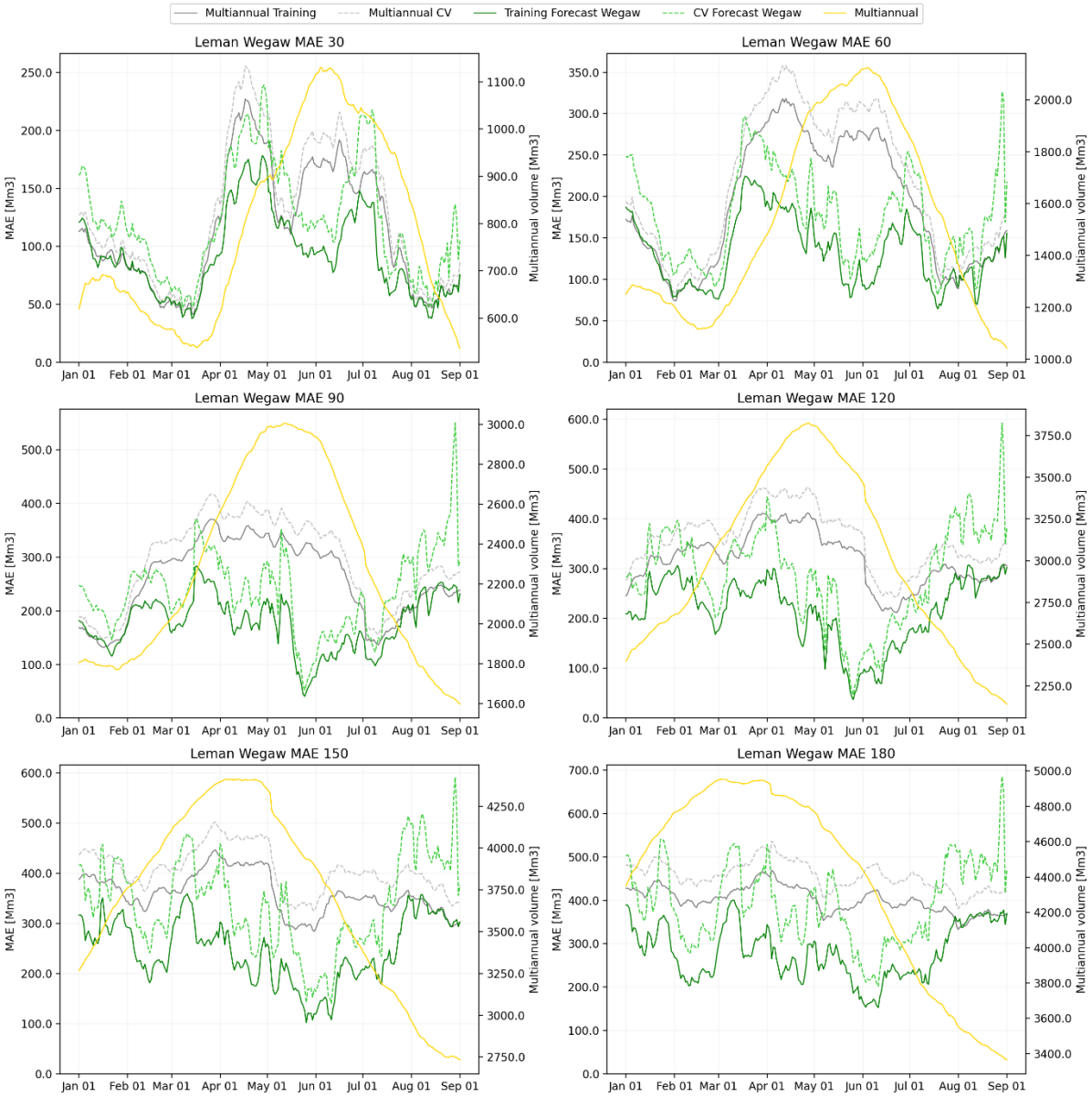
d. Léman, daily errors, Wegaw SWE, training+cross-validation



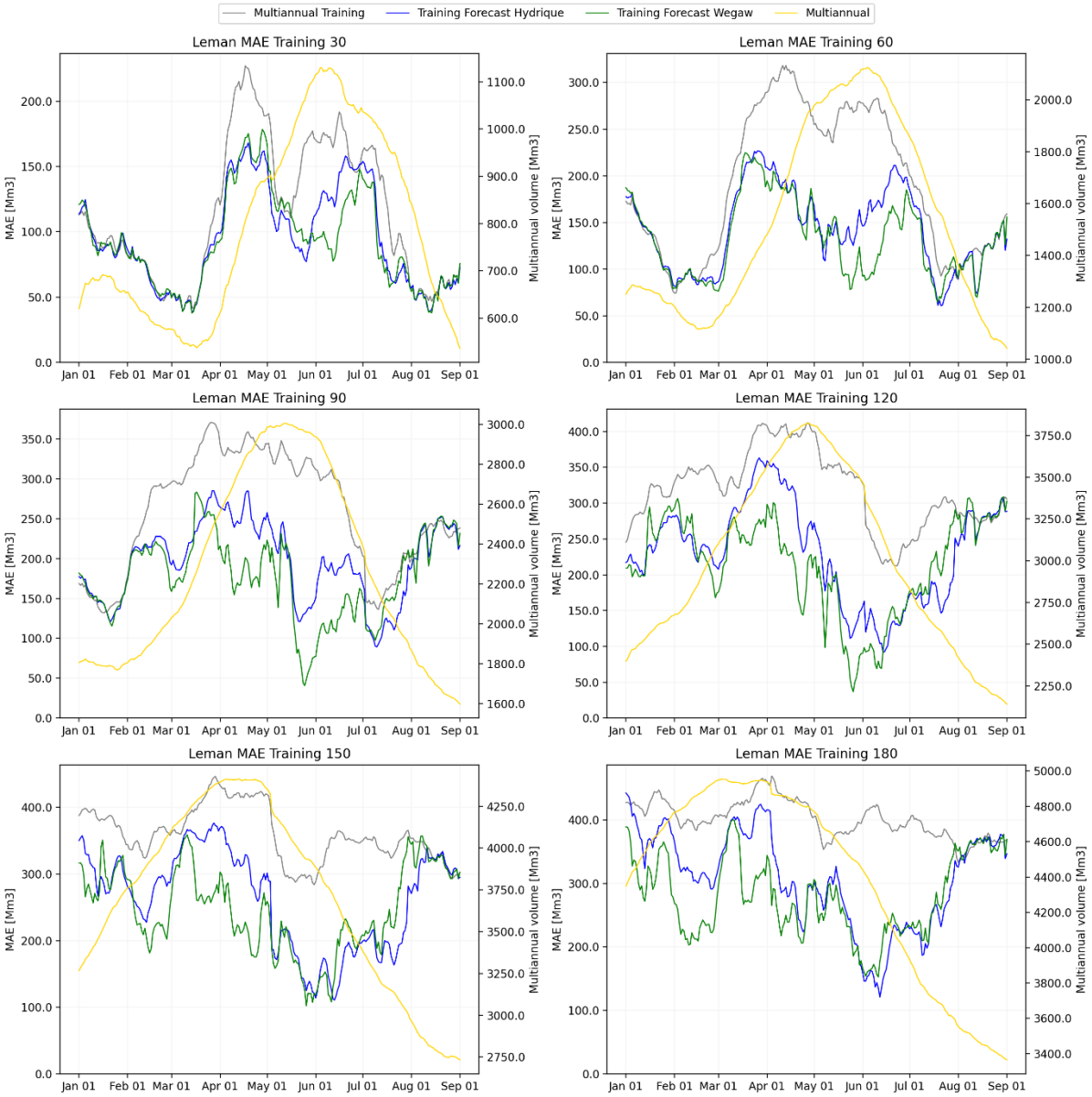
e. Léman, daily MAE, Hydrique SWE, training and cross-validation



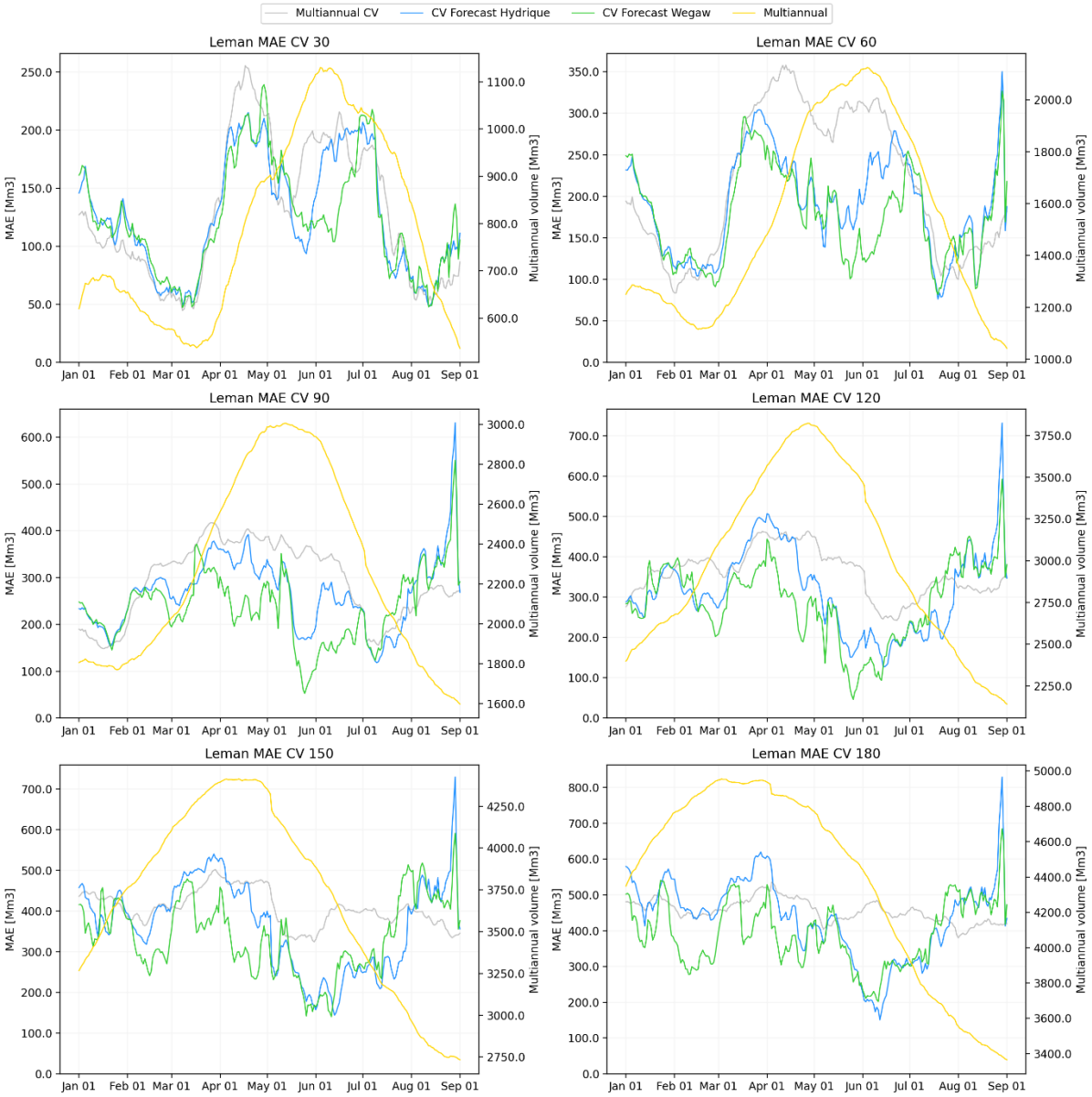
f. Léman, daily MAE, Wegaw SWE, training+cross-validation



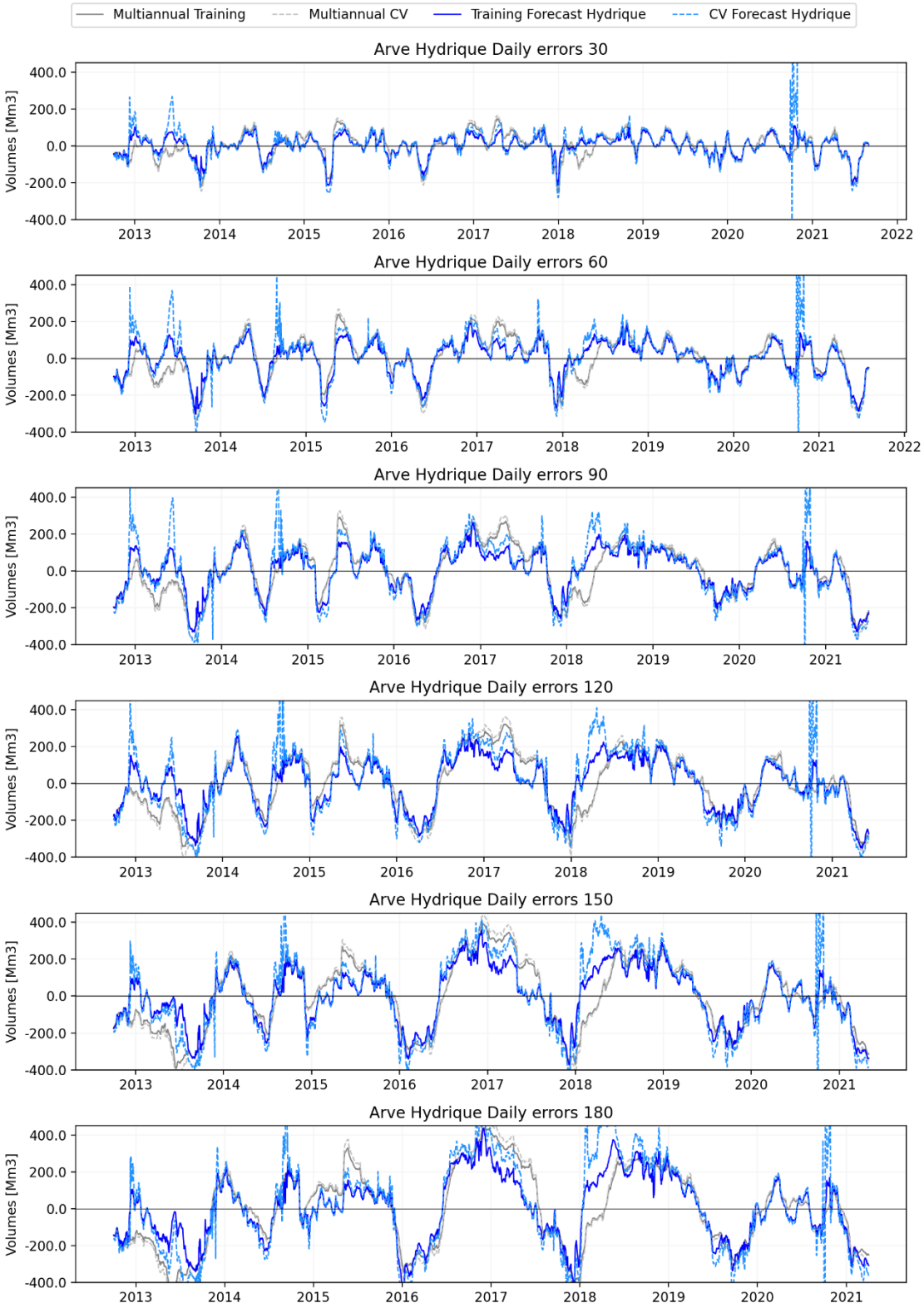
g. Léman, MAE, Hydrique + Wegaw, training



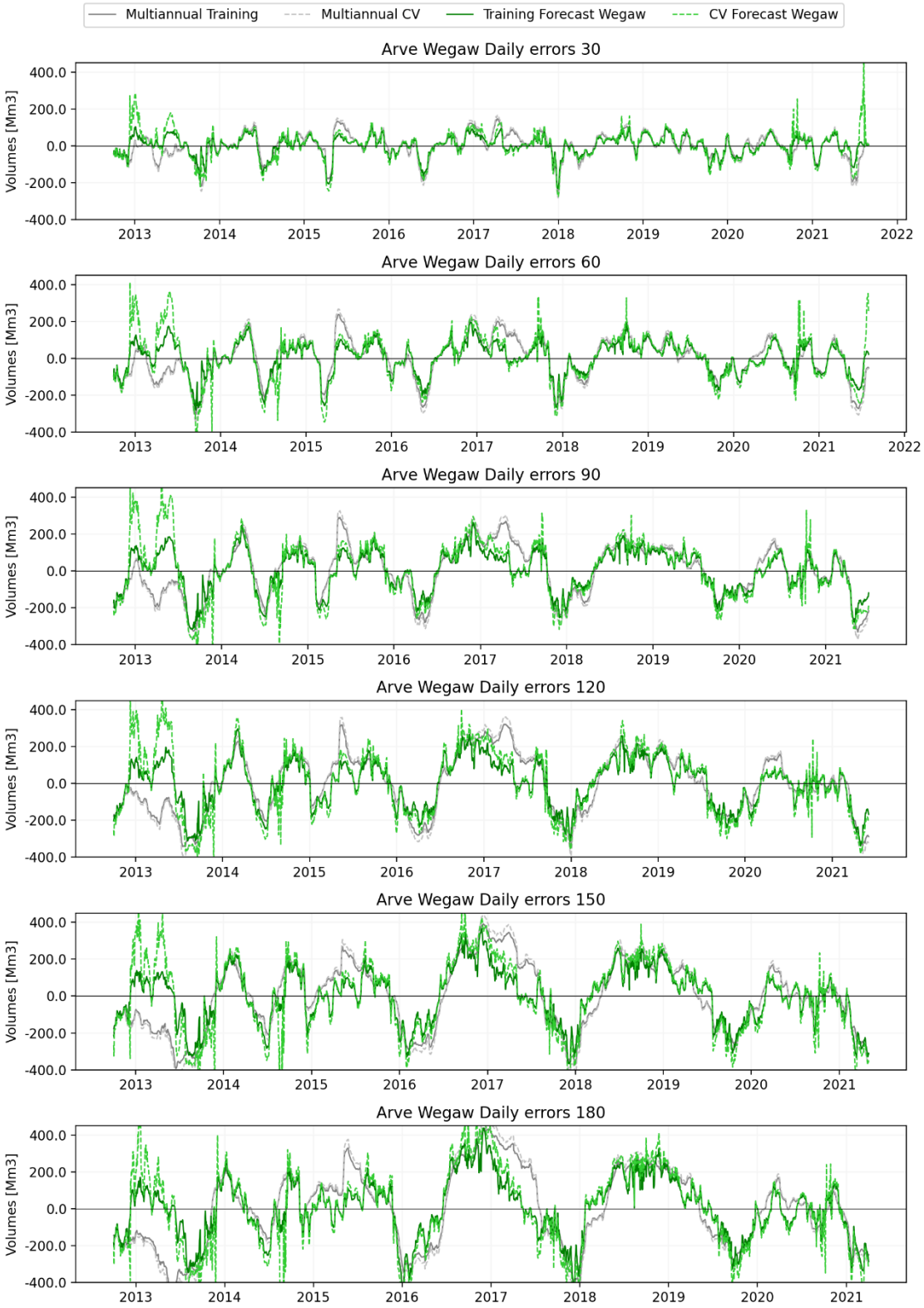
h. Léman, MAE, Hydrique + Wegaw SWE, cross-validation



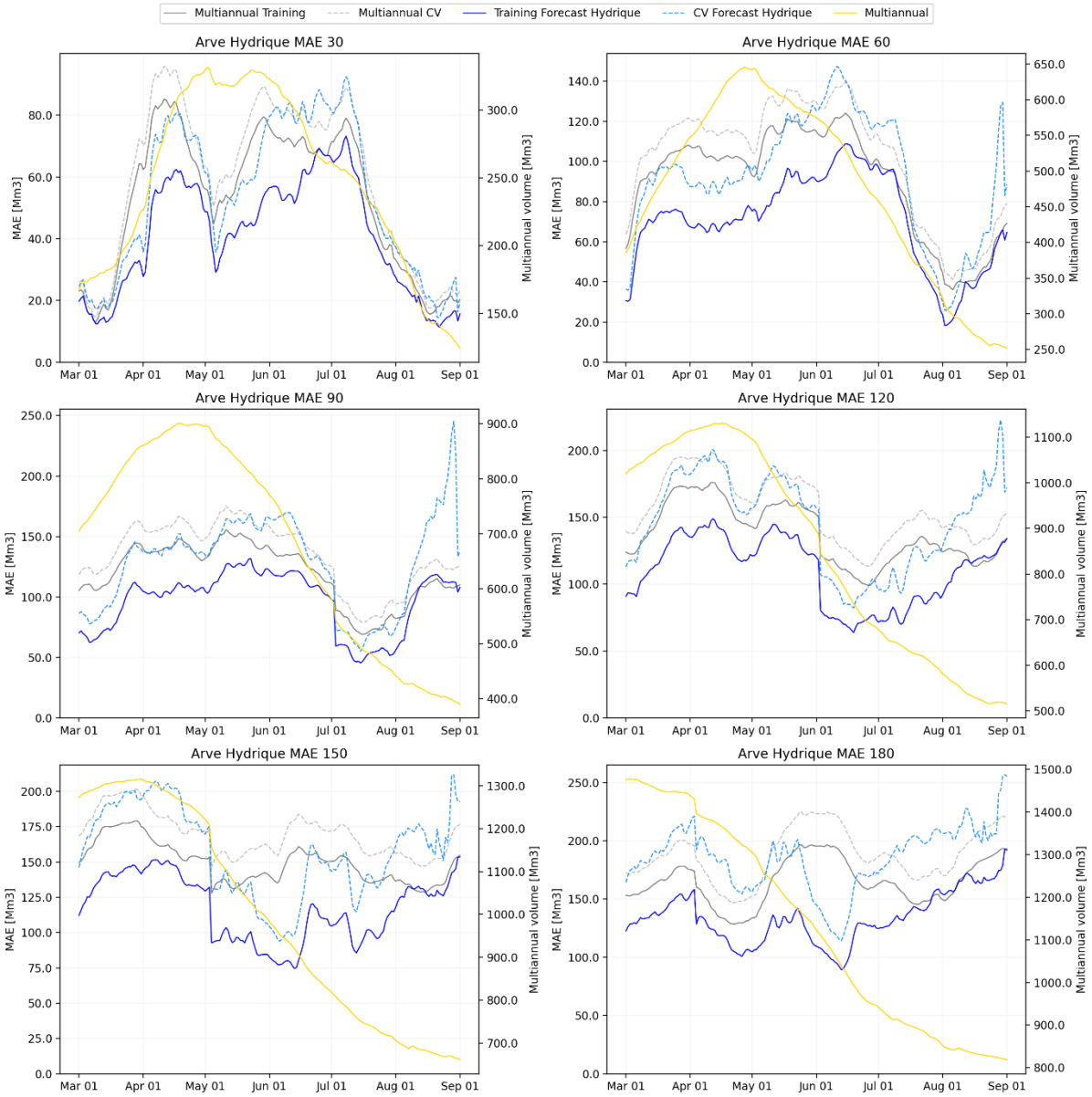
i. Arve, daily errors, Hydrique SWE, training+cross-validation



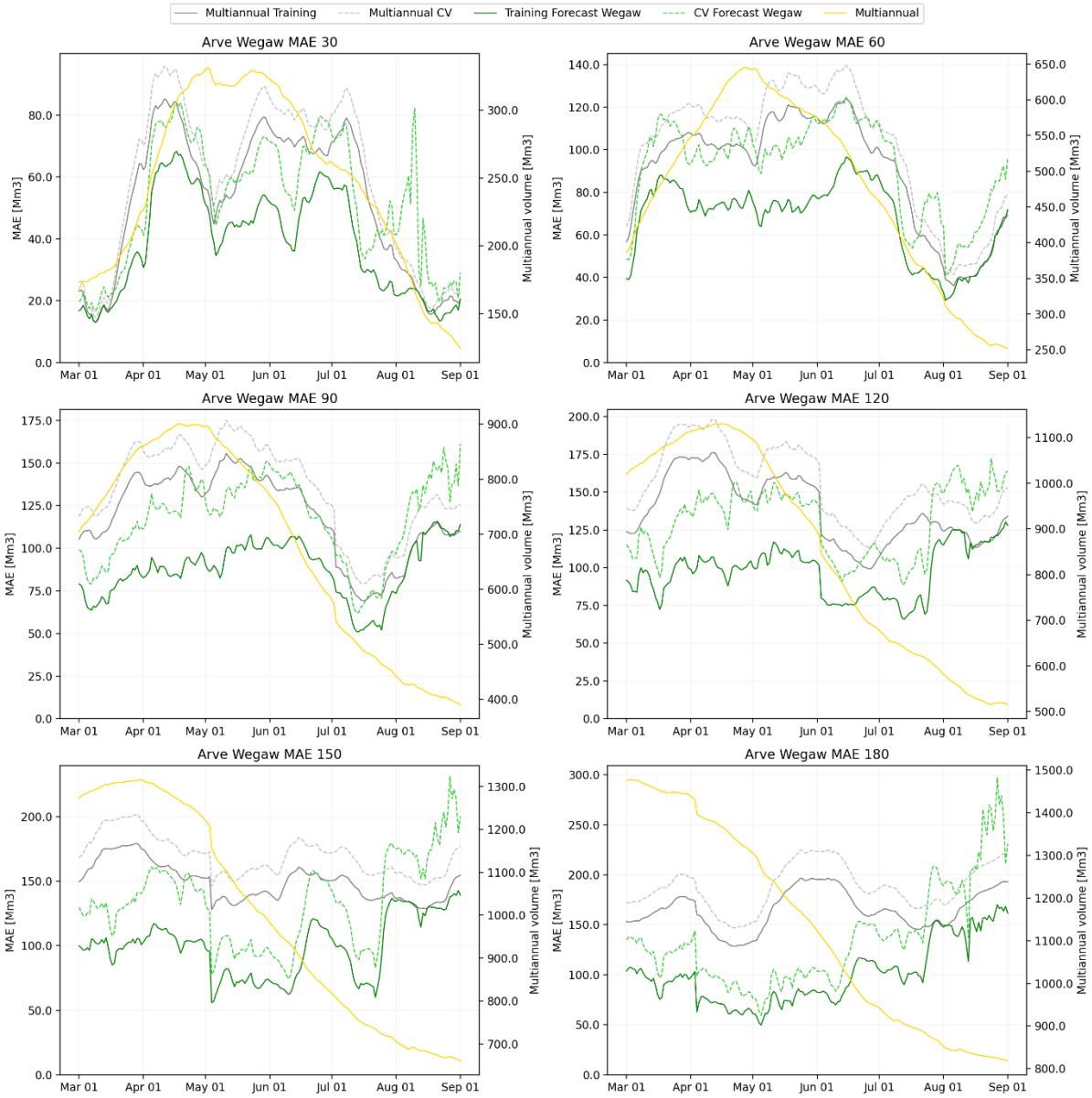
j. Arve, daily errors, Wegaw SWE, training+cross-validation



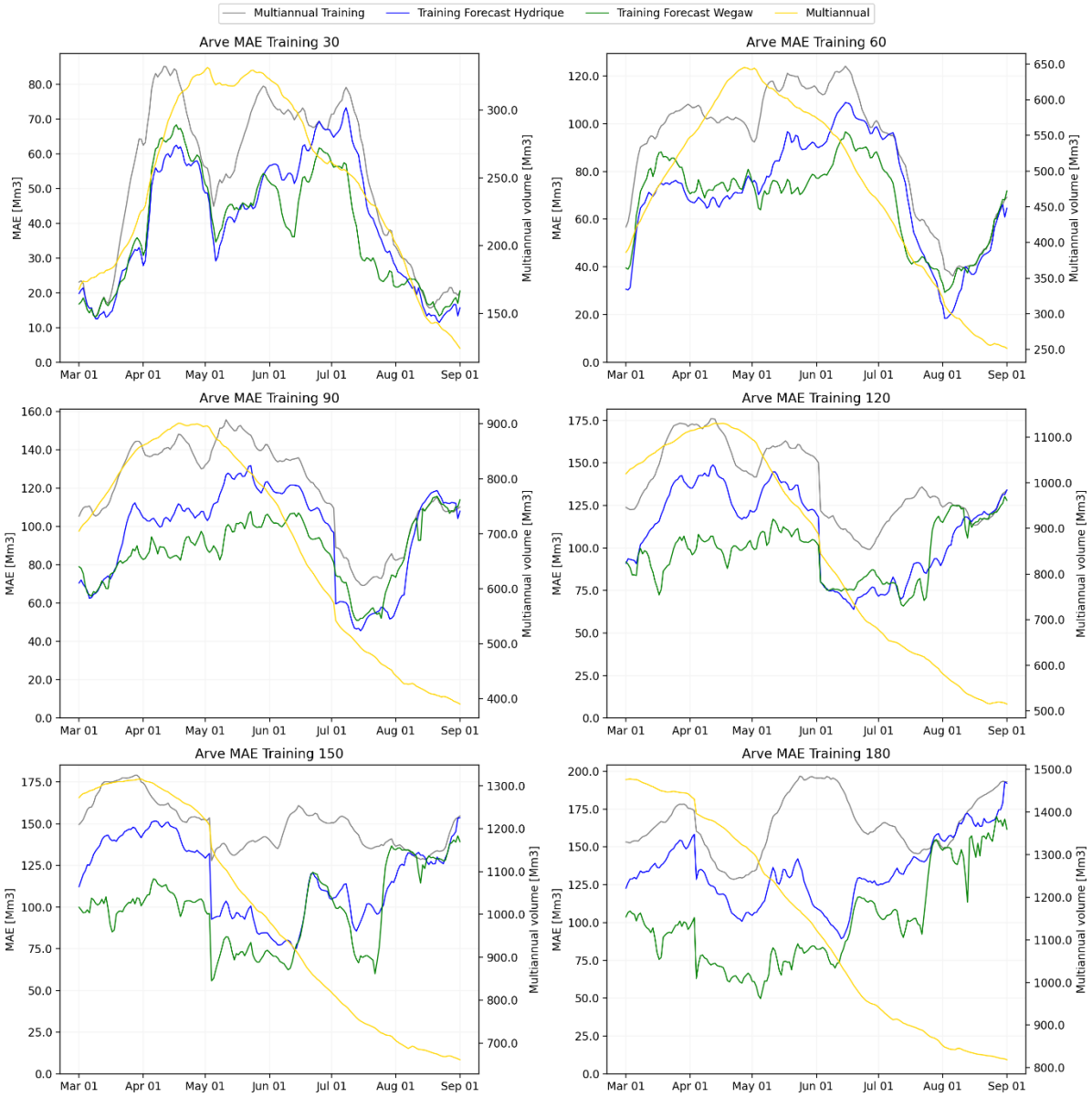
k. Arve, daily MAE, Hydrique SWE, training and cross-validation



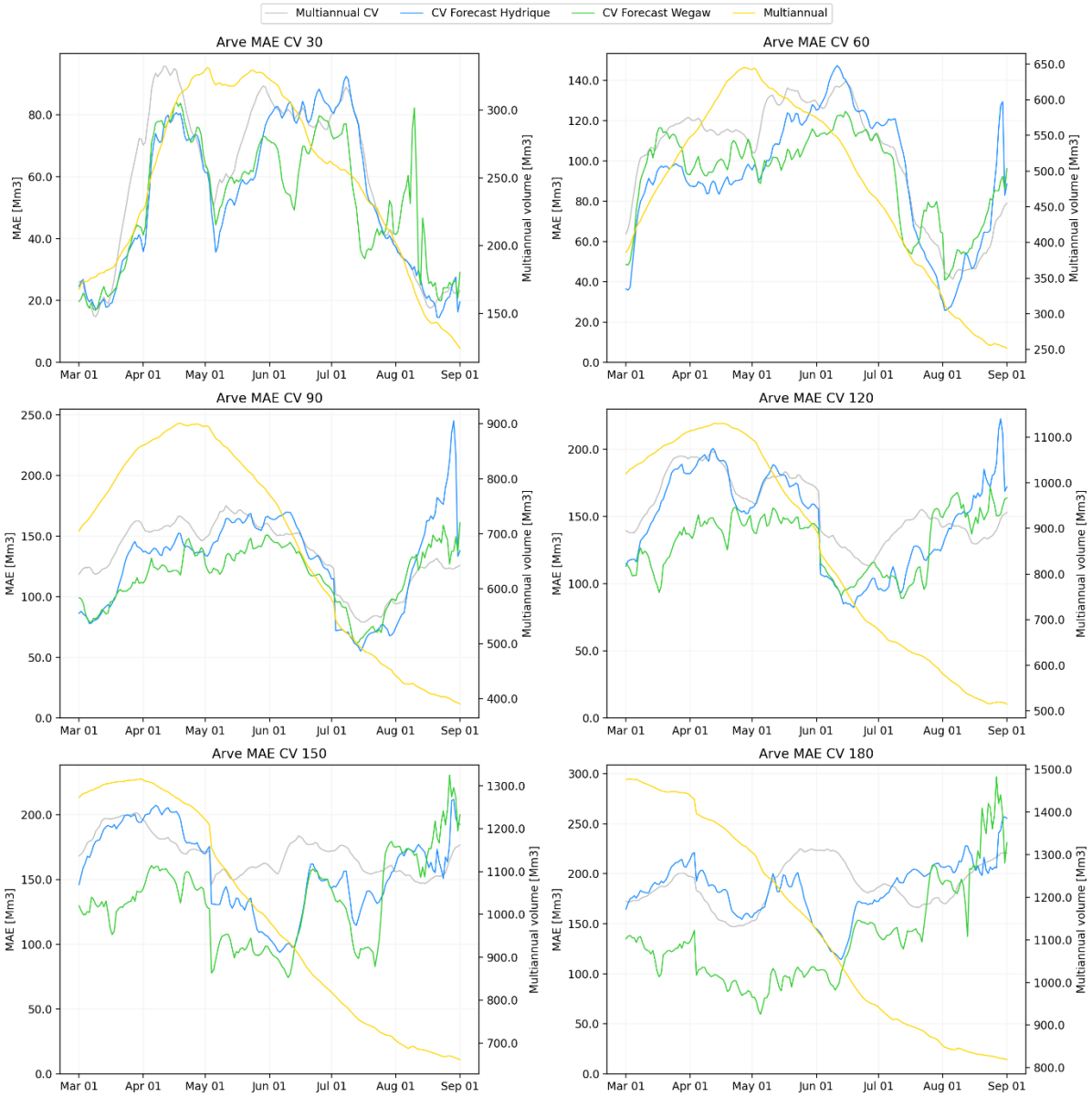
I. Arve, daily MAE, Wegaw SWE, training and cross-validation



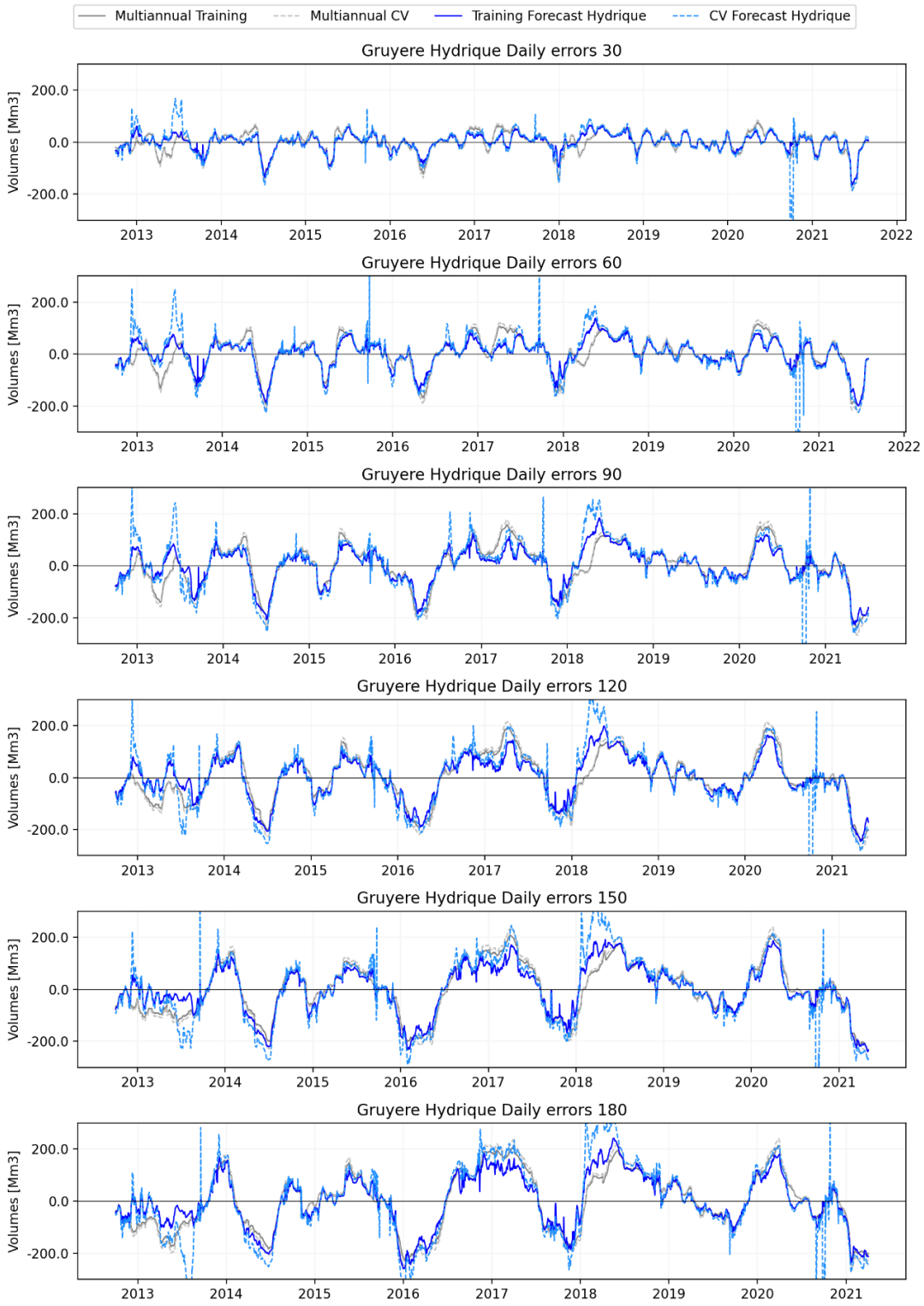
m. Arve, MAE, Hydrique + Wegaw, training



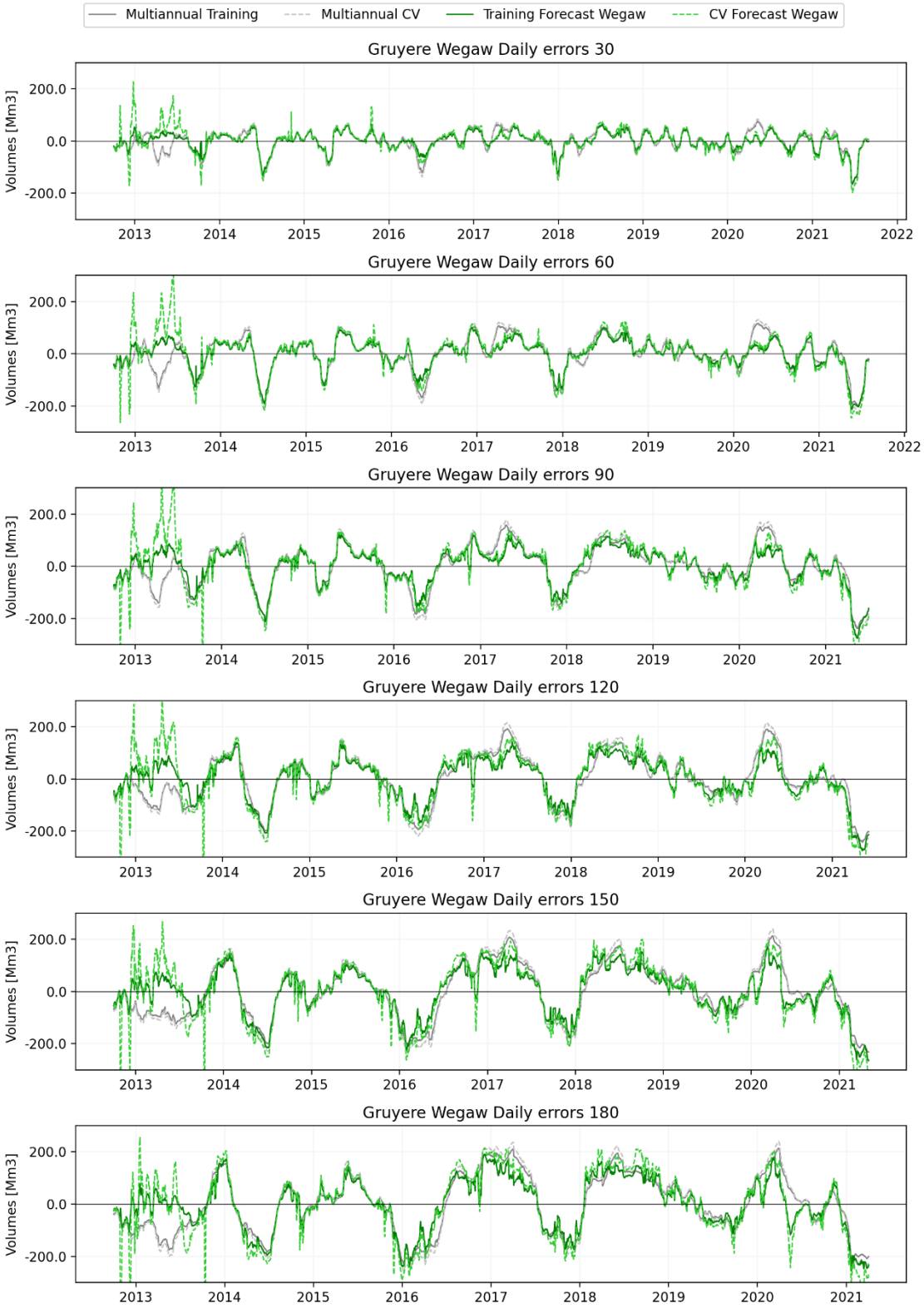
n. Arve, MAE, Hydrique + Wegaw, cross-validation



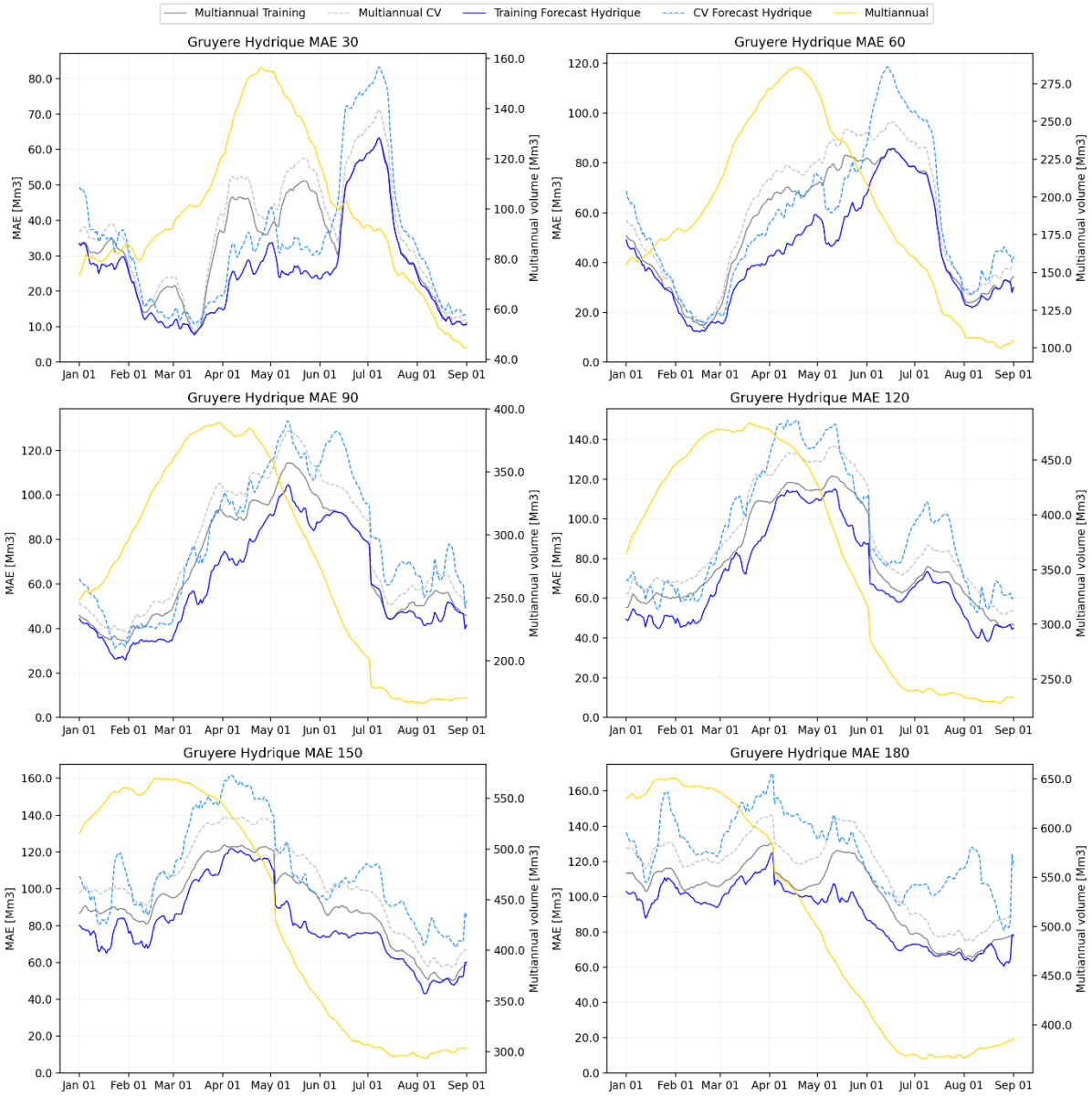
o. Lac de Gruyère, daily errors, Hydrique SWE, training+cross-validation



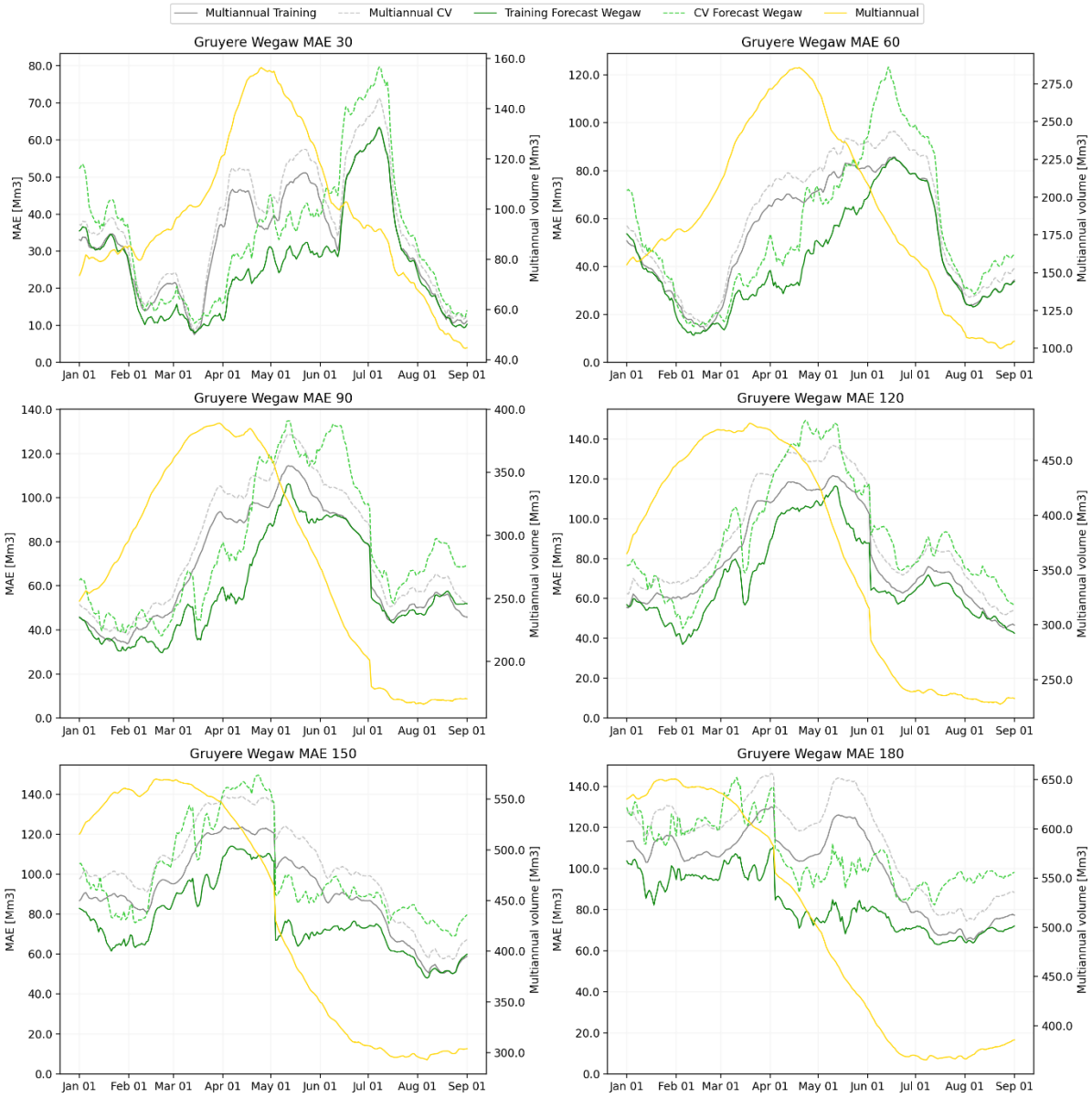
p. Lac de Gruyère, daily errors, Wegaw SWE, training+cross-validation



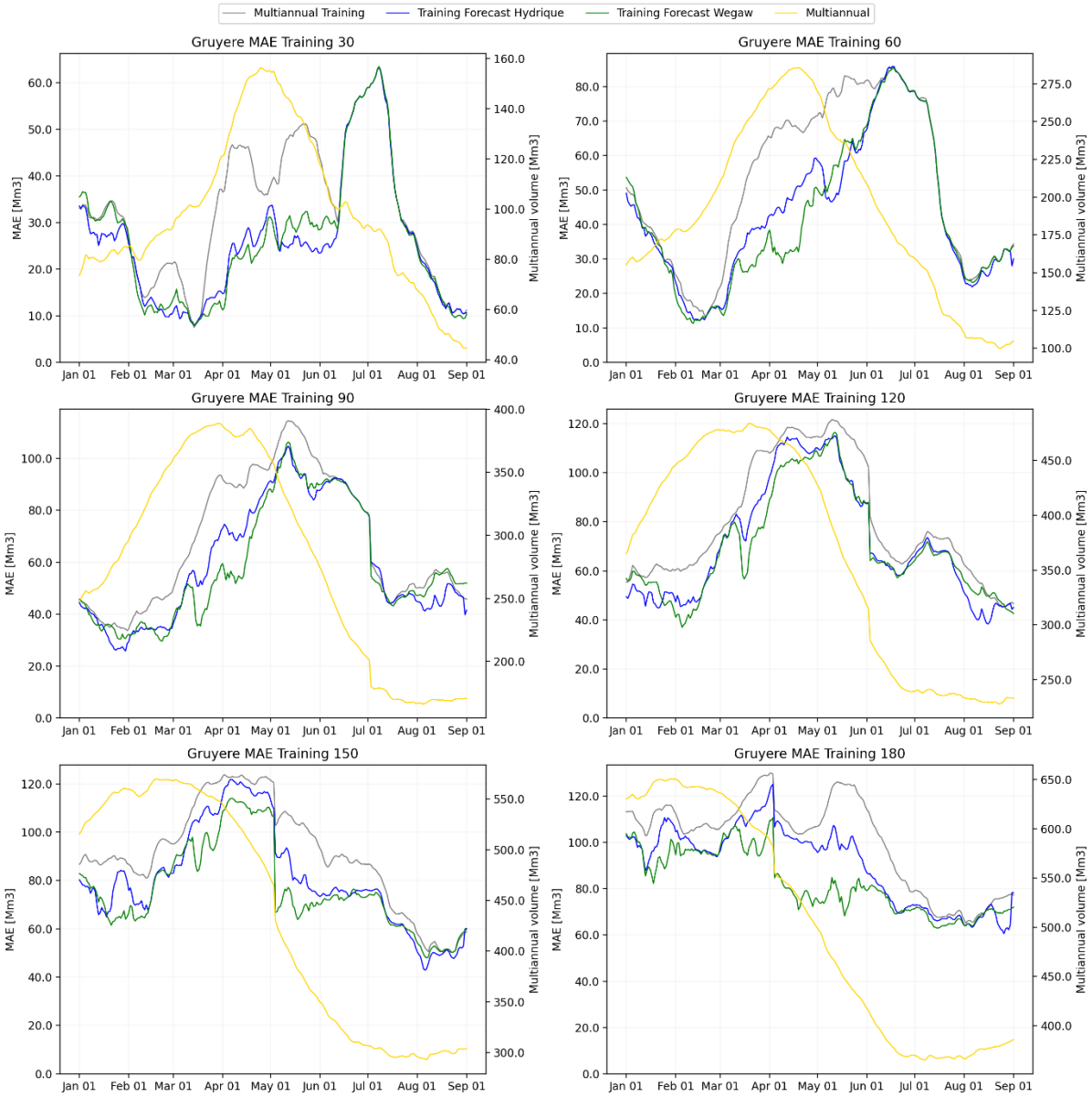
q. Lac de Gruyère, daily MAPE, Hydrique SWE, training and cross-validation



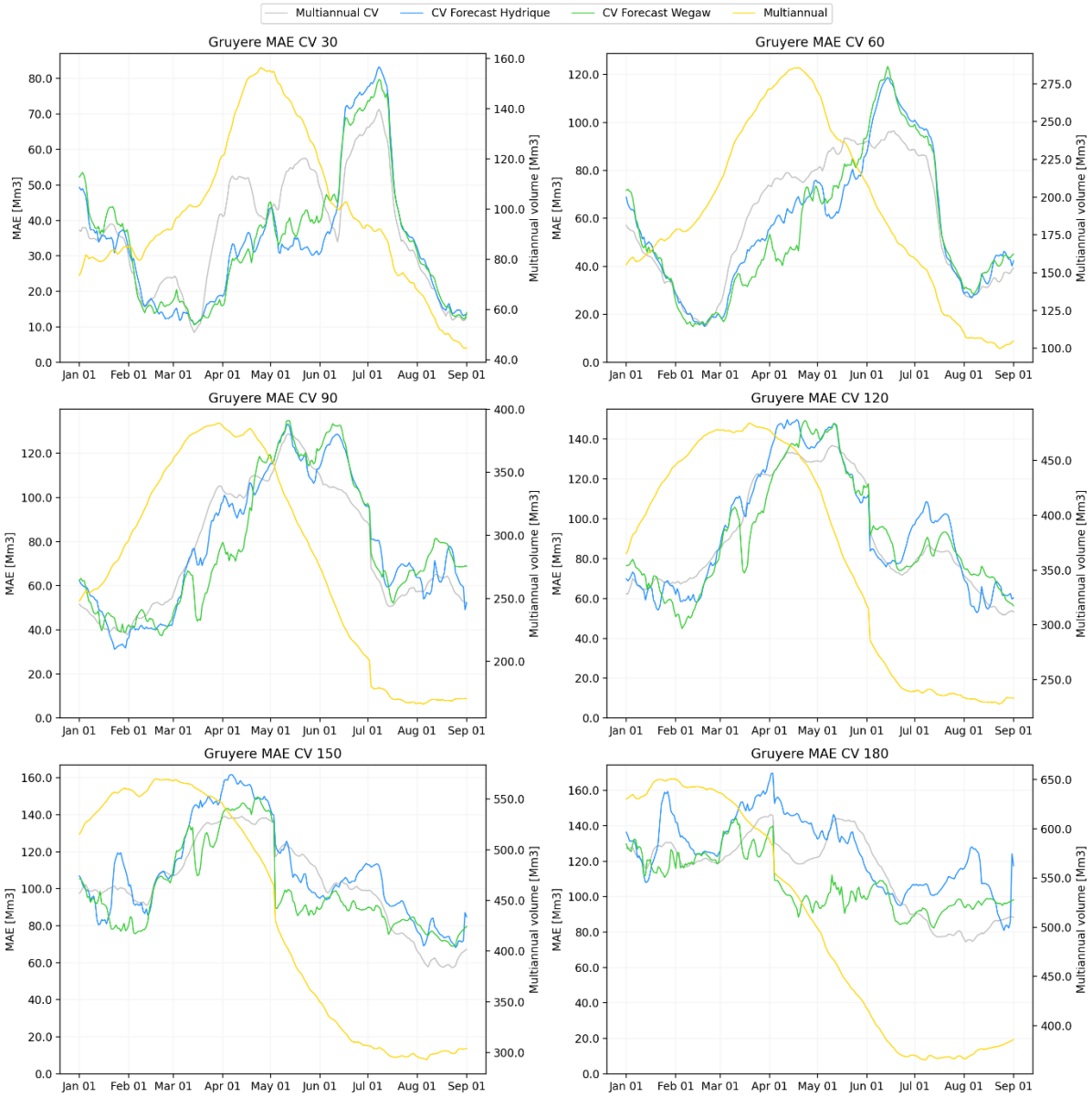
r. Lac de Gruyère, daily MAPE, Wegaw SWE, training and cross-validation



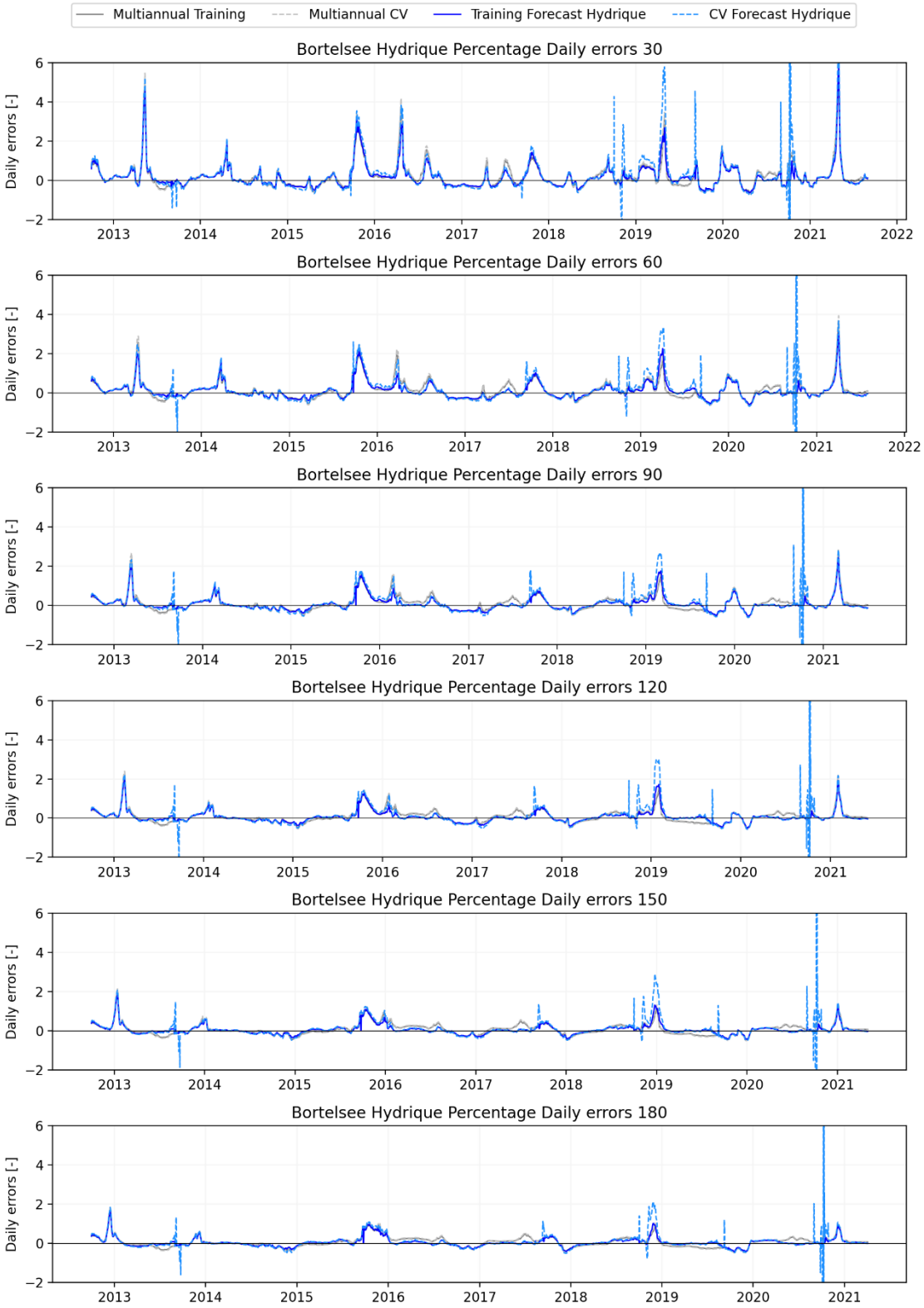
s. Lac de Gruyère, MAPE, Hydrique + Wegaw, training



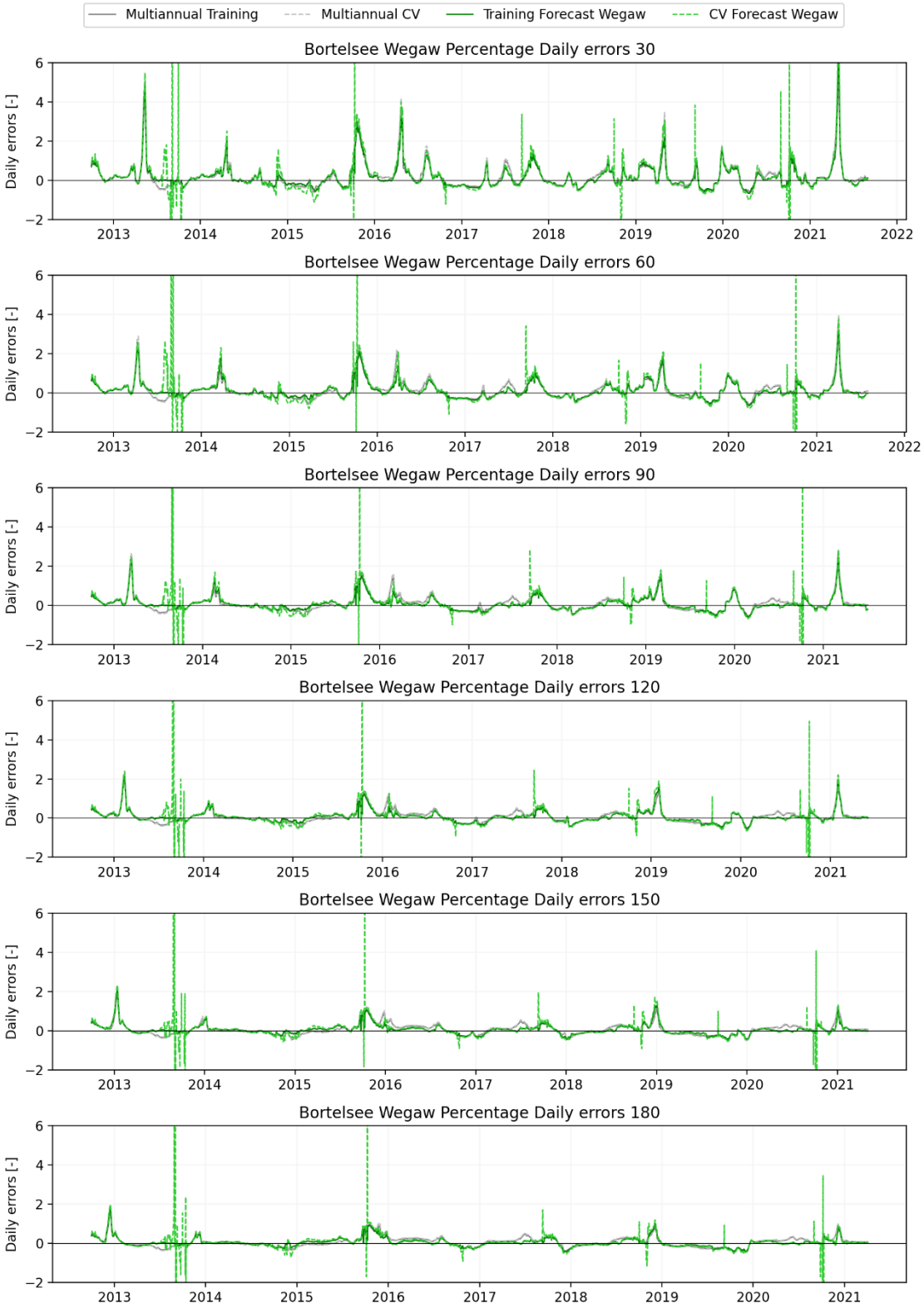
t. Lac de Gruyère, MAPE, Hydrique + Wegaw, cross-validation



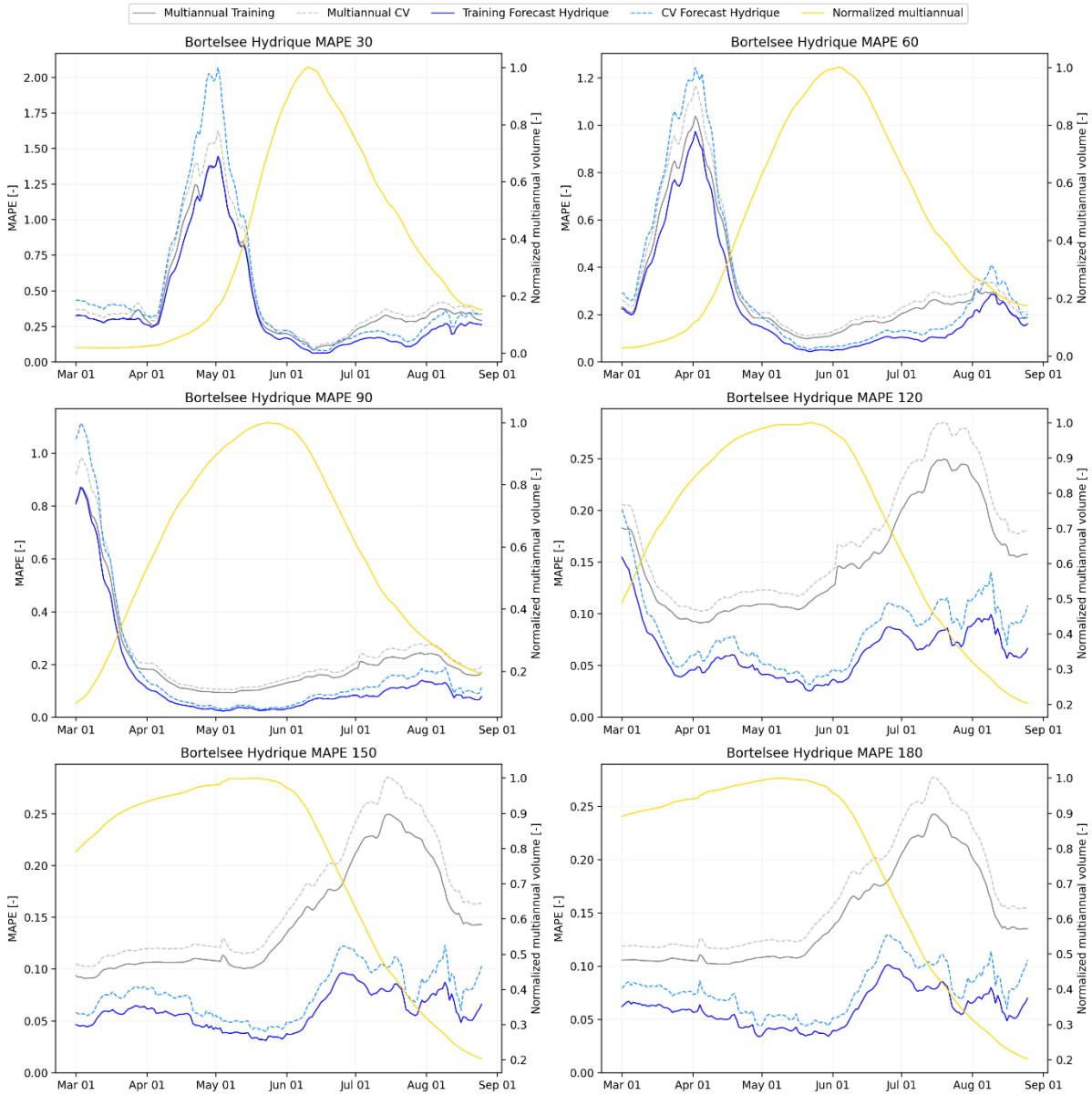
u. Bortelsee, daily errors, Hydrique SWE, training+cross-validation



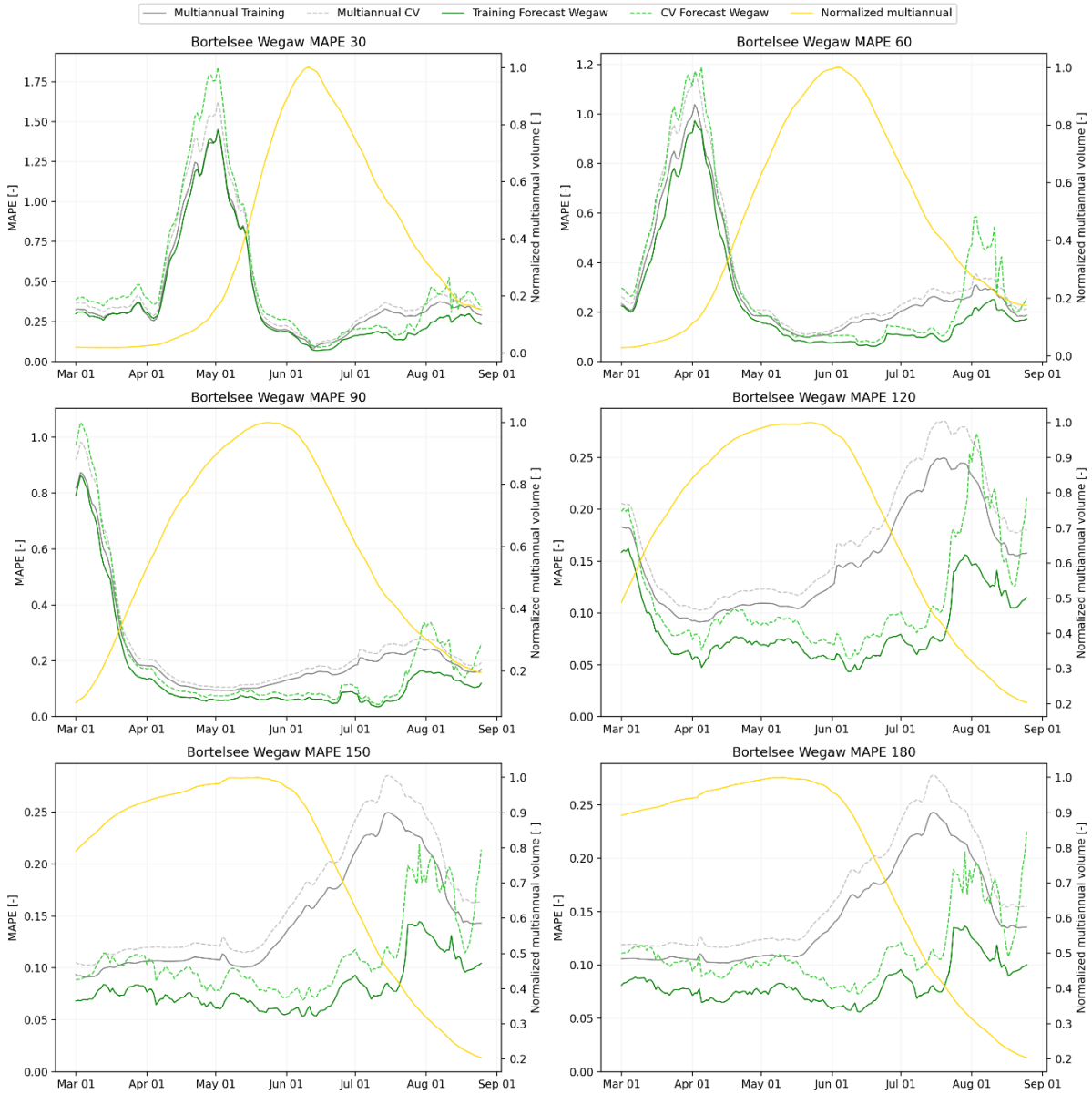
v. Bortelsee, daily errors, Wegaw SWE, training+cross-validation



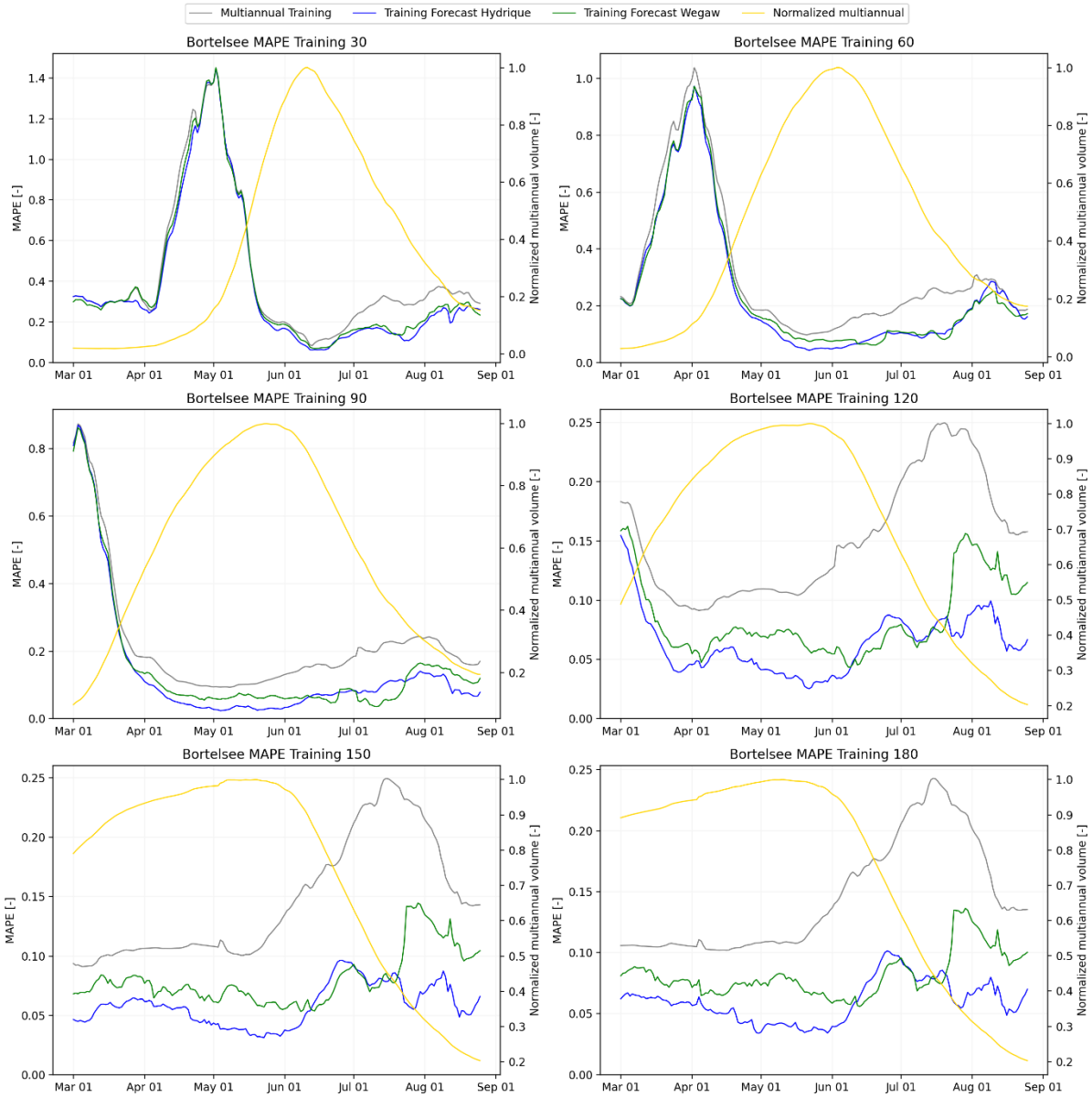
w. Bortelsee, daily MAPE, Hydrique SWE, training and cross-validation



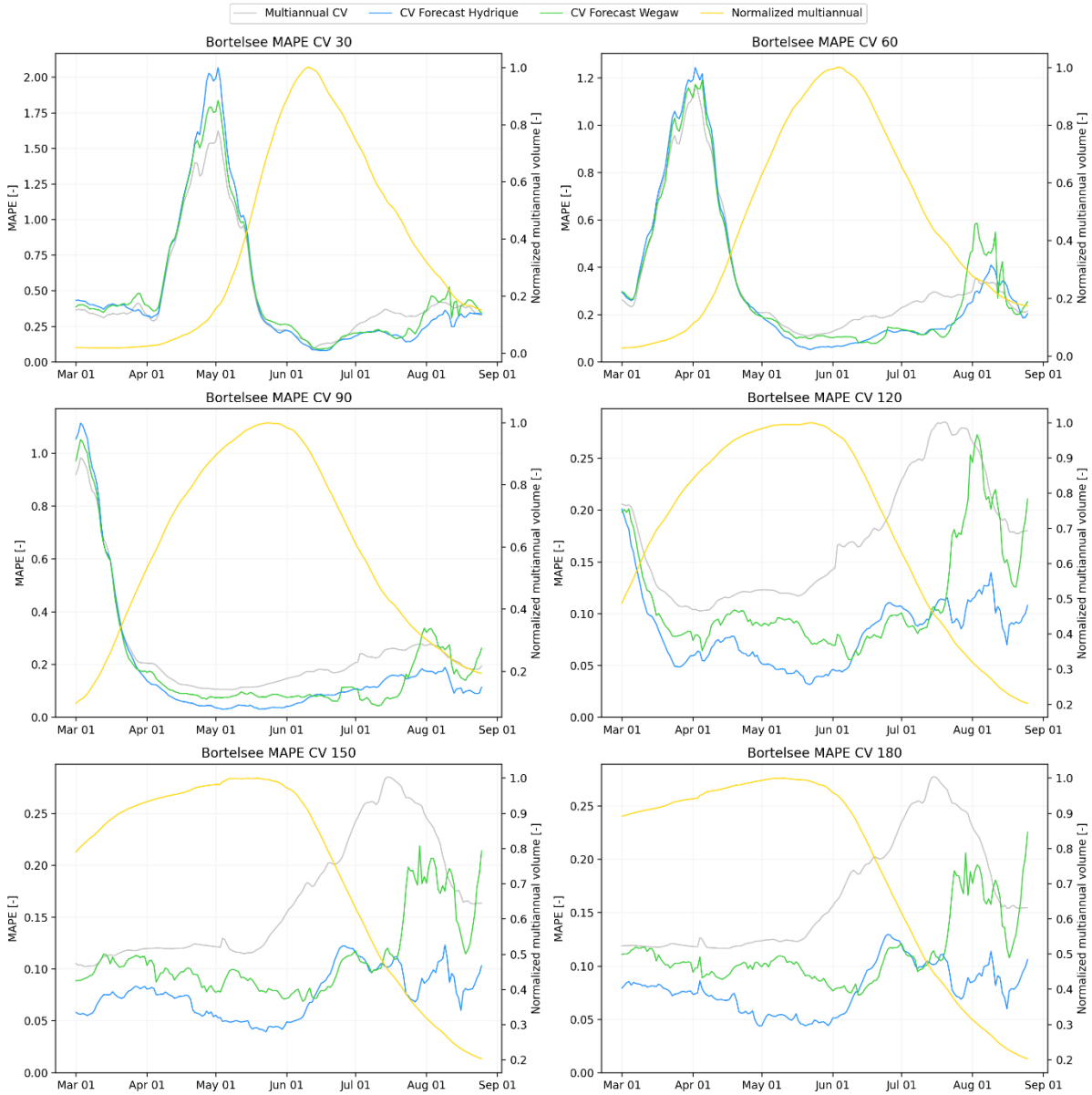
x. Bortelsee, daily MAPE, Wegaw SWE, training and cross-validation



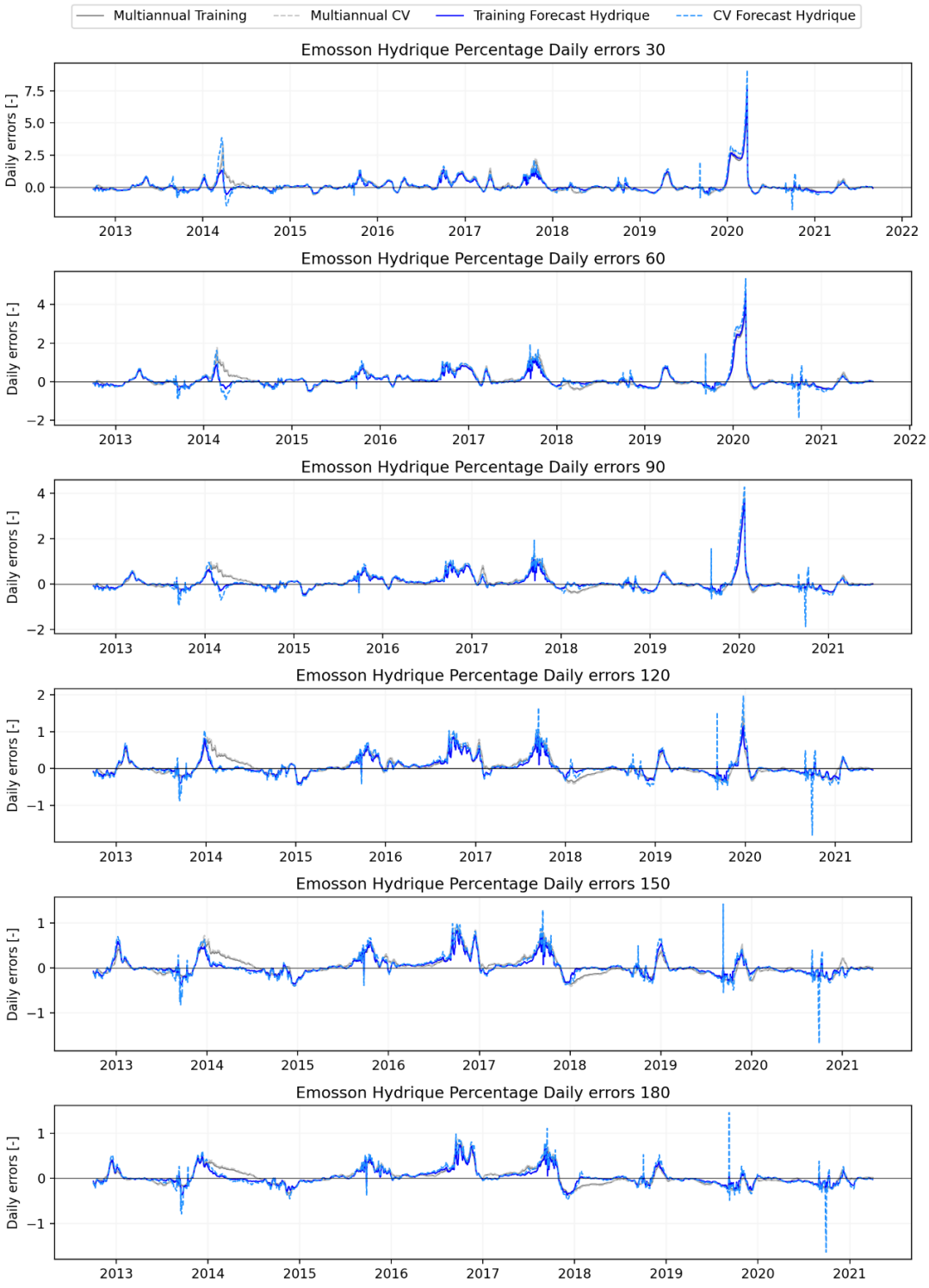
y. Bortelsee, MAPE, Hydrique + Wegaw, training



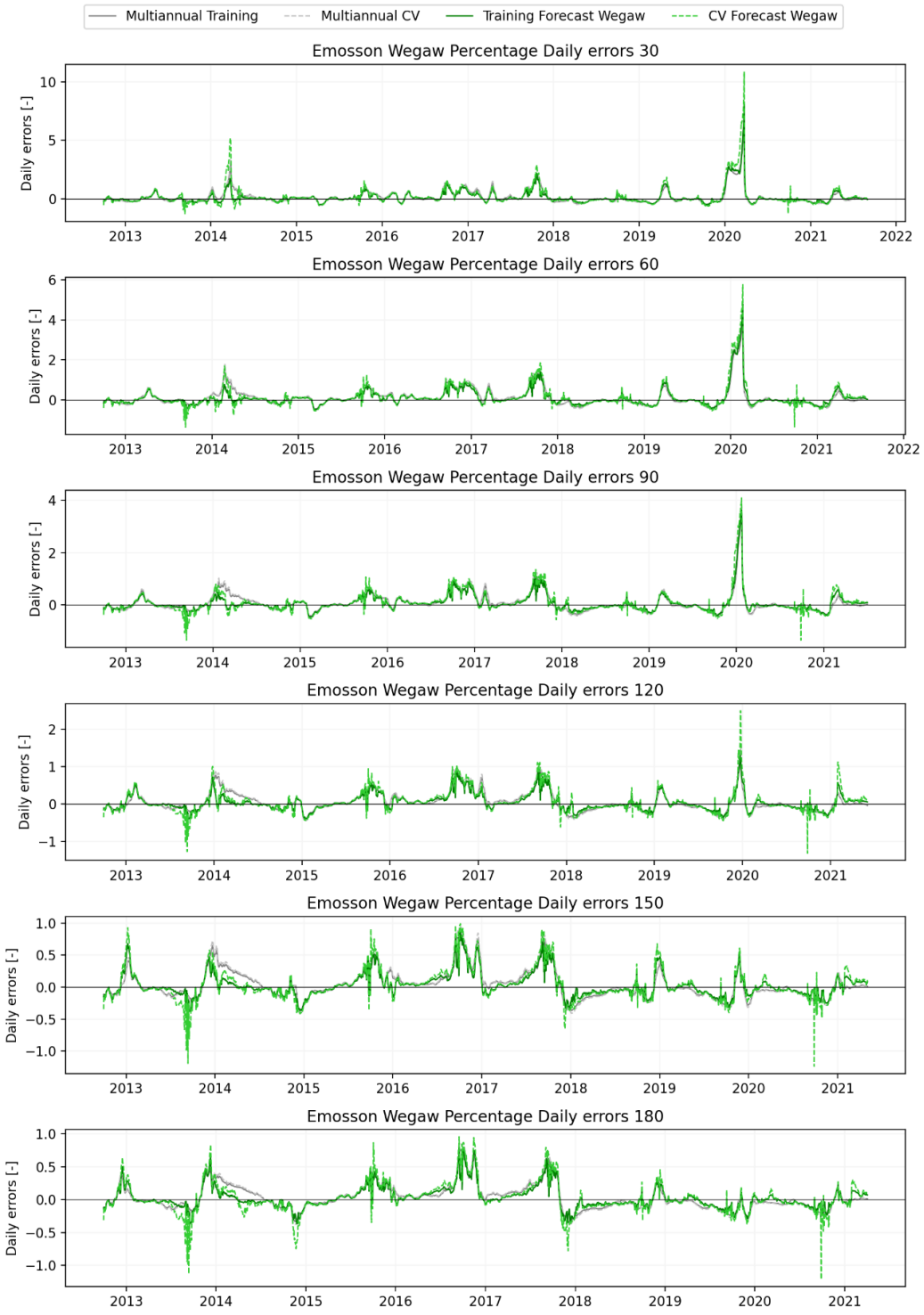
z. Bortelsee, MAPE, Hydrique + Wegaw, cross-validation



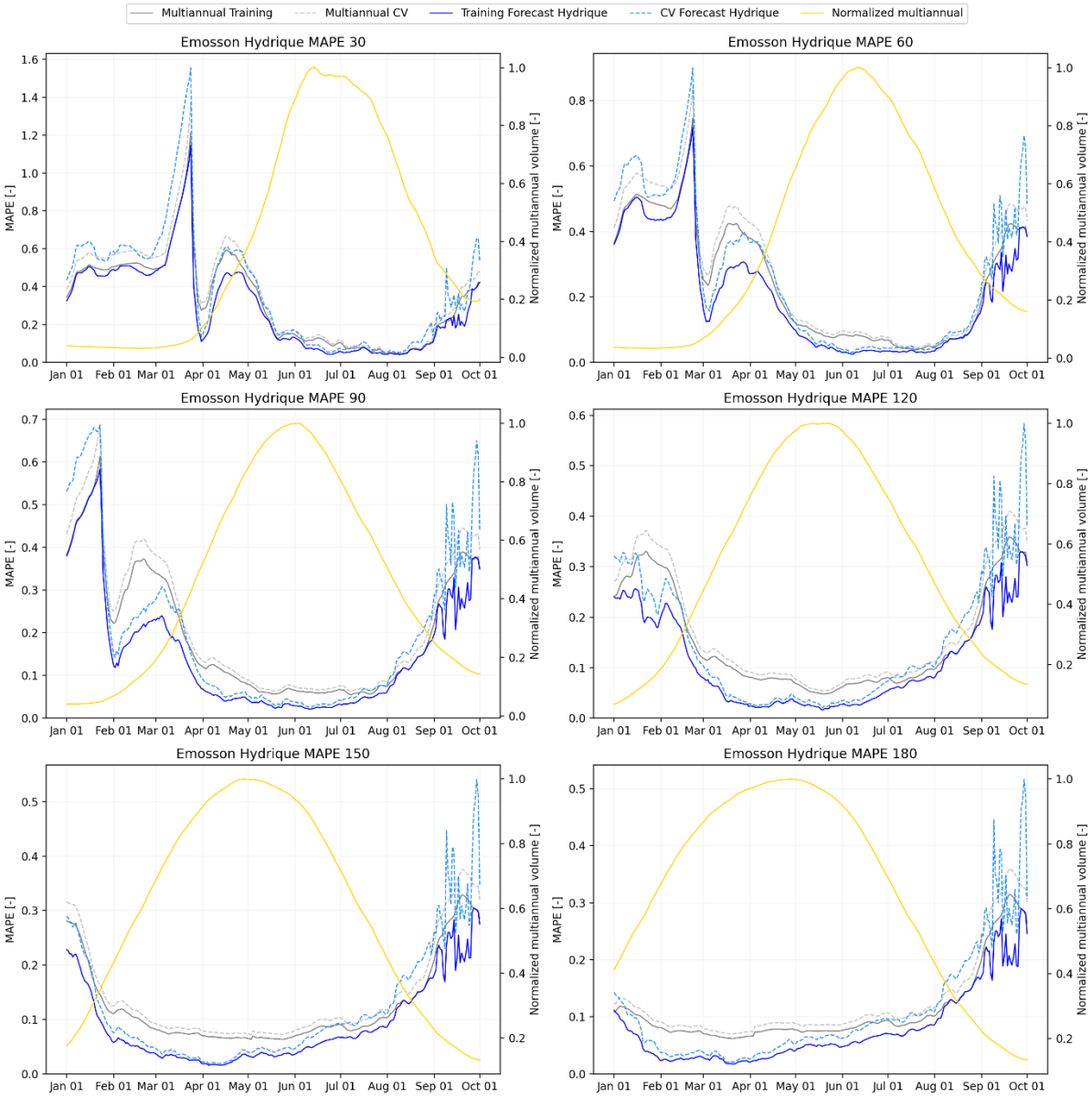
aa. Emosson coll. est, daily errors, Hydrique SWE, training+cross-validation



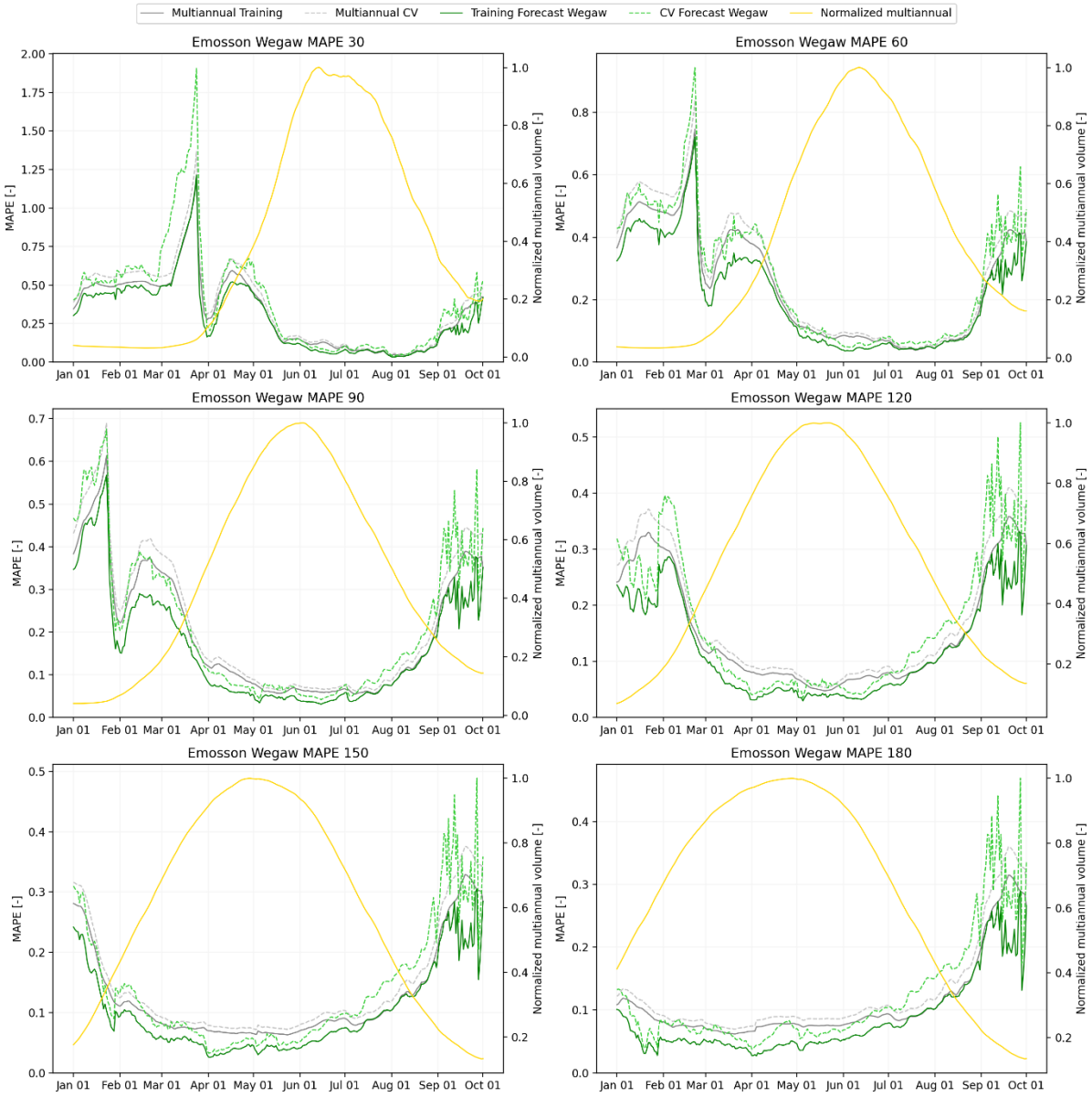
bb. Emosson coll. est, daily errors, Wegaw SWE, training+cross-validation



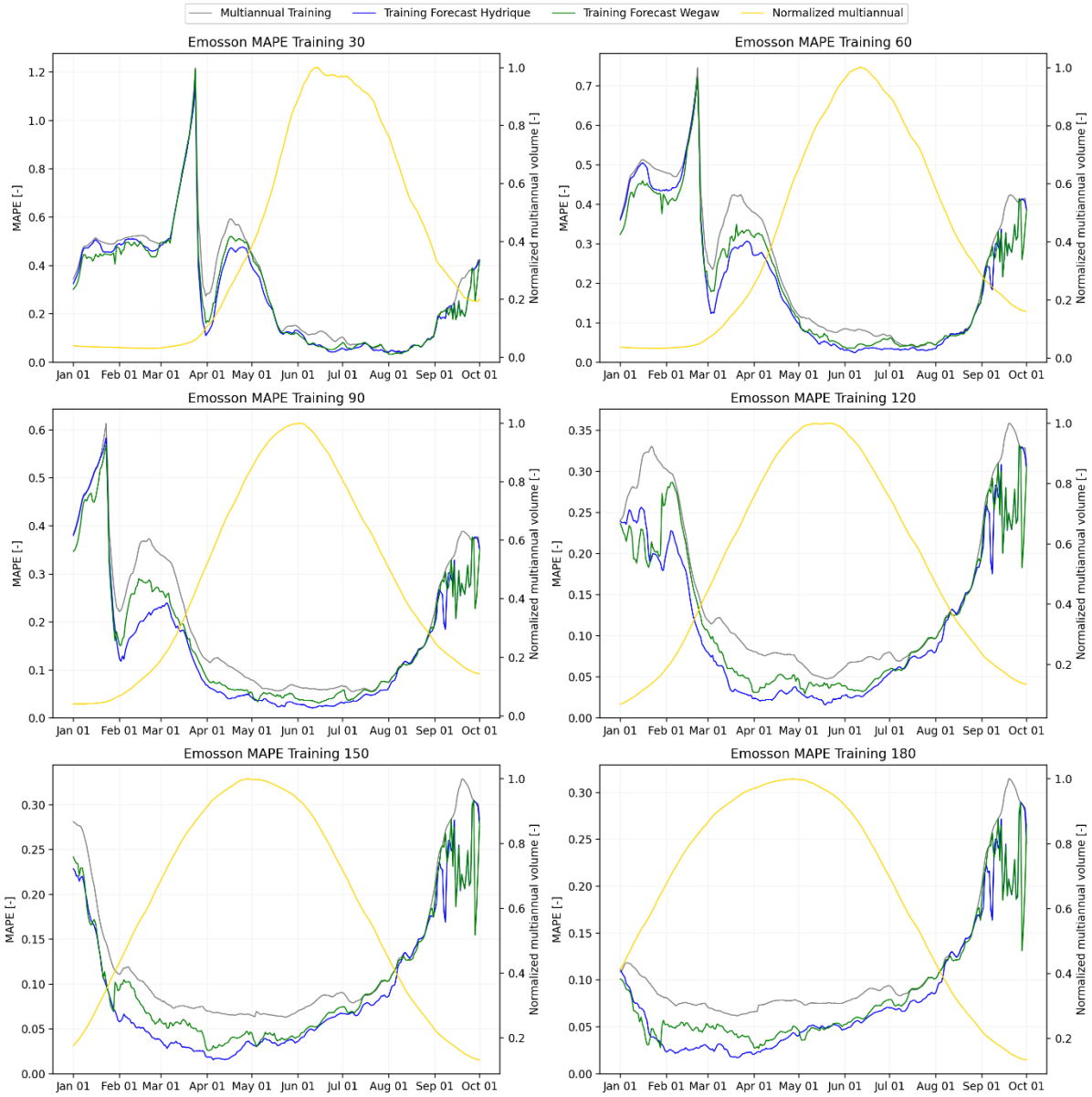
cc. Emosson coll. est, daily MAPE, Hydrique SWE, training and cross-validation



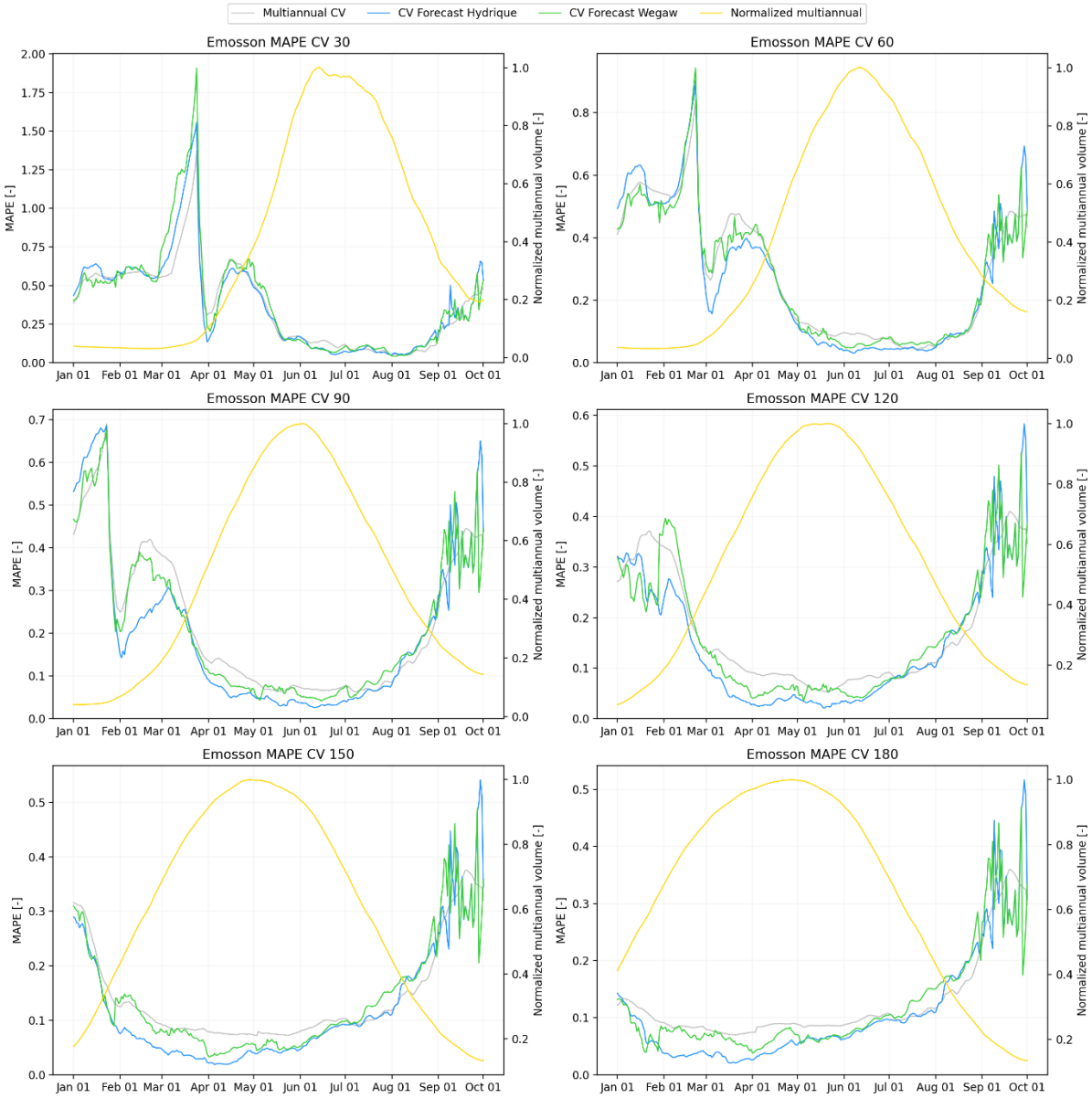
dd. Emosson coll. est, daily MAPE, Wegaw SWE, training and cross-validation



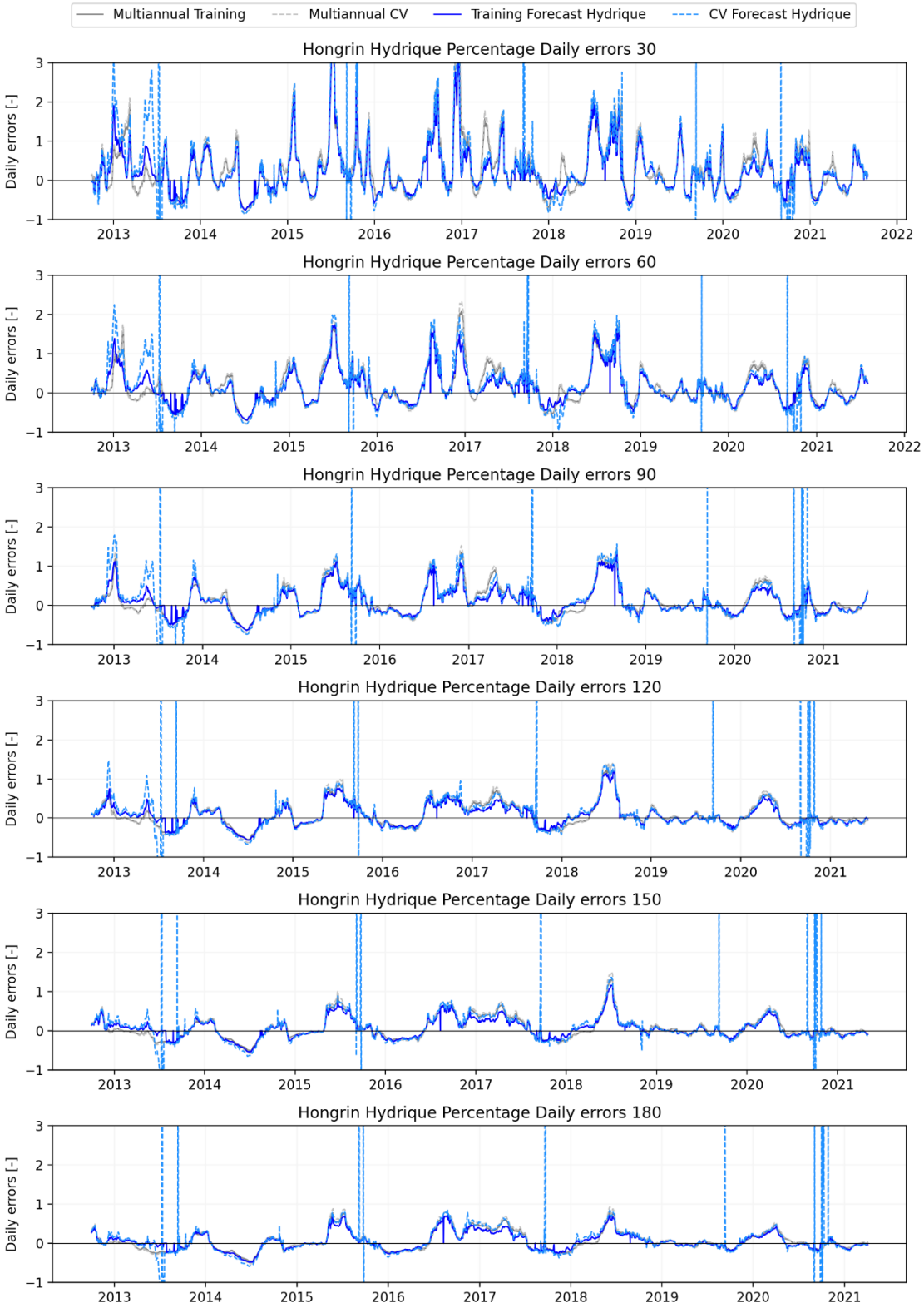
ee. Emosson coll. est, MAPE, Hydrique + Wegaw, training



ff. Emosson coll. est, MAPE, Hydrique + Wegaw, cross-validation



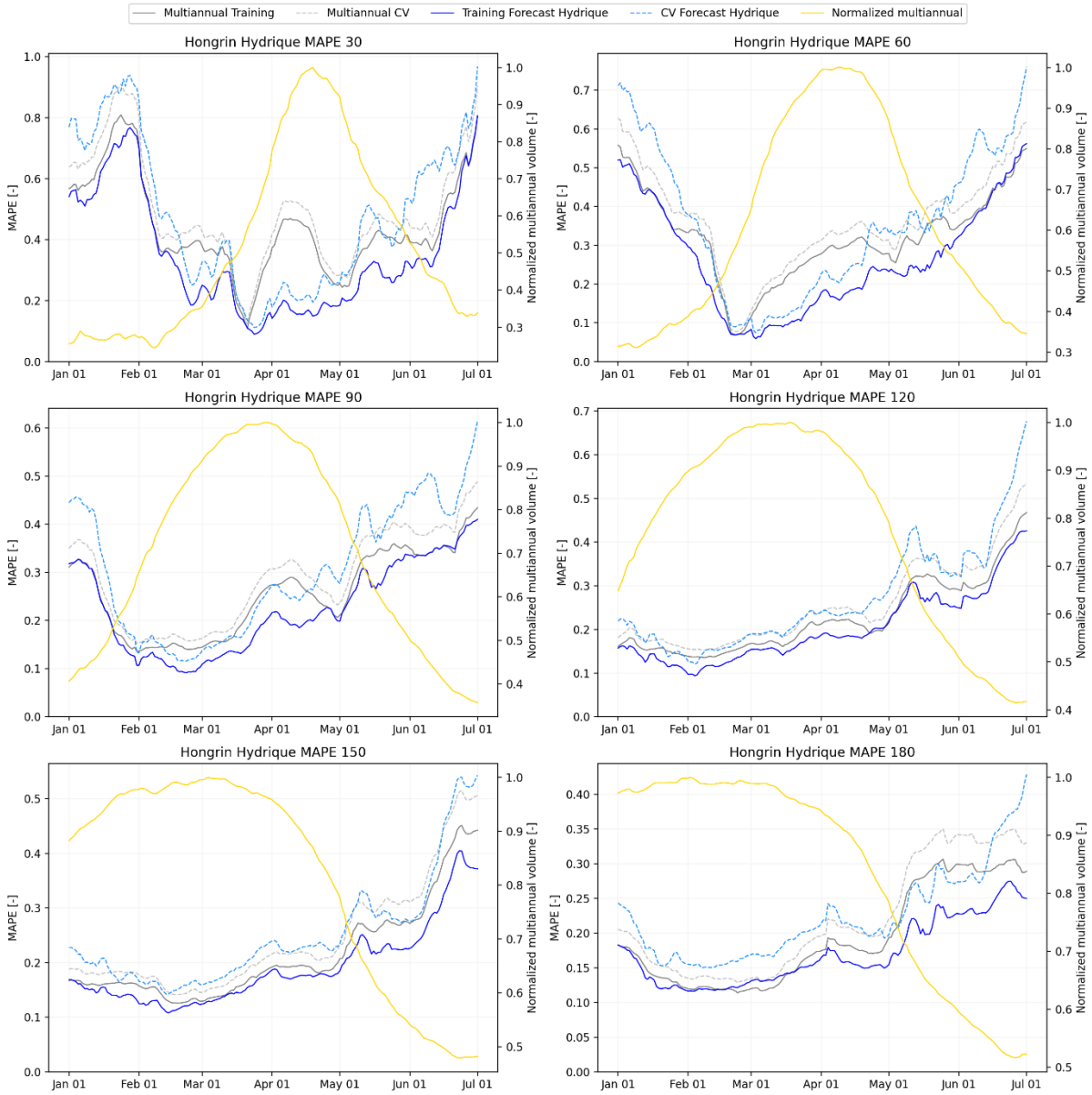
gg. Hongrin, daily errors, Hydrique SWE, training+cross-validation



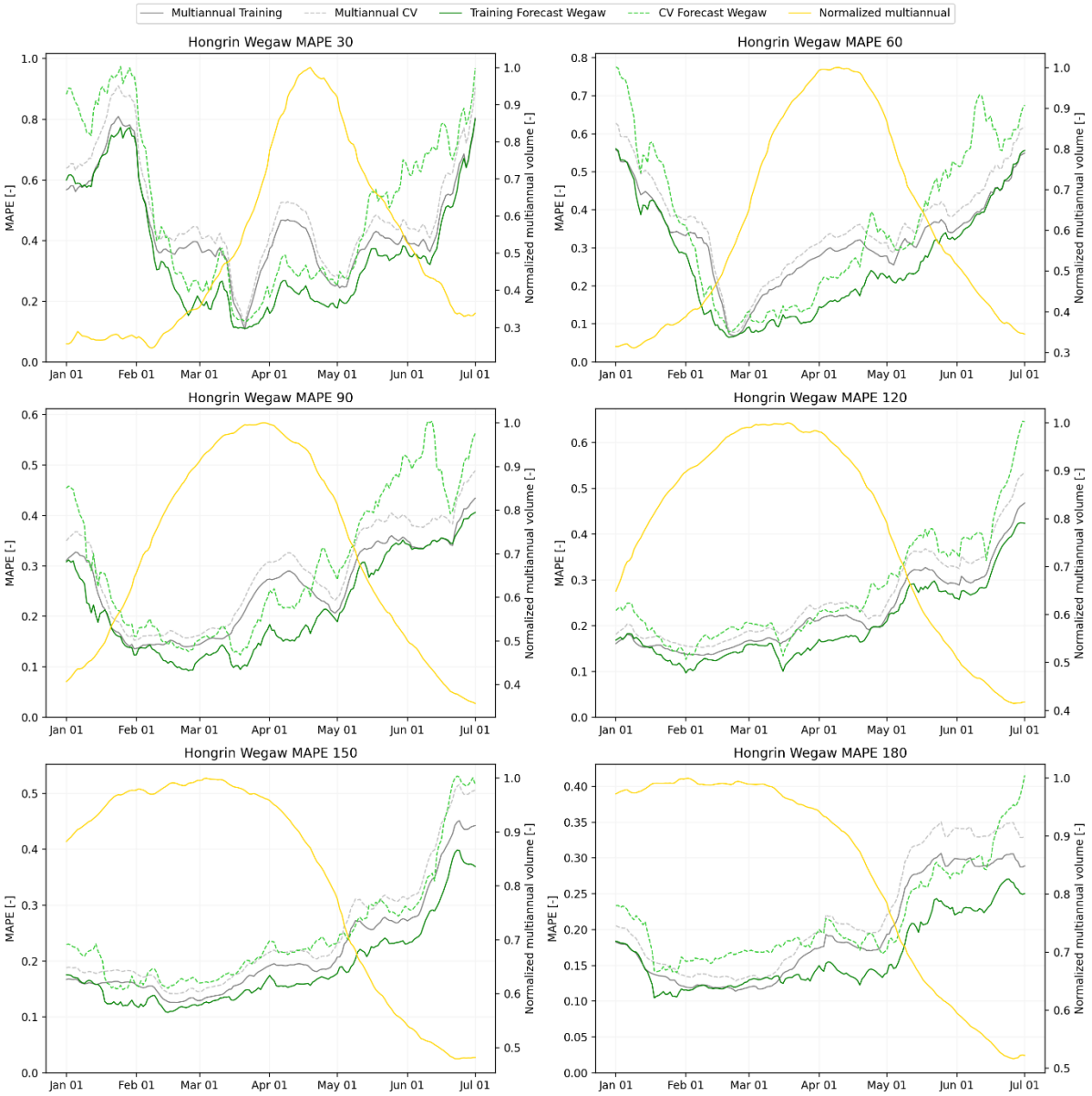
hh. Hongrin, daily errors, Wegaw SWE, training+cross-validation



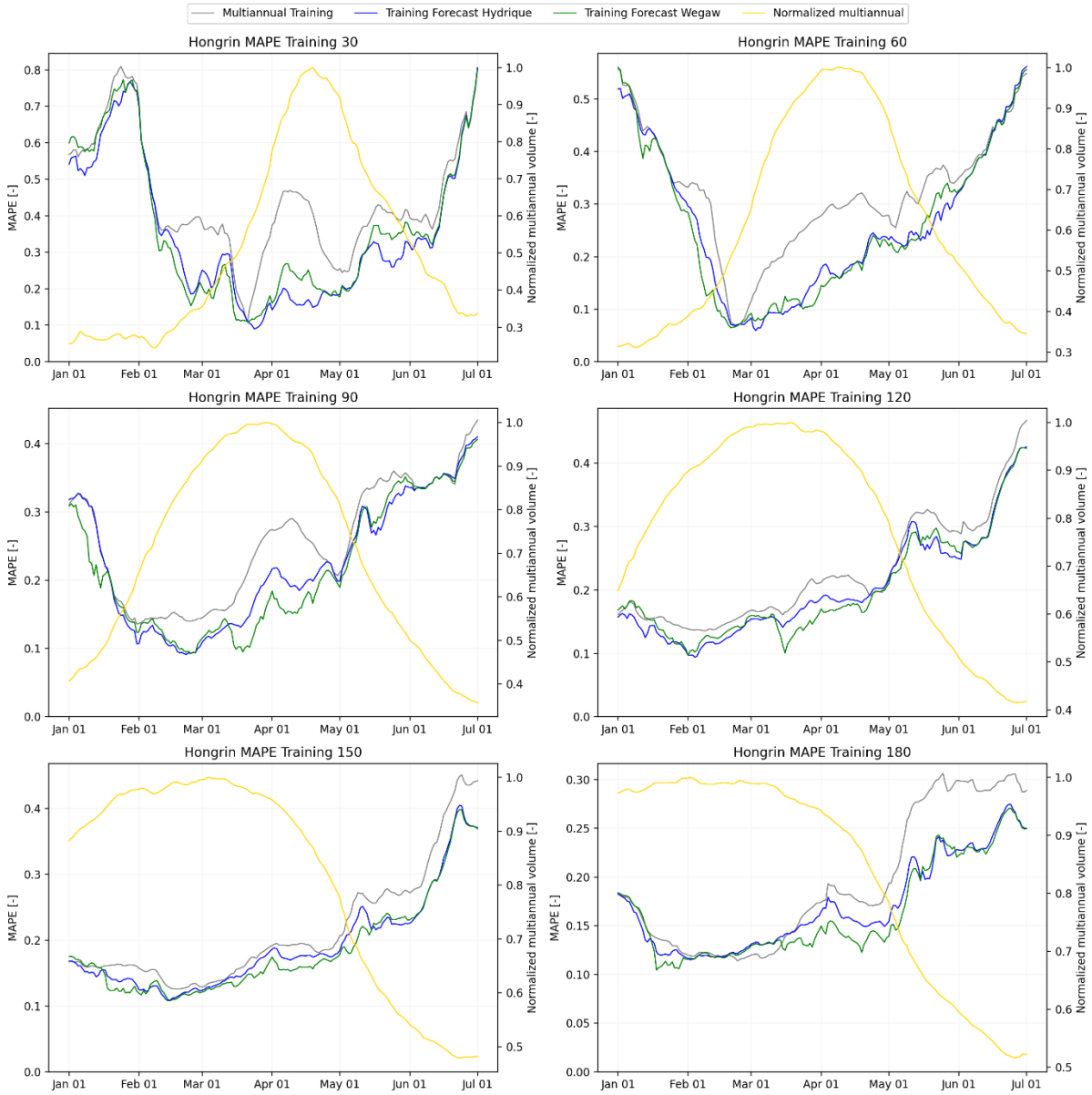
ii. Hongrin, daily MAPE, Hydrique SWE, training and cross-validation



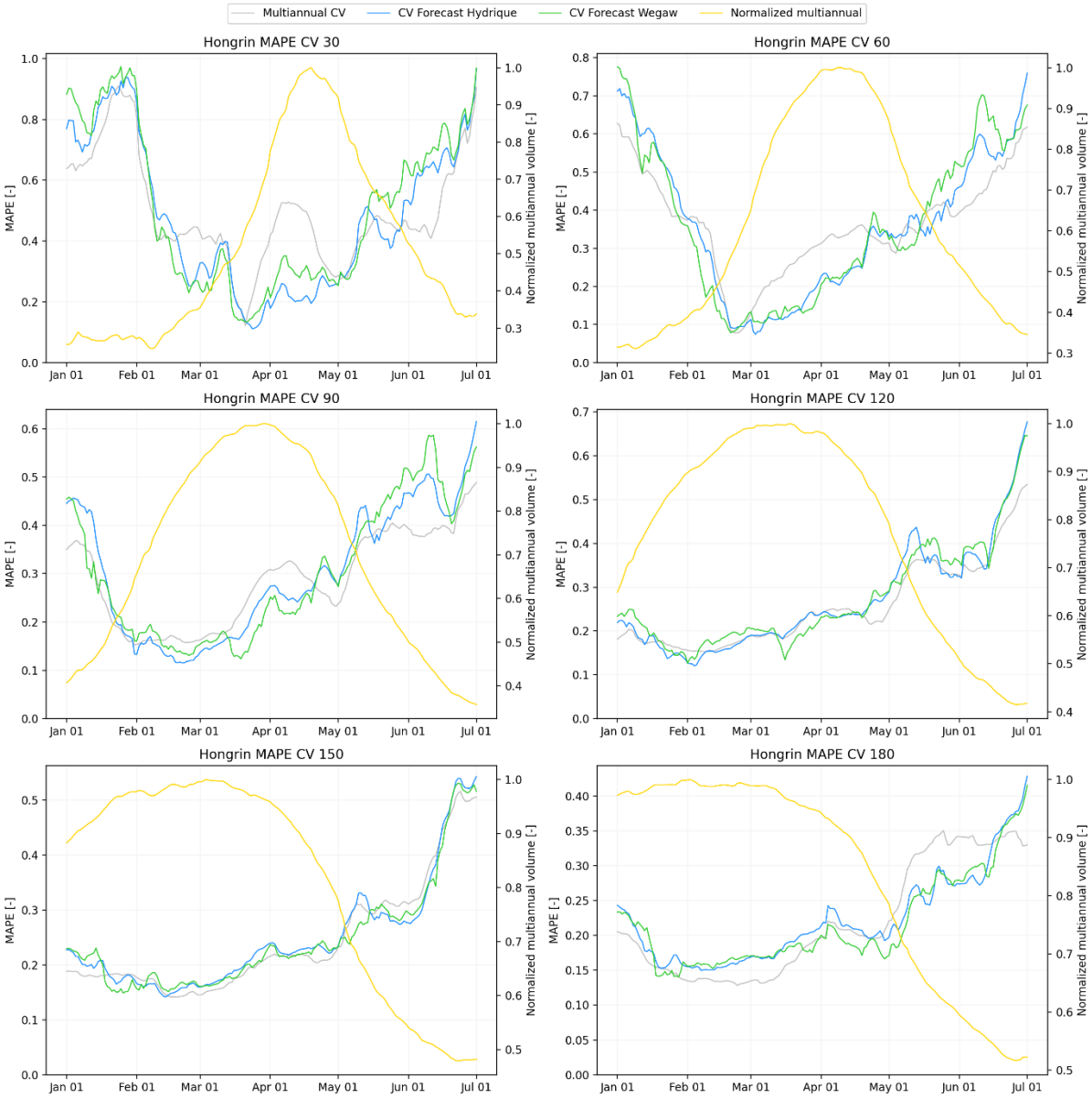
jj. Hongrin, daily MAPE, Wegaw SWE, training and cross-validation



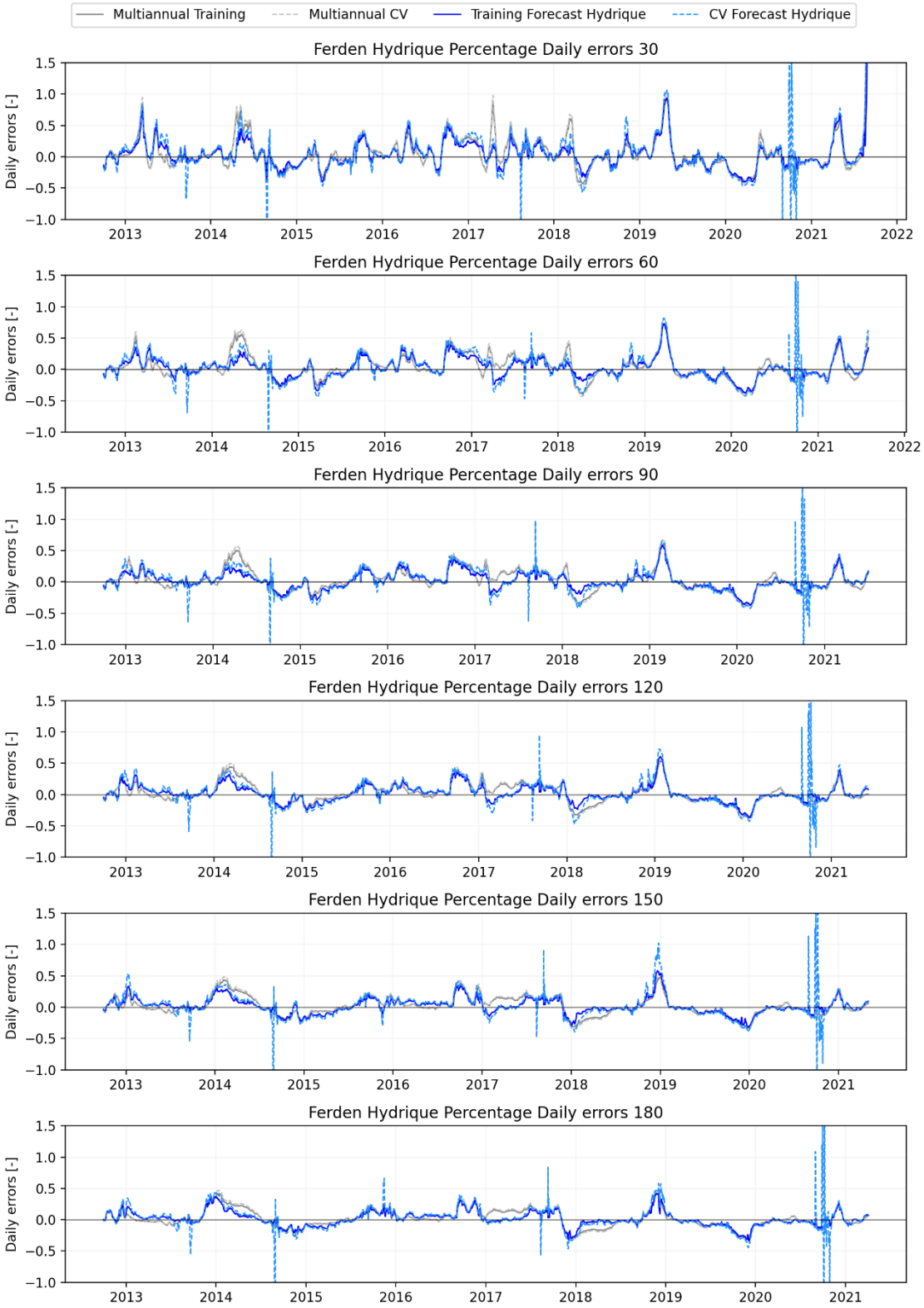
kk. Hongrin, MAPE, Hydrique + Wegaw, training



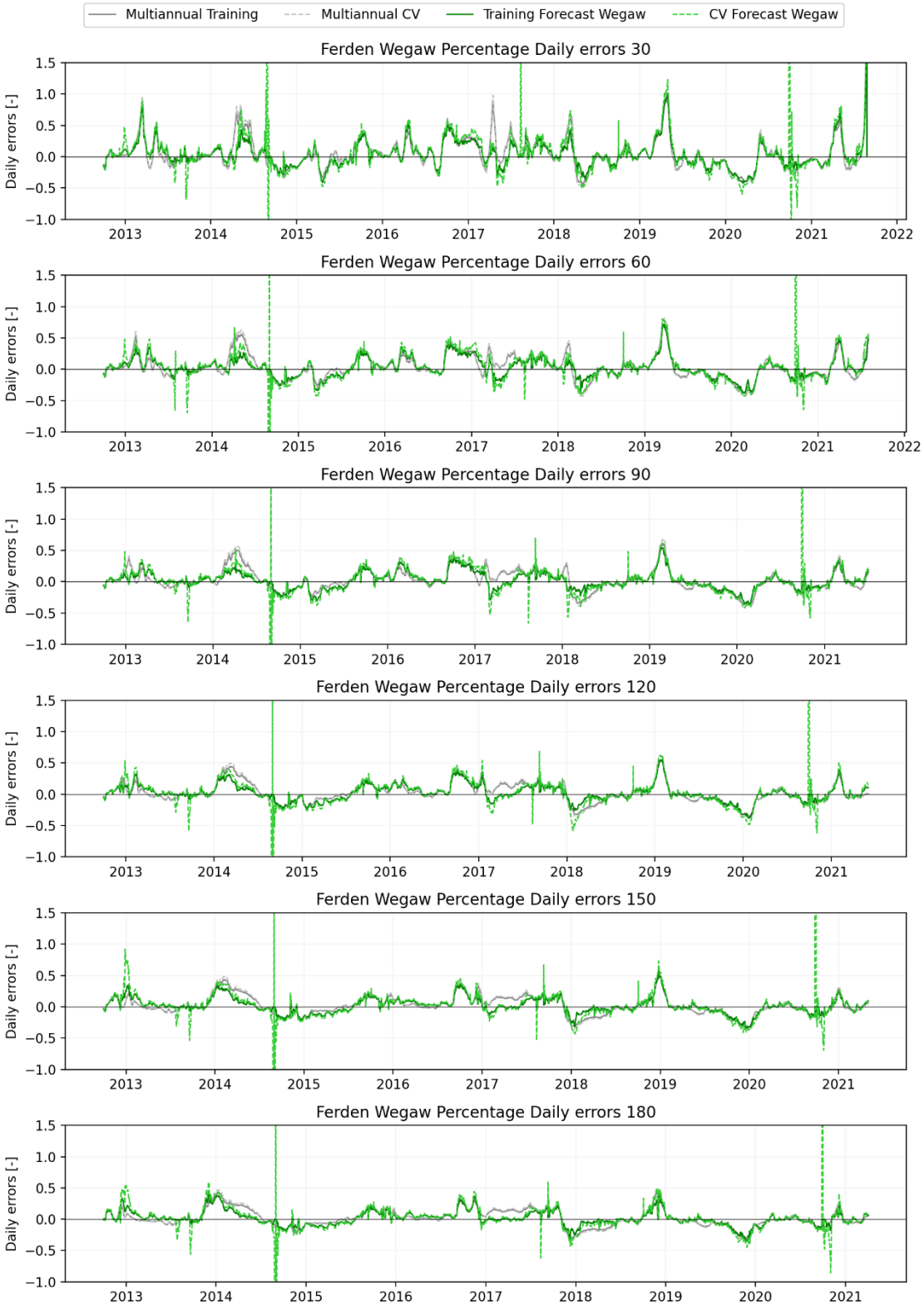
II. Hongrin, MAPE, Hydrique + Wegaw, cross-validation



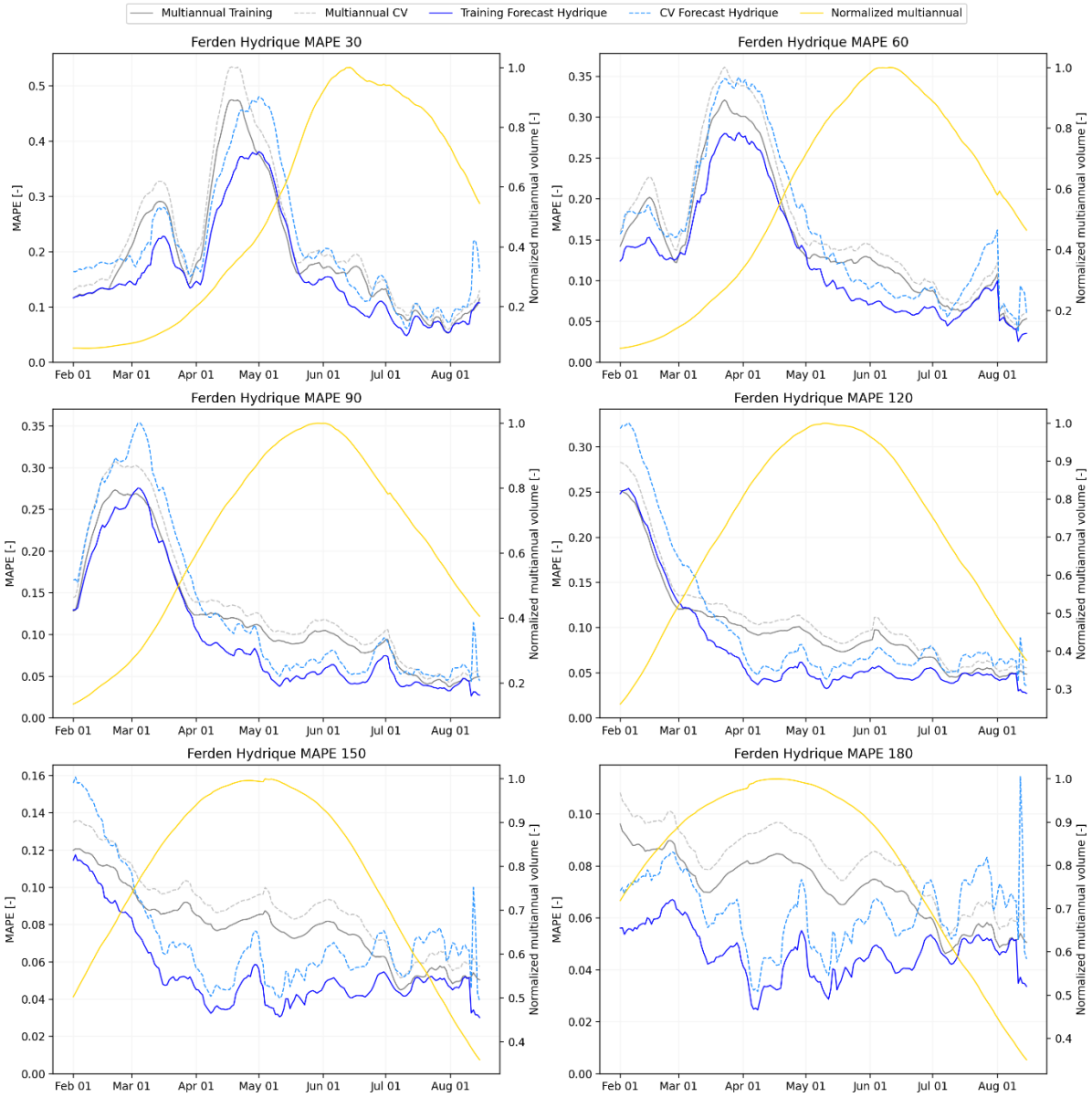
mm. Ferden, daily errors, Hydrique SWE, training+cross-validation



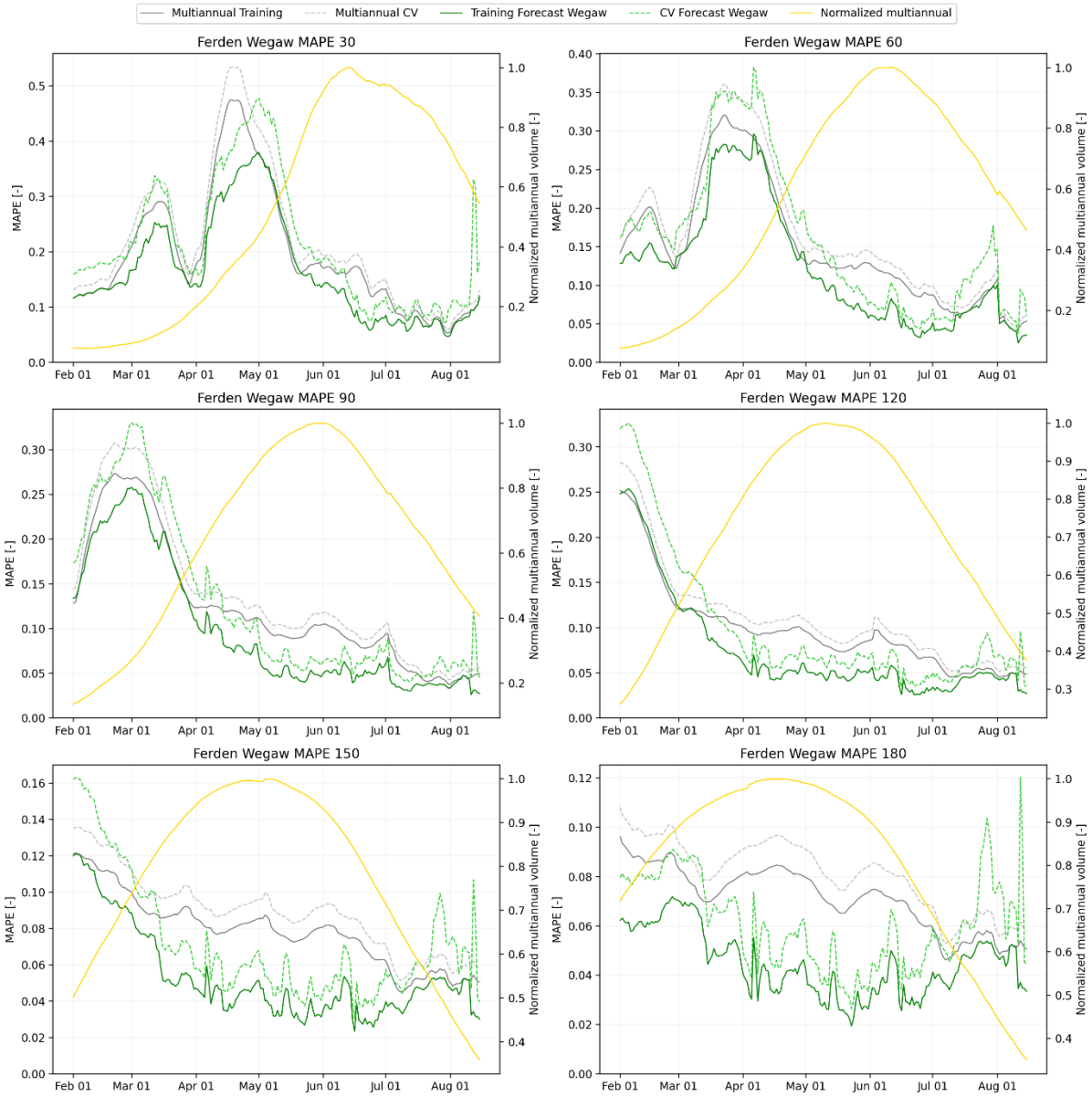
nn. Ferden, daily errors, Wegaw SWE, training+cross-validation



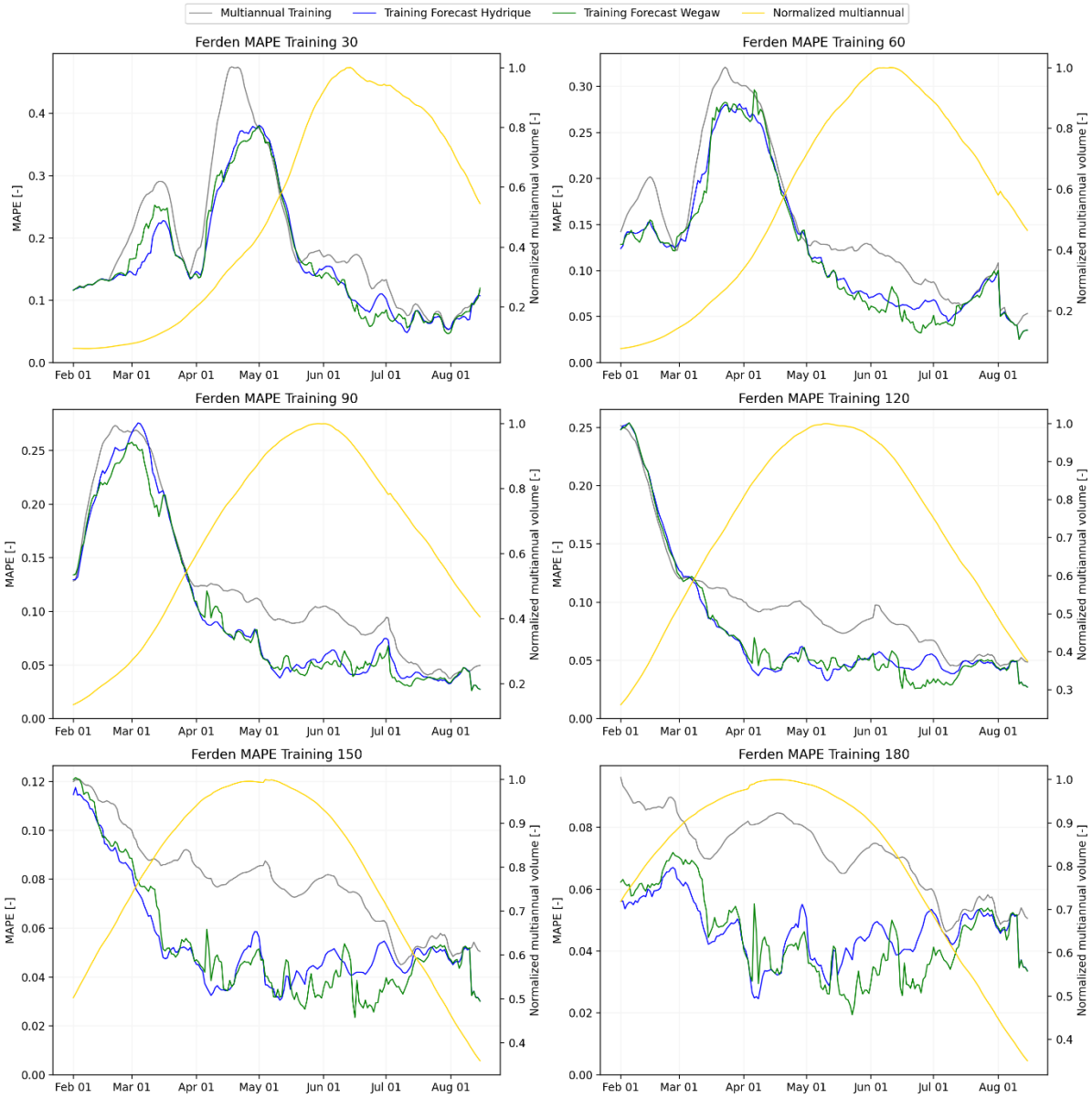
oo. Ferden, daily MAPE, Hydrique SWE, training and cross-validation



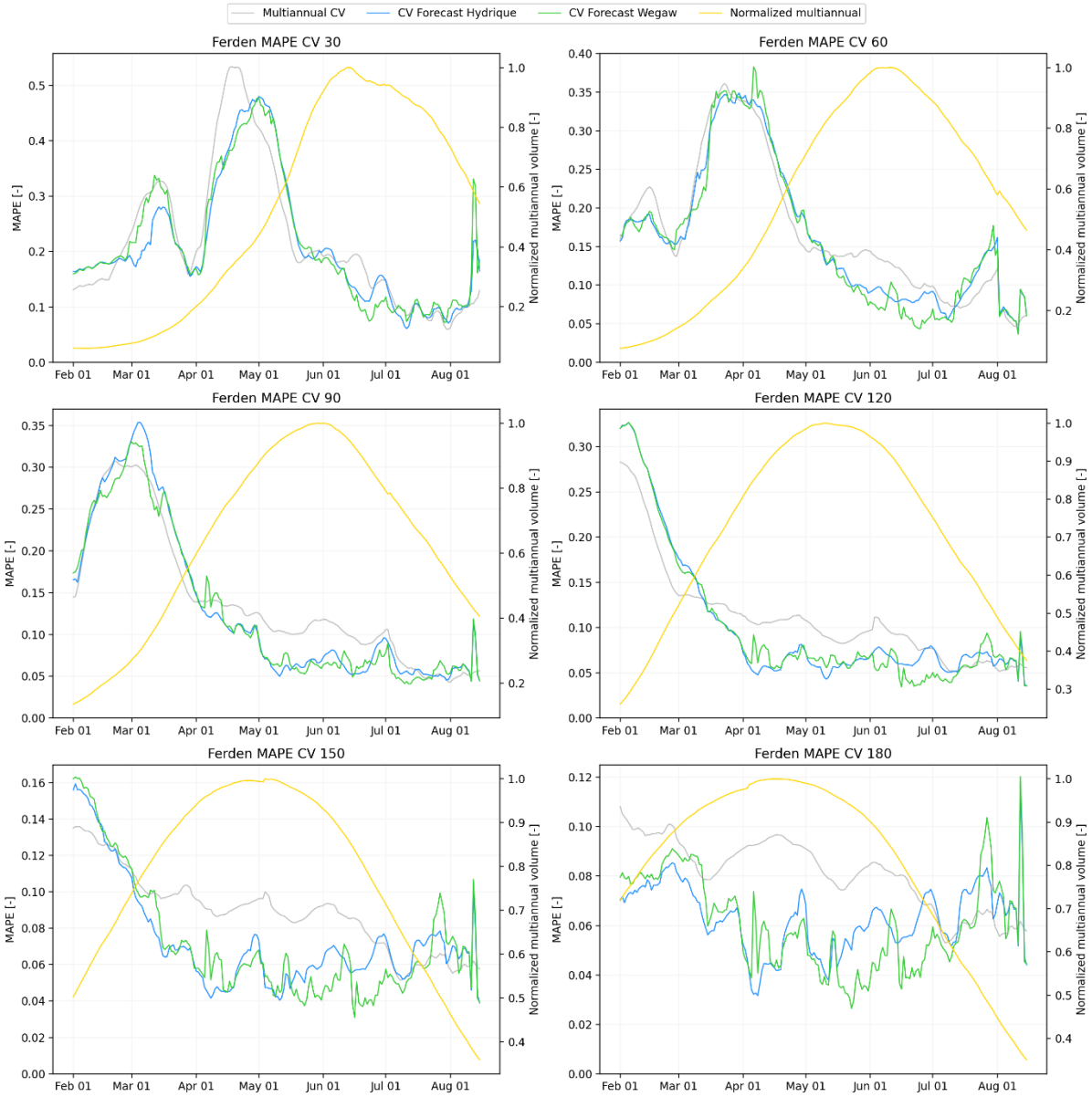
pp. Ferden, daily MAPE, Wegaw SWE, training and cross-validation



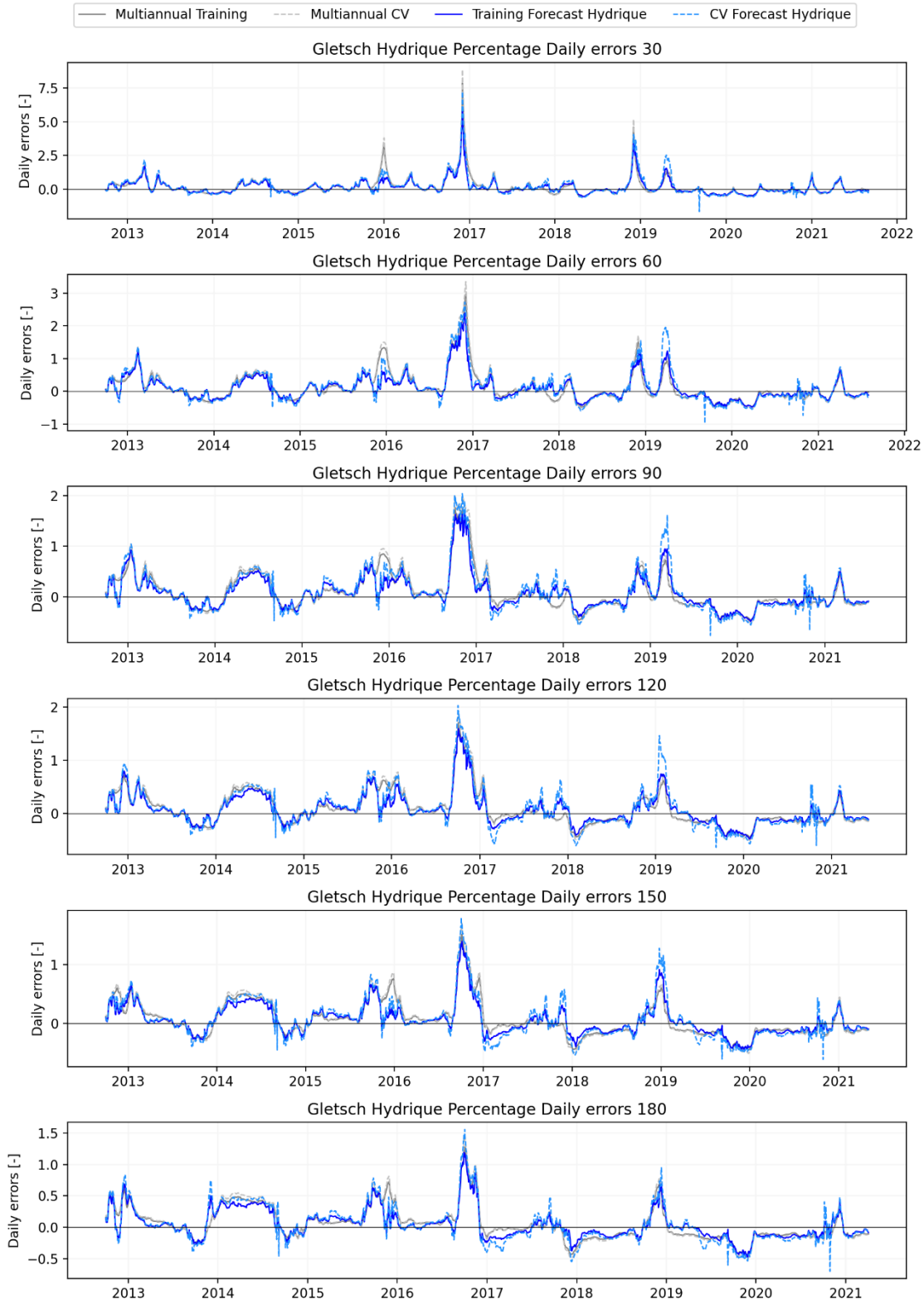
qq. Ferden, MAPE, Hydrique + Wegaw, training



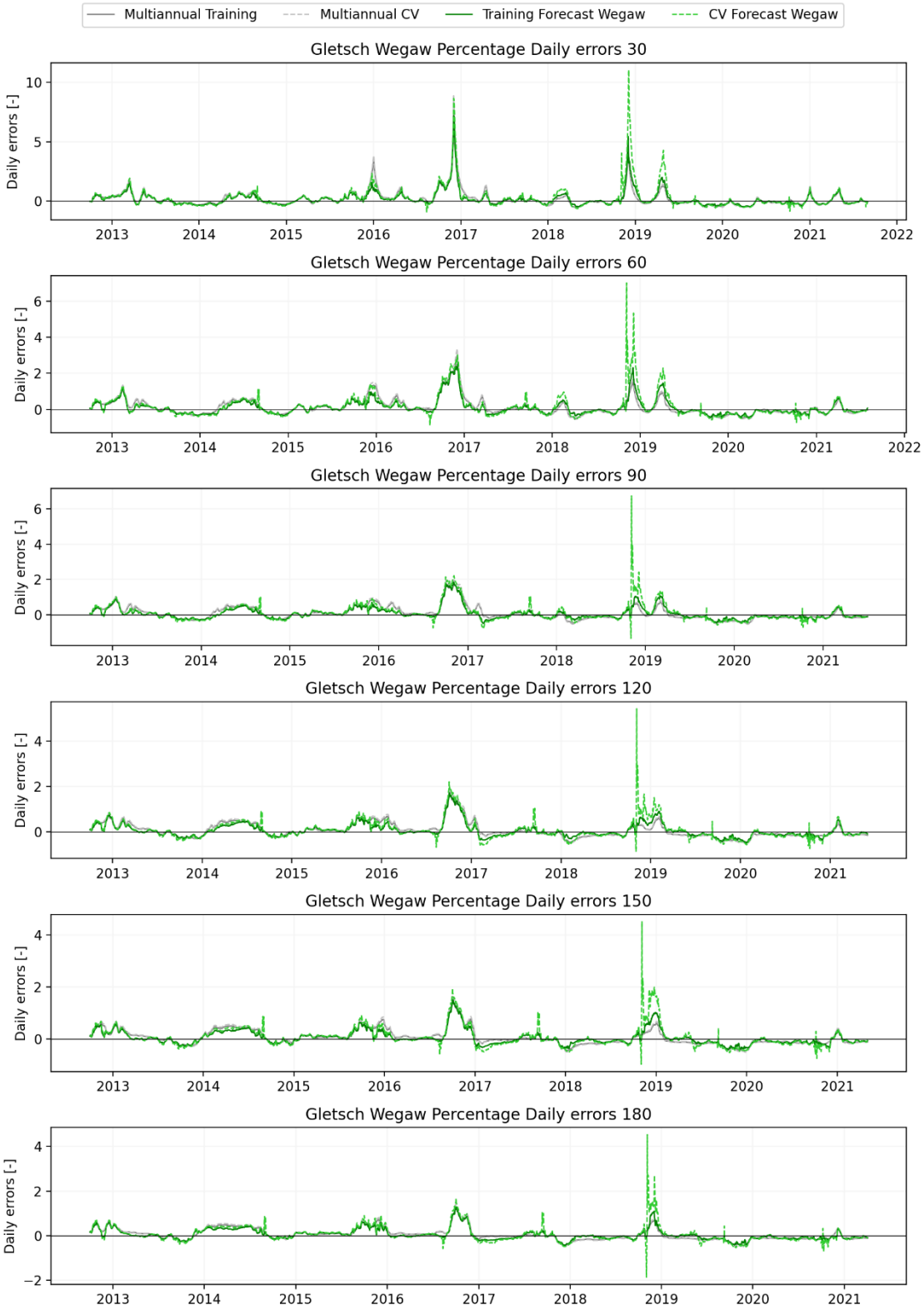
rr. Ferden, MAPE, Hydrique + Wegaw, cross-validation



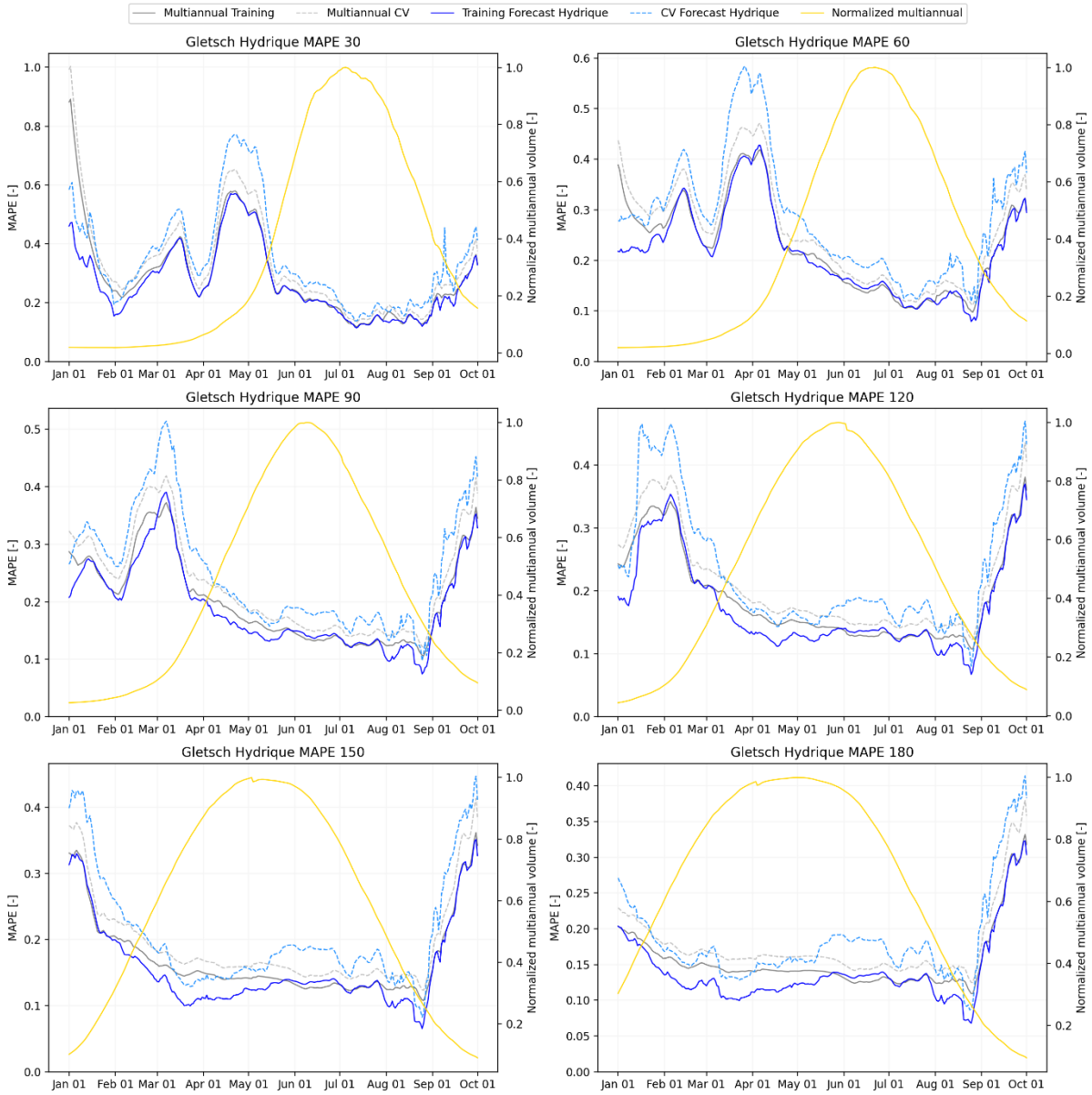
ss. Gletsch, daily errors, Hydrique SWE, training+cross-validation



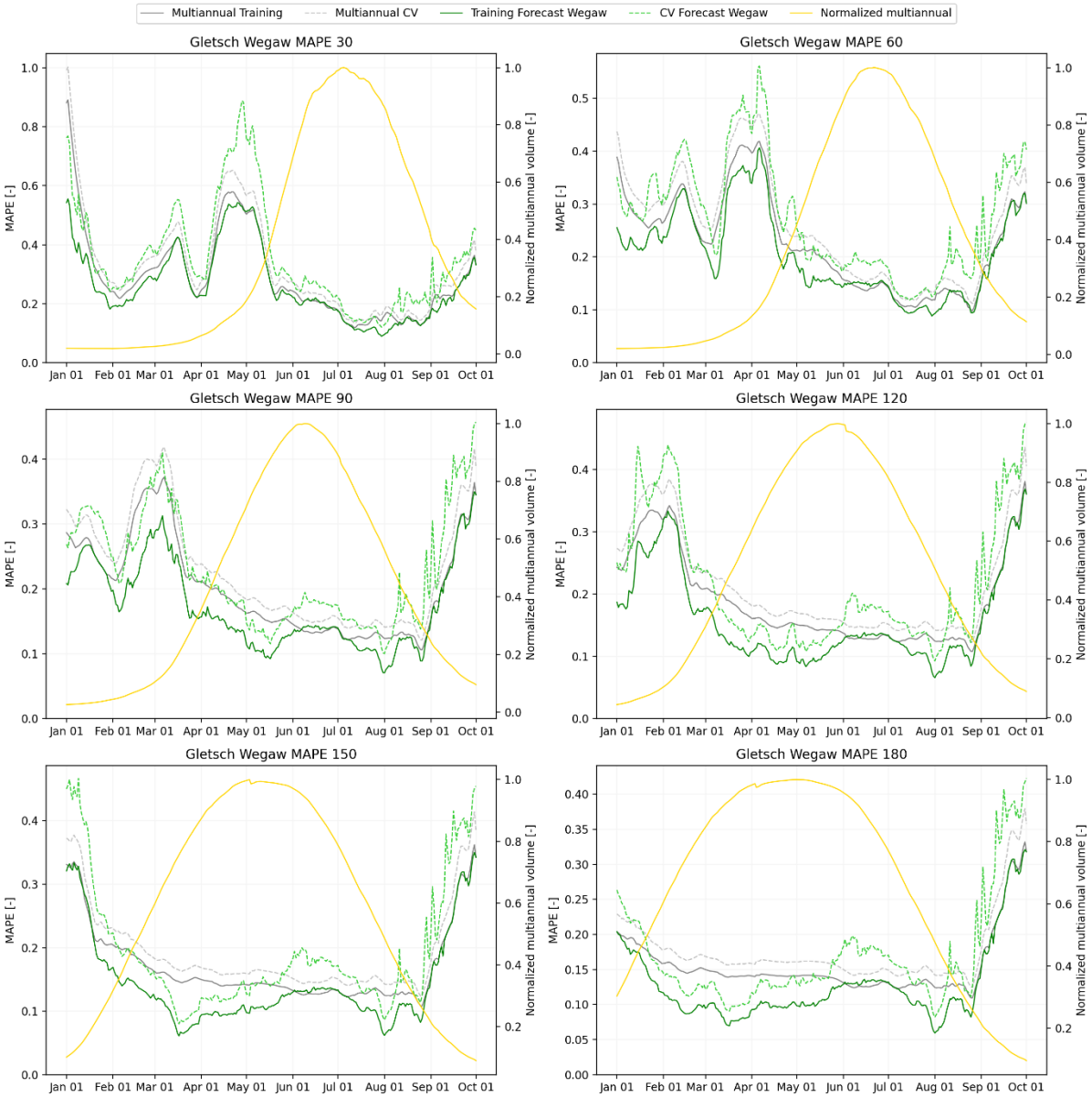
tt. Gletsch, daily errors, Wegaw SWE, training+cross-validation



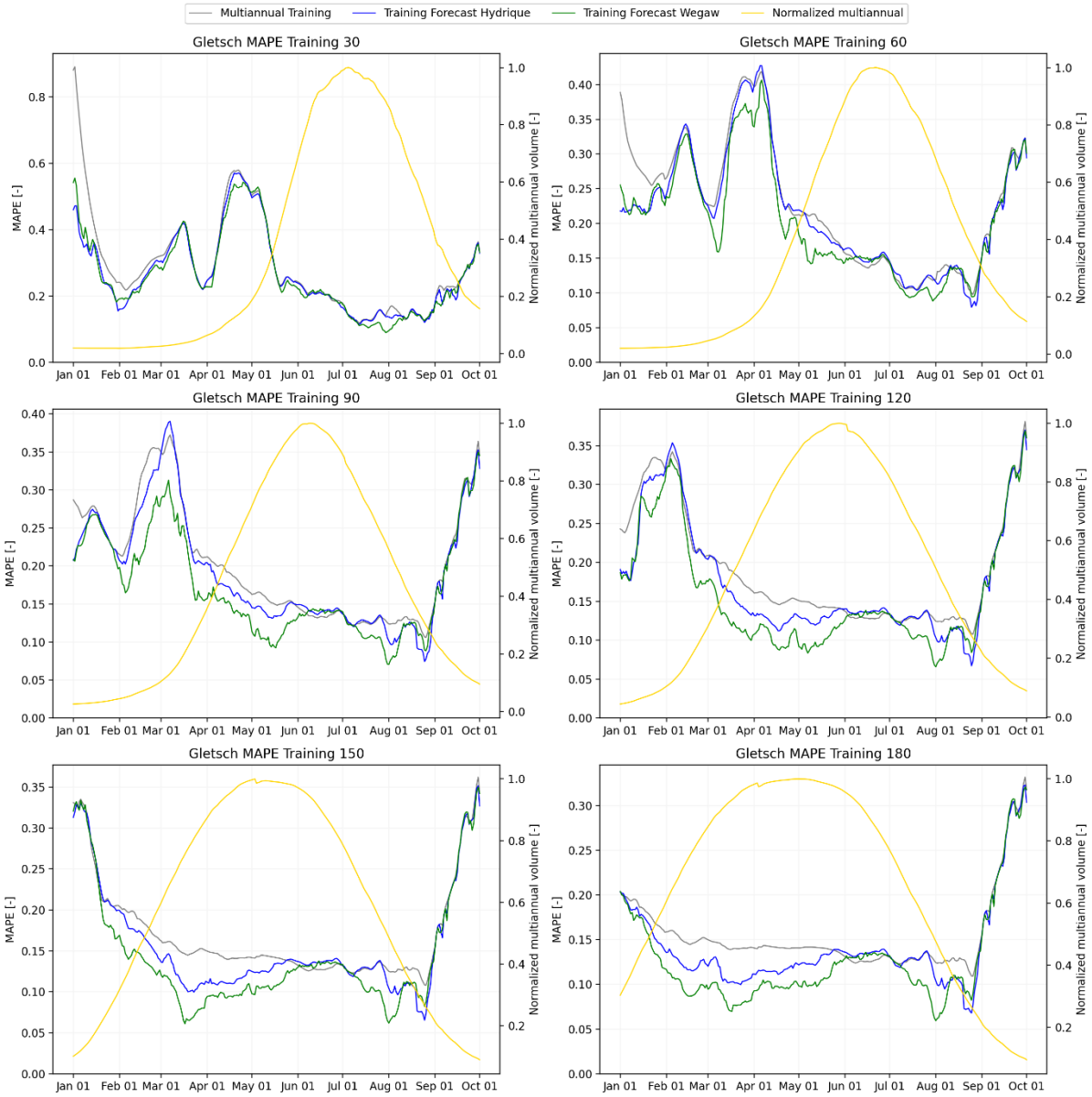
uu. Gletsch, daily MAPE, Hydrique SWE, training and cross-validation



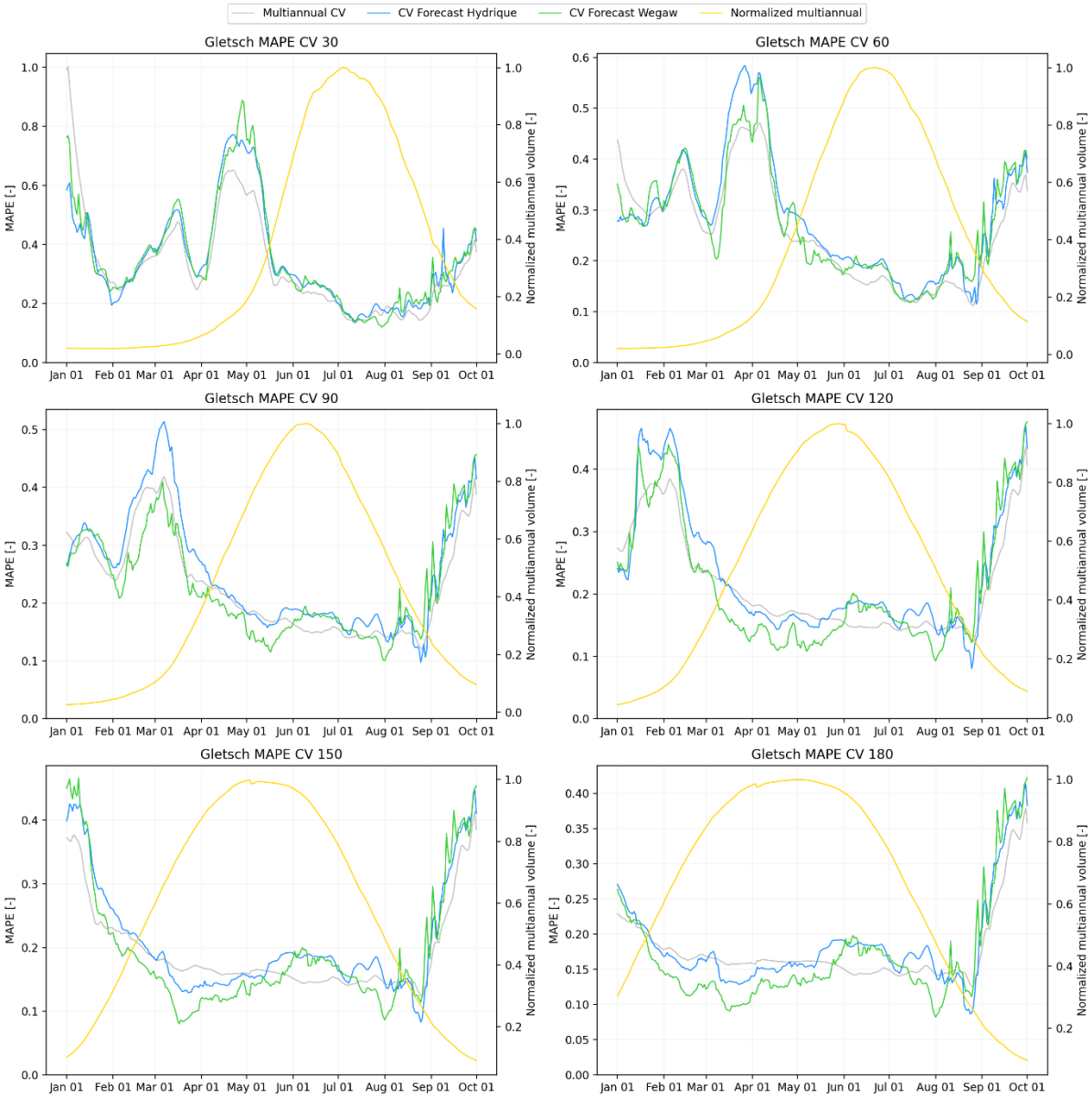
vv. Gletsch, daily MAPE, Wegaw SWE, training and cross-validation



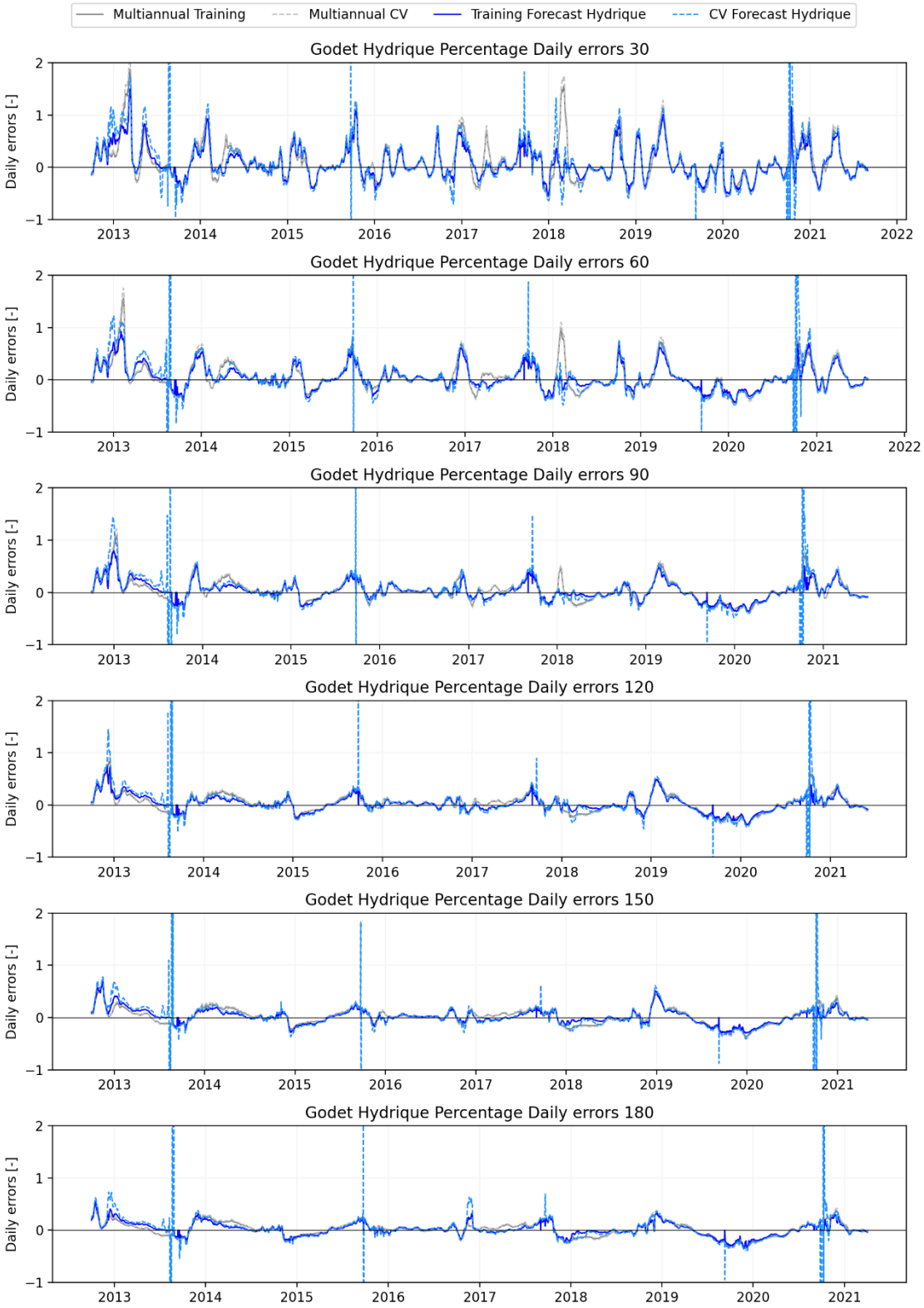
ww. Gletsch, MAPE, Hydrique + Wegaw, training



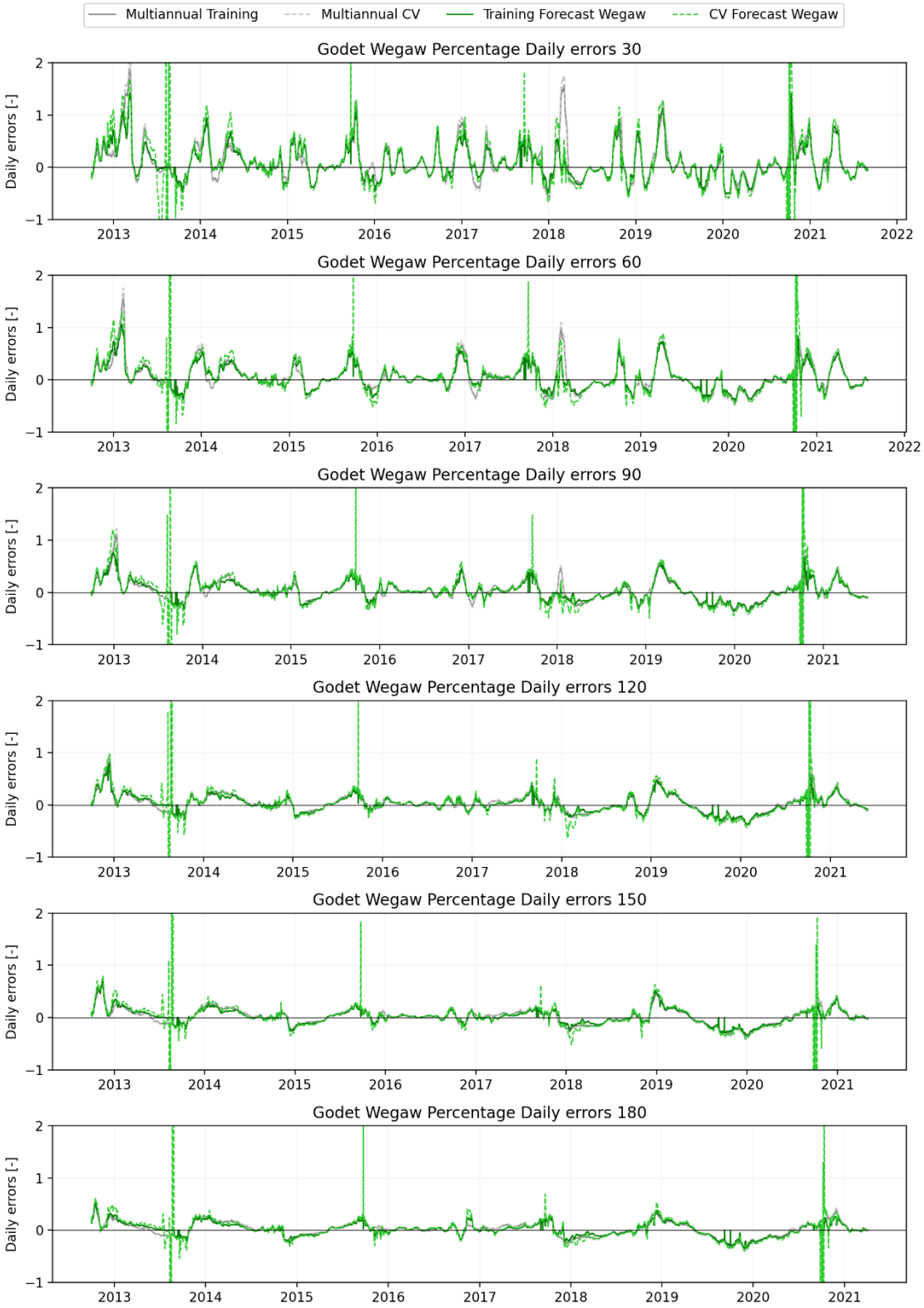
xx. Gletsch, MAPE, Hydrique + Wegaw, cross-validation



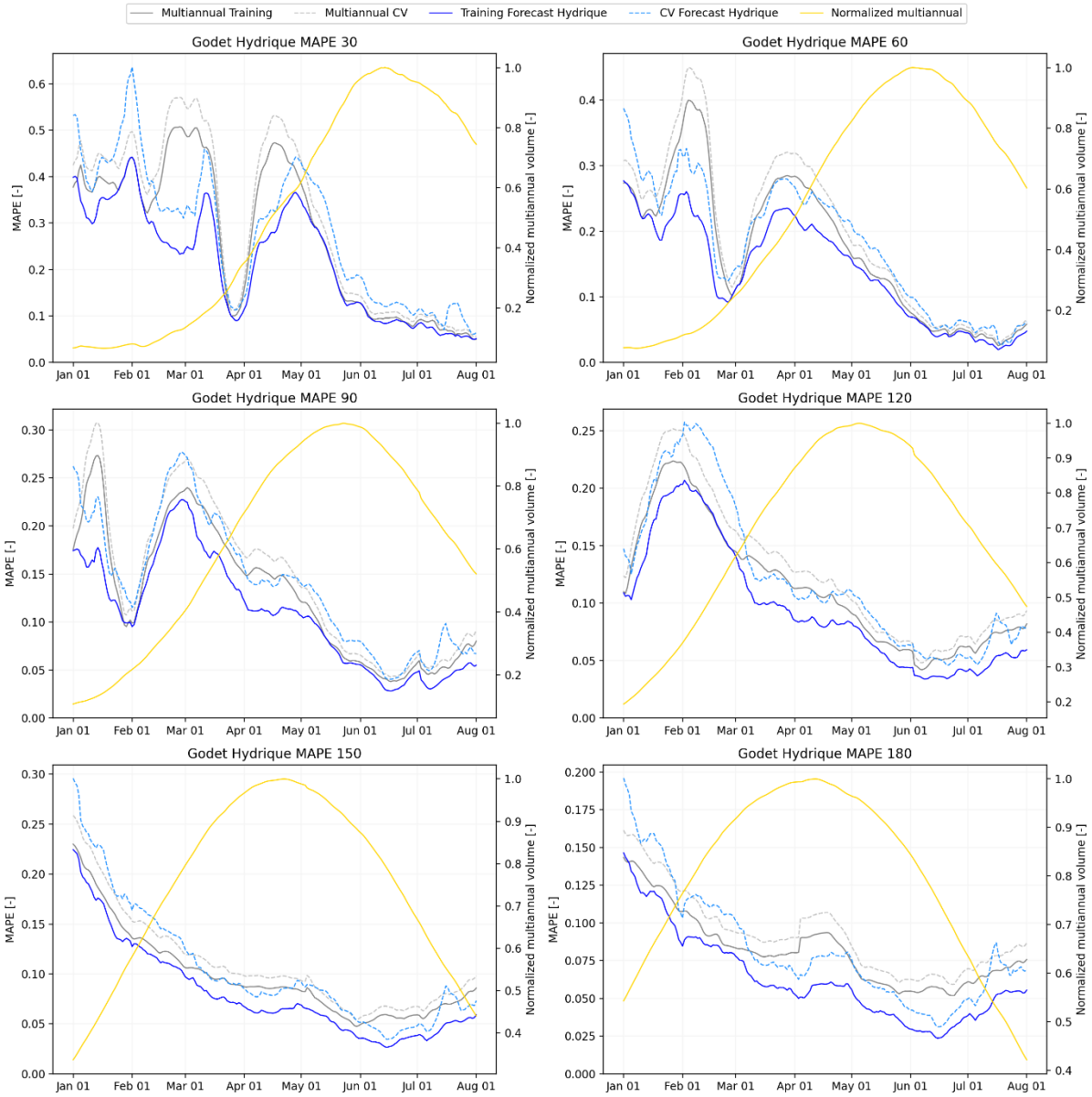
yy. Godet, daily errors, Hydrique SWE, training+cross-validation



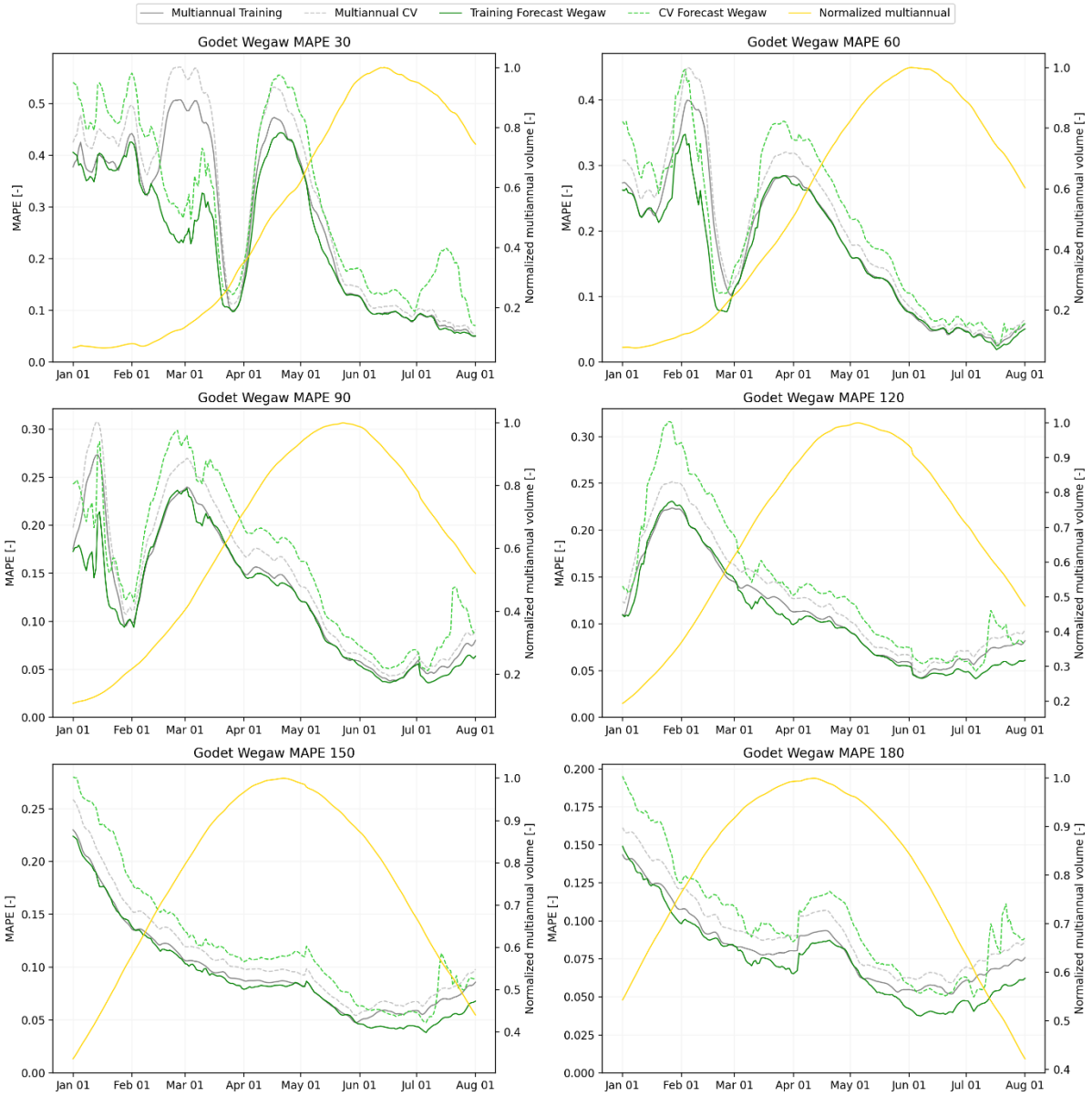
zz. Godet, daily errors, Wegaw SWE, training+cross-validation



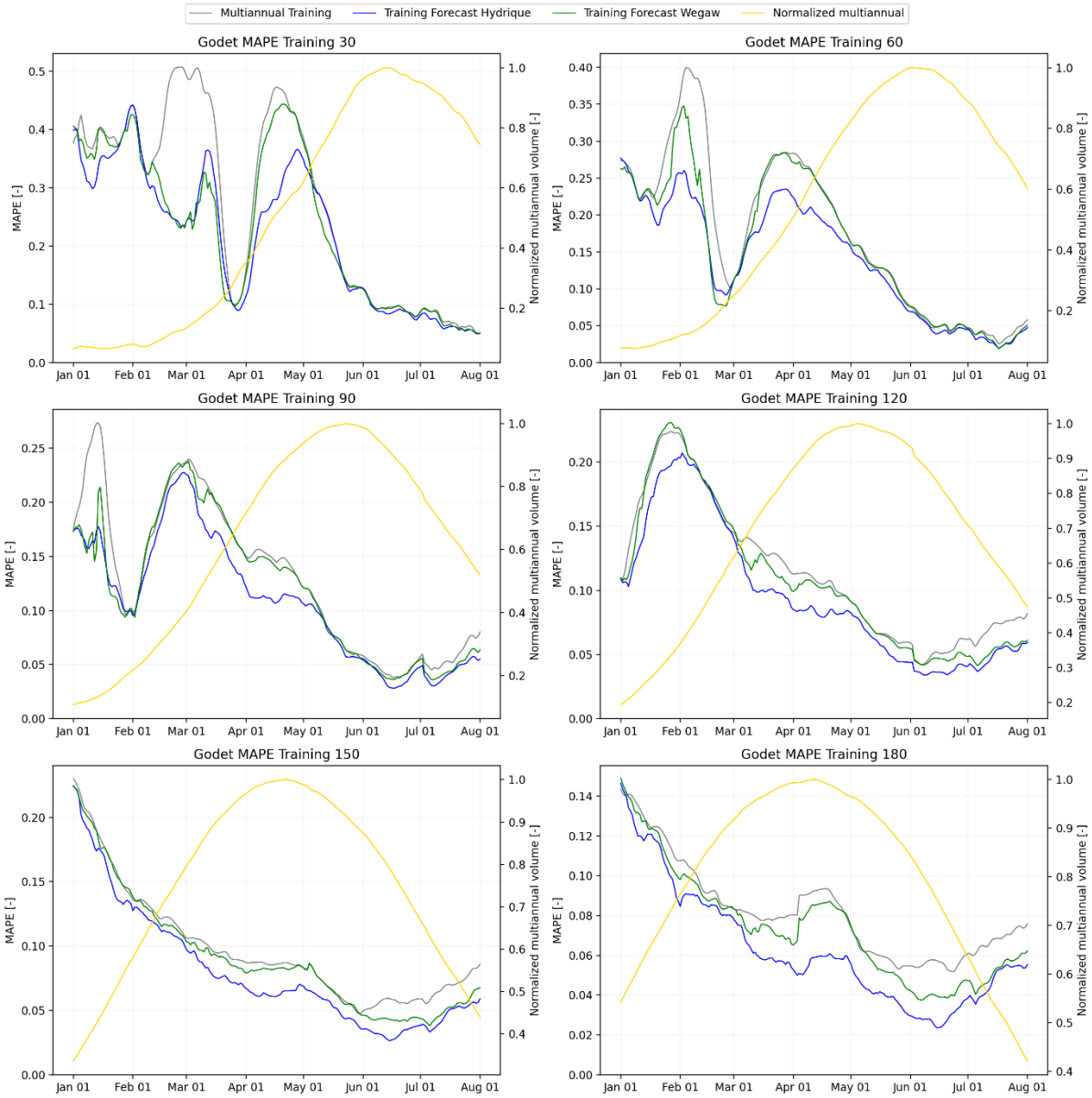
aaa. Godet, daily MAPE, Hydrique SWE, training and cross-validation



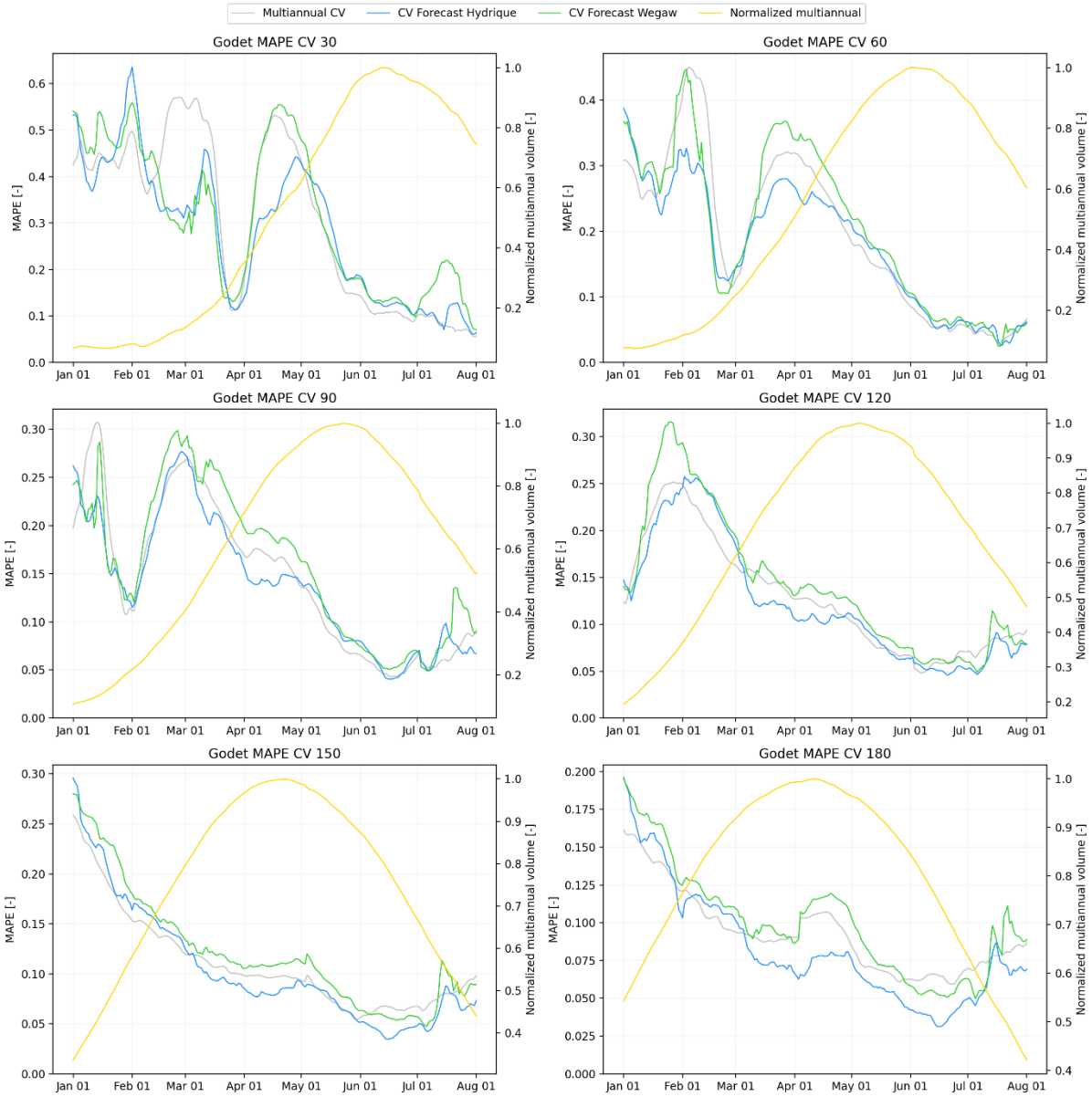
bbb. Godet, daily MAPE, Wegaw SWE, training and cross-validation



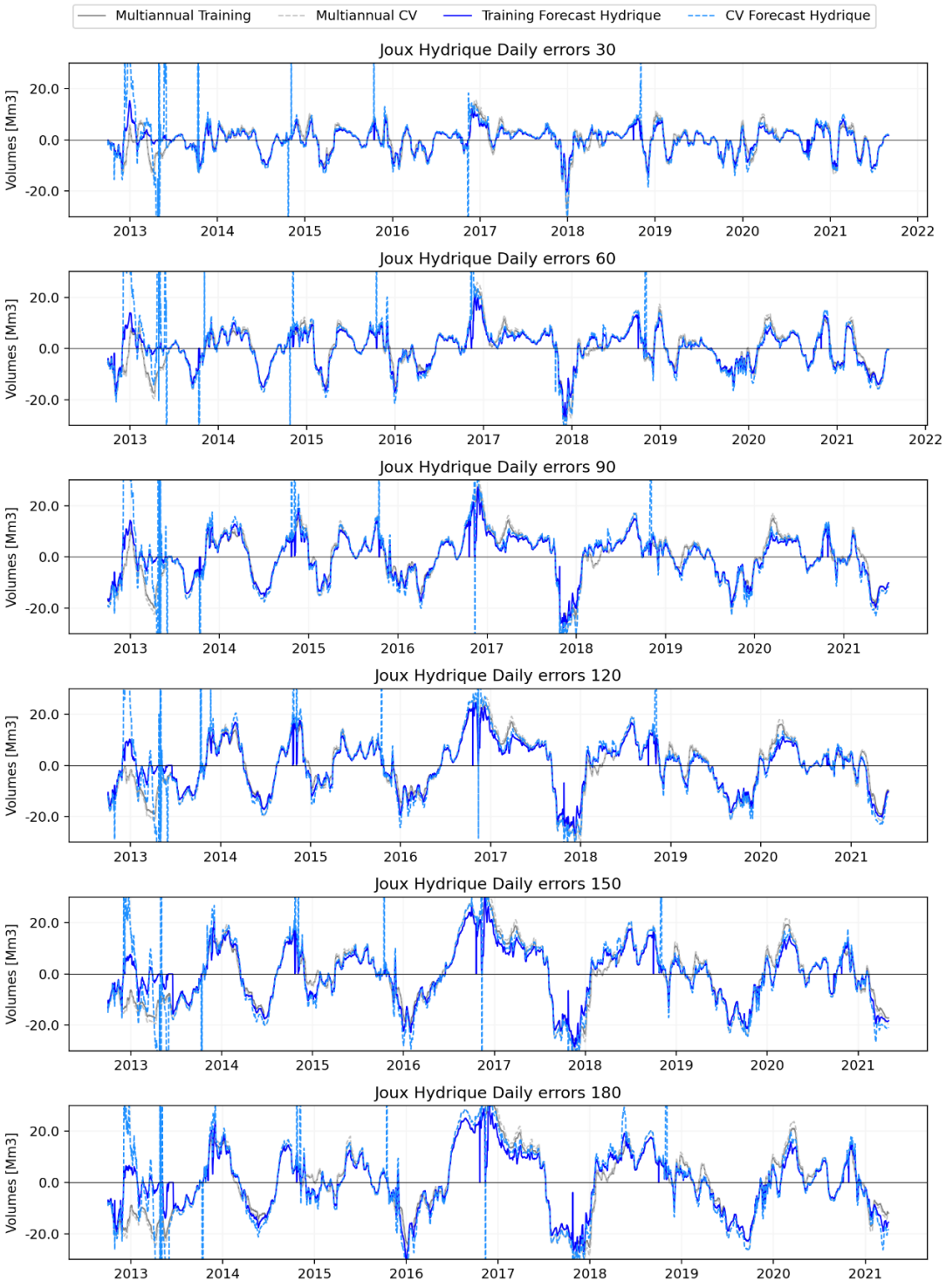
ccc. Godet, MAPE, Hydrique + Wegaw, training



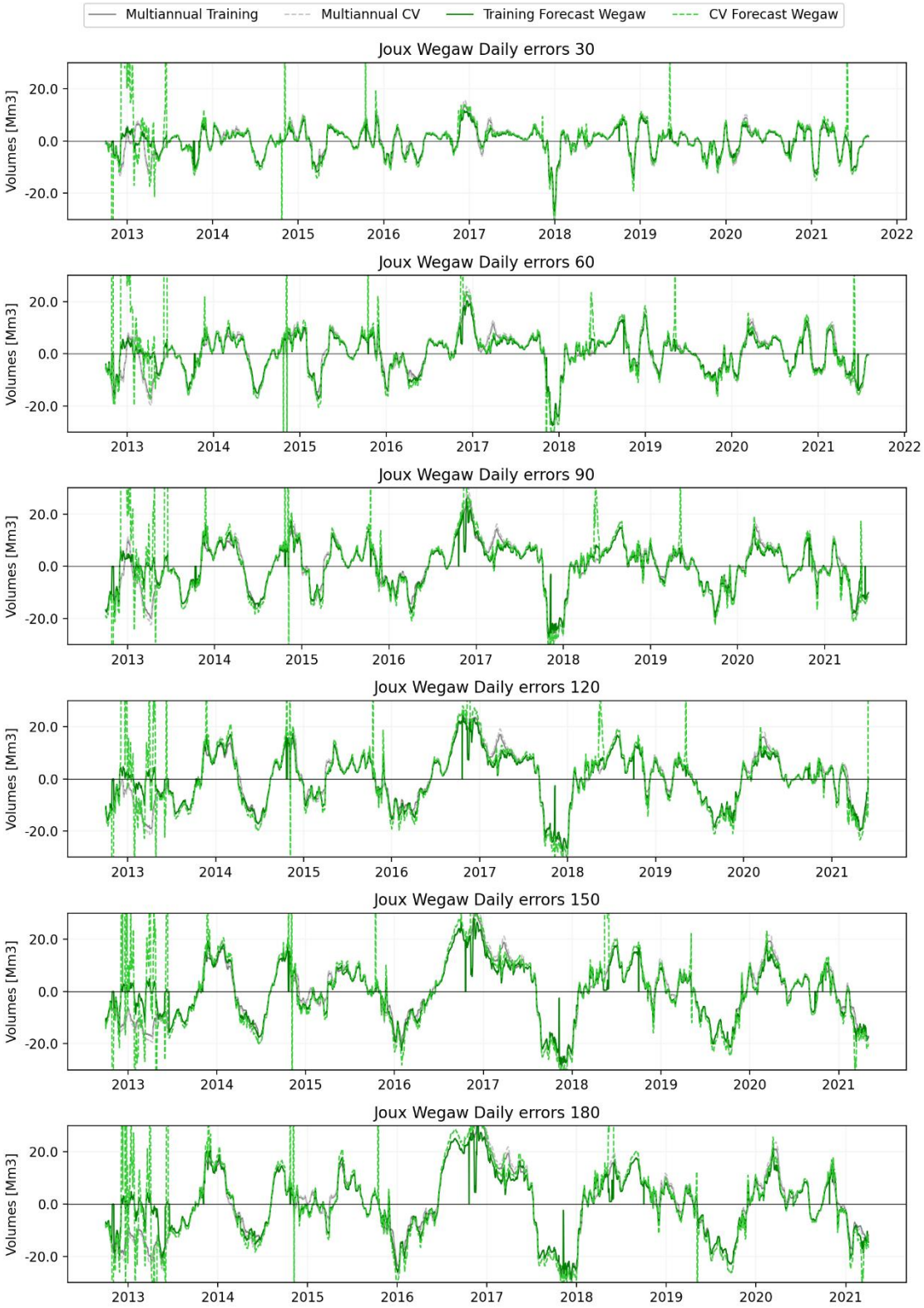
ddd. Godet, MAPE, Hydrique + Wegaw, cross-validation



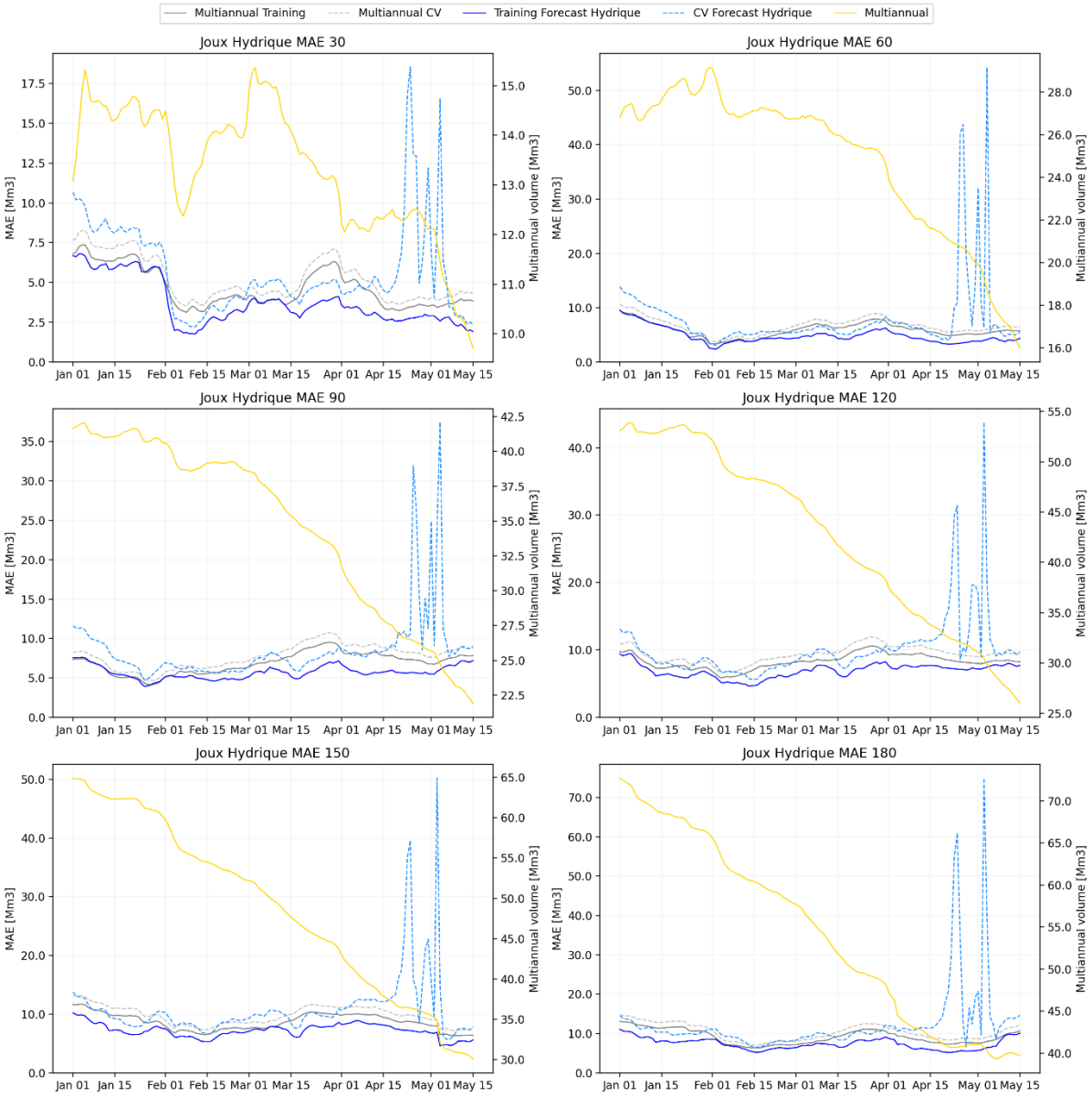
eee. Lac de Joux, daily errors, Hydrique SWE, training+cross-validation



fff. Lac de Joux, daily errors, Wegaw SWE, training+cross-validation



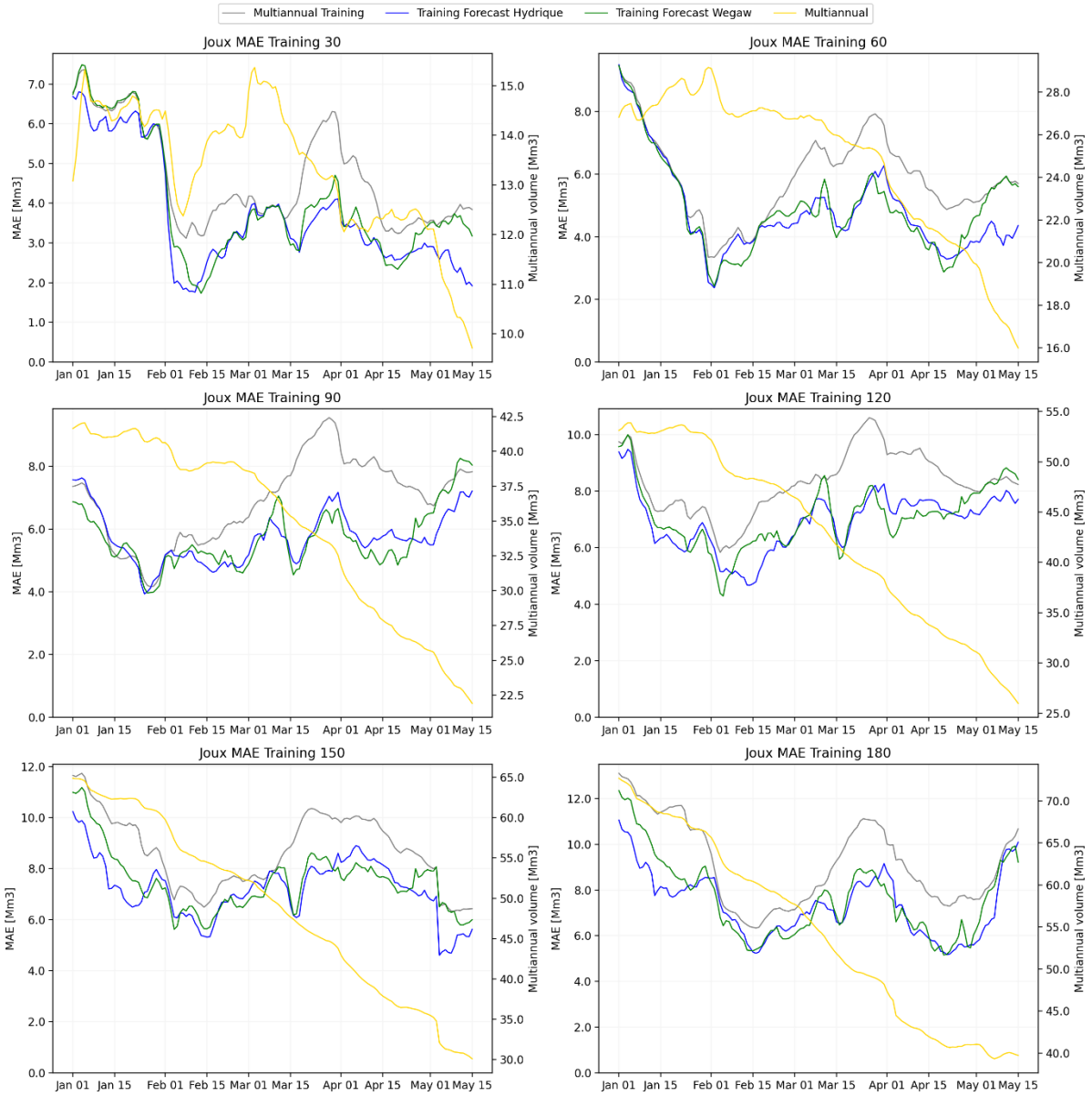
ggg. Lac de Joux, daily MAE, Hydrique SWE, training and cross-validation



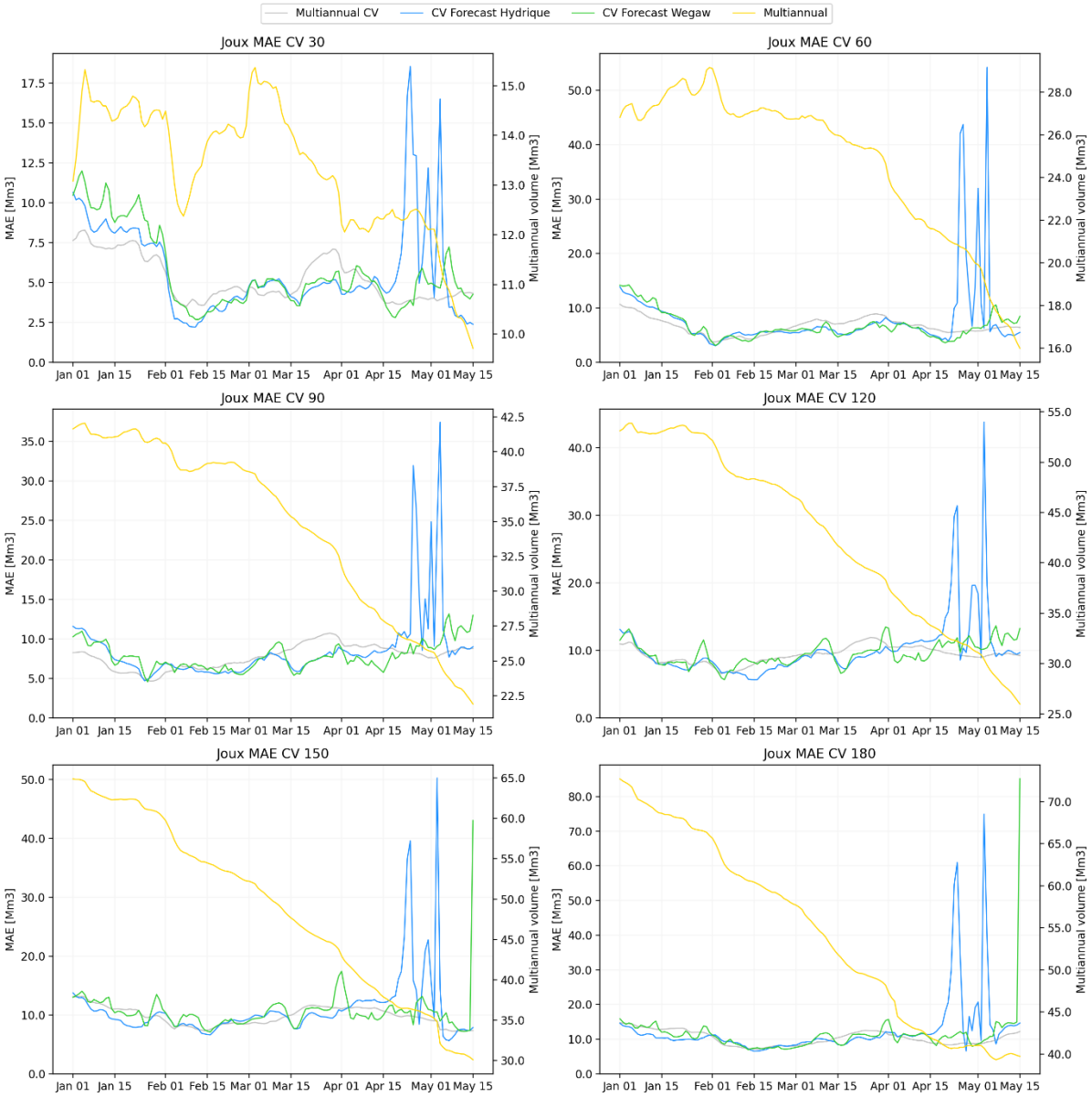
hhh. Lac de Joux, daily MAE, Wegaw SWE, training and cross-validation



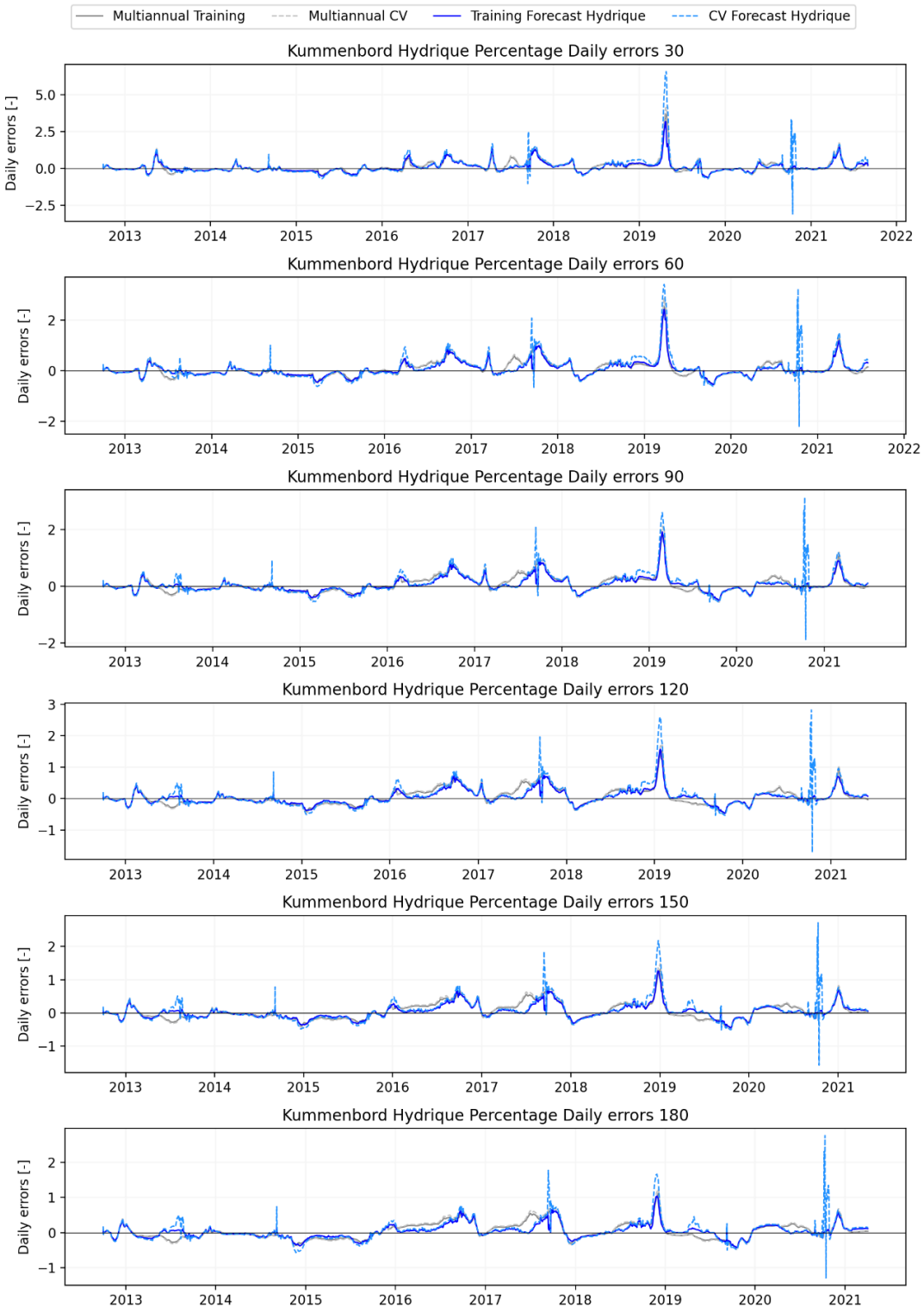
iii. Lac de Joux, MAE, Hydrique + Wegaw, training



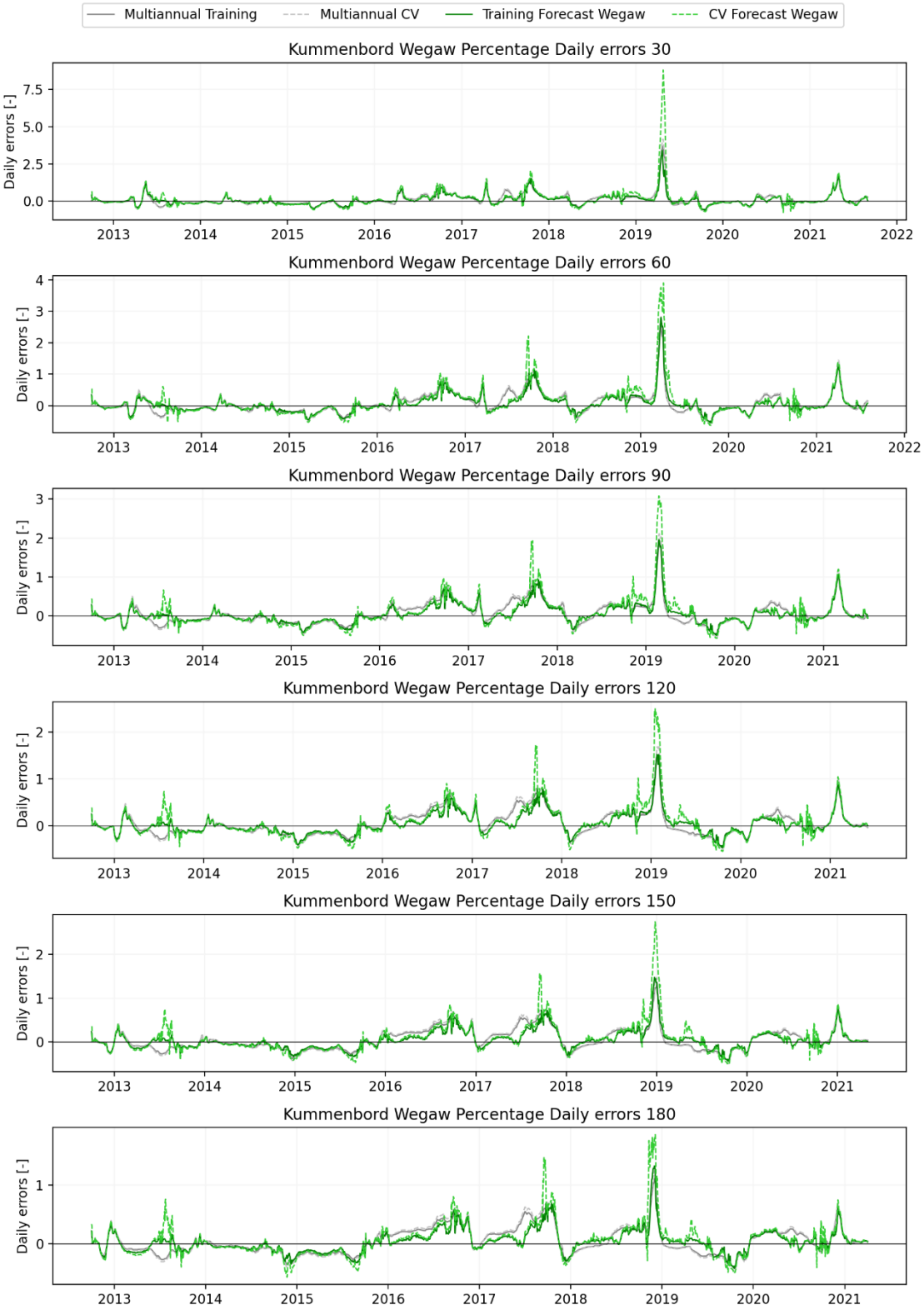
jjj. Lac de Joux, MAE, Hydrique + Wegaw, cross-validation



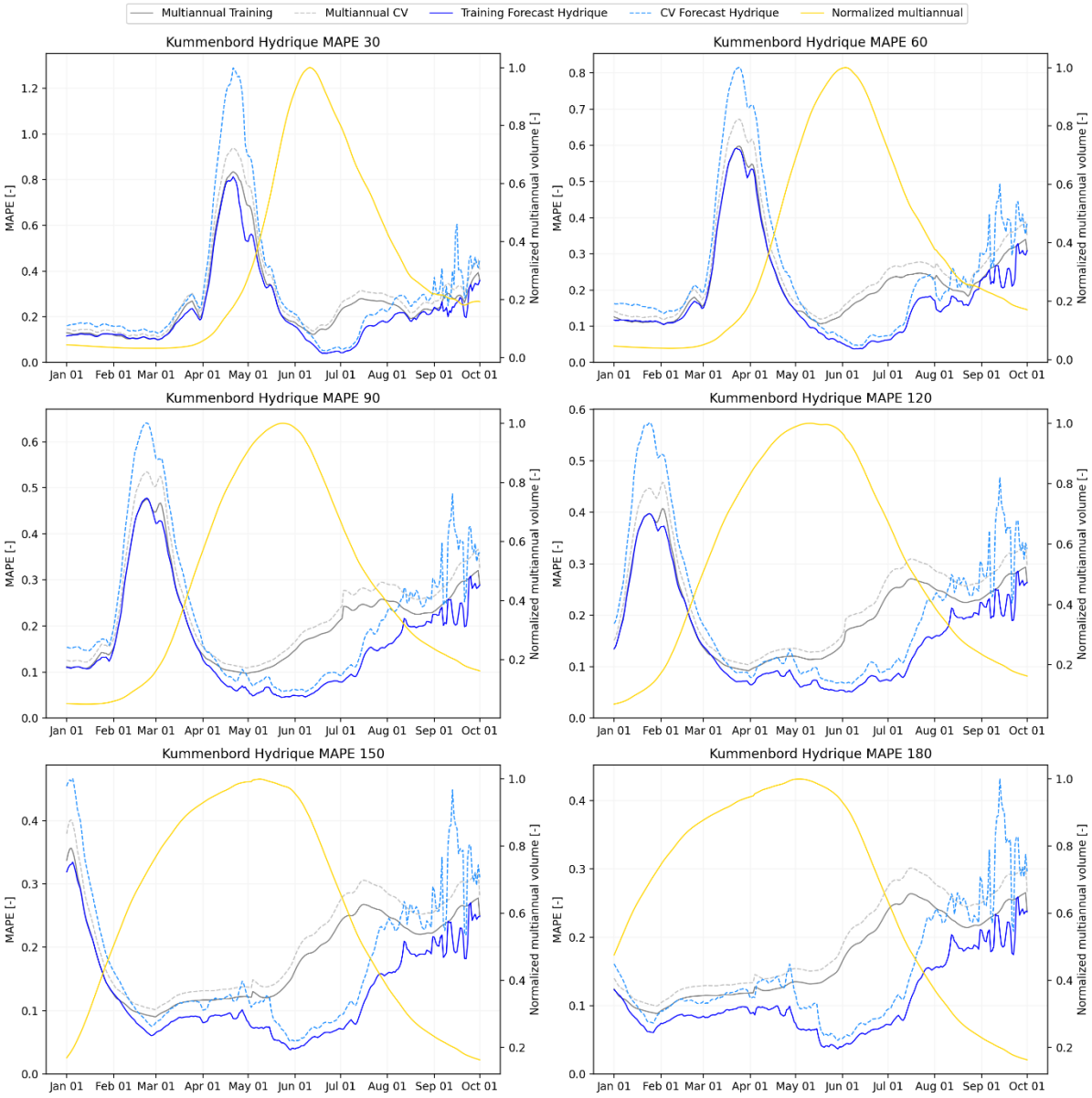
kkk. Kummenbord, daily errors, Hydrique SWE, training+cross-validation



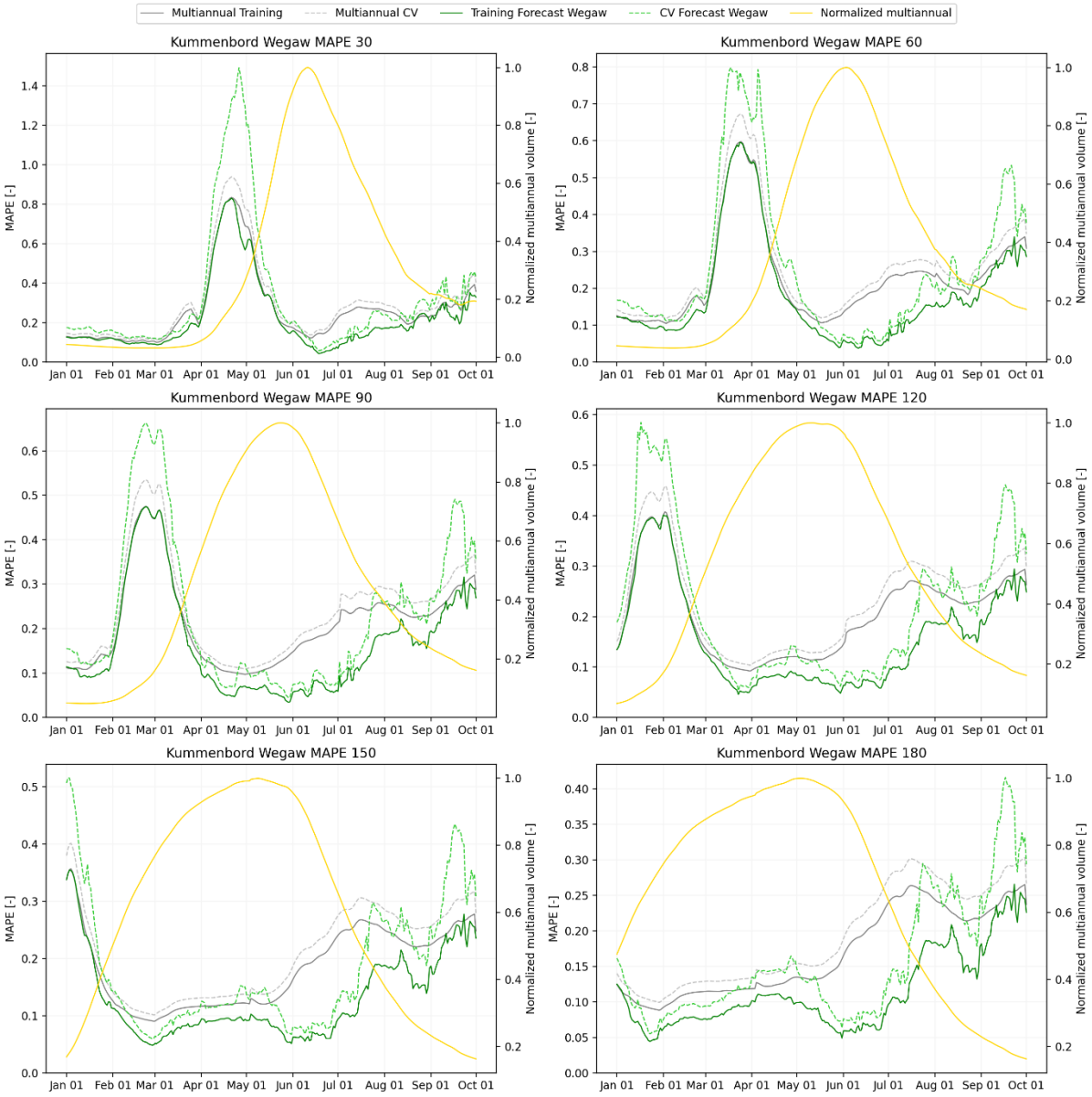
III. Kummenbord, daily errors, Wegaw SWE, training+cross-validation



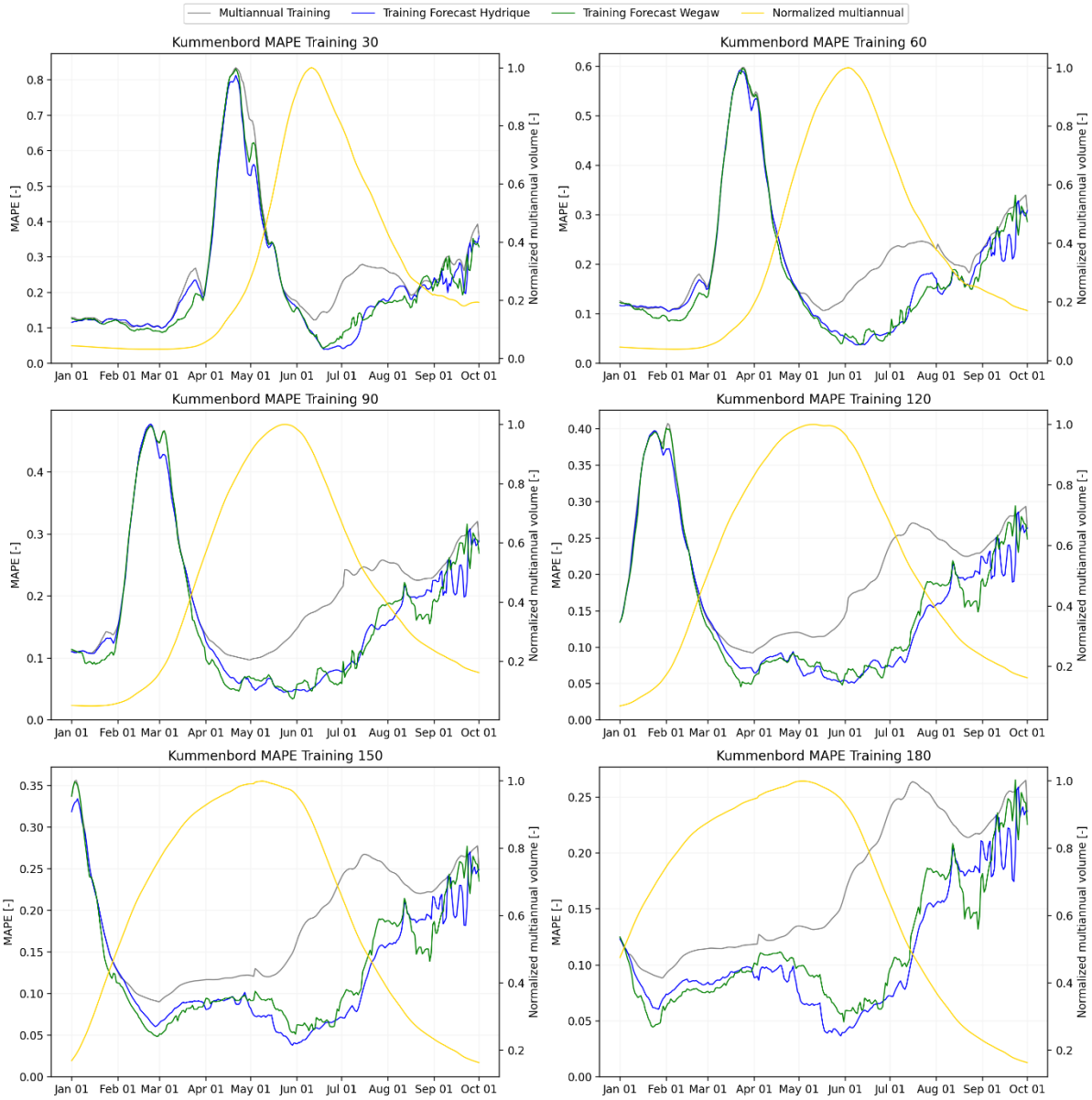
mmm. Kummenbord, daily MAPE, Hydrique SWE, training and cross-validation



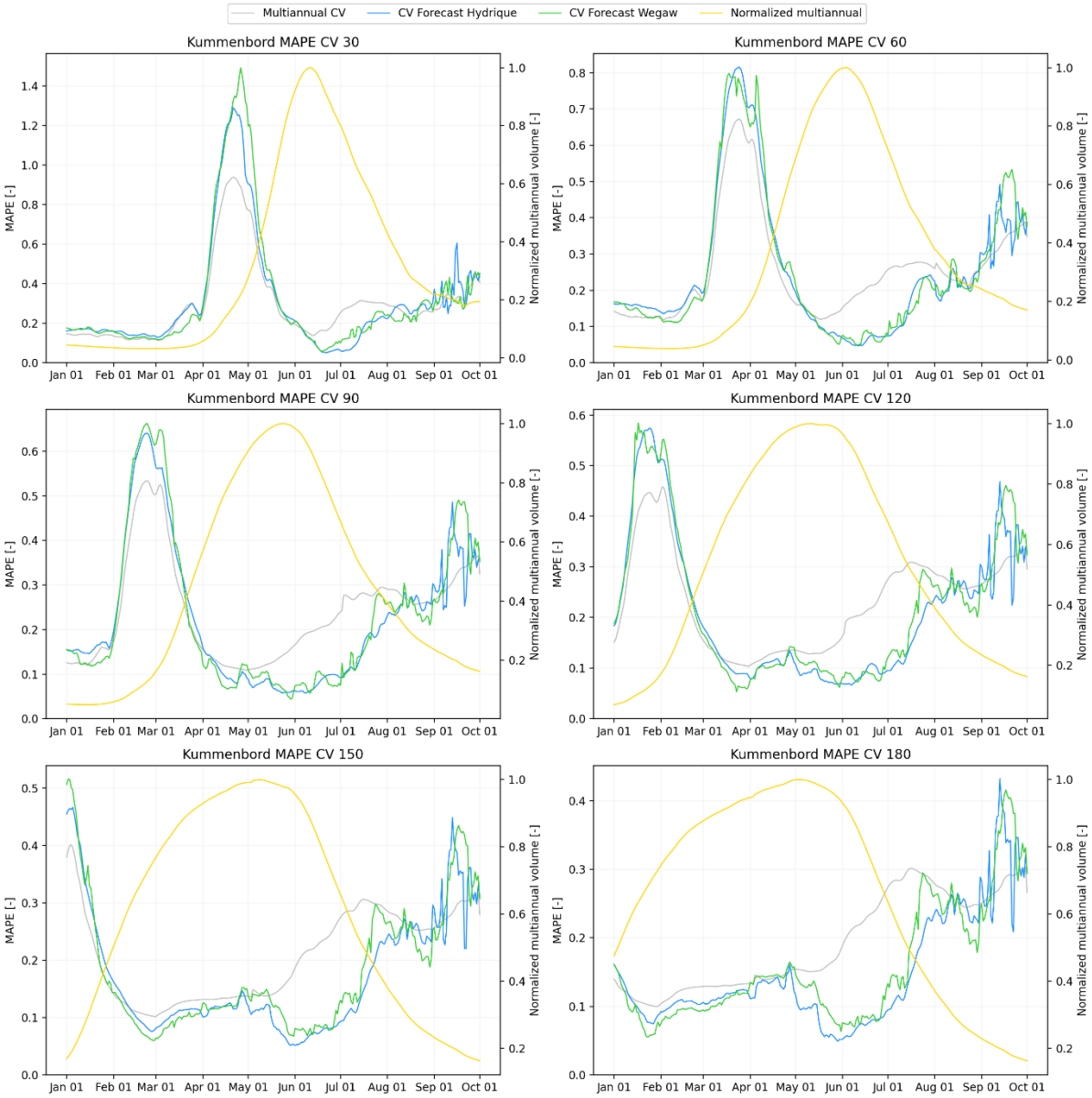
nnn. Kummenbord, daily MAPE, Wegaw SWE, training and cross-validation



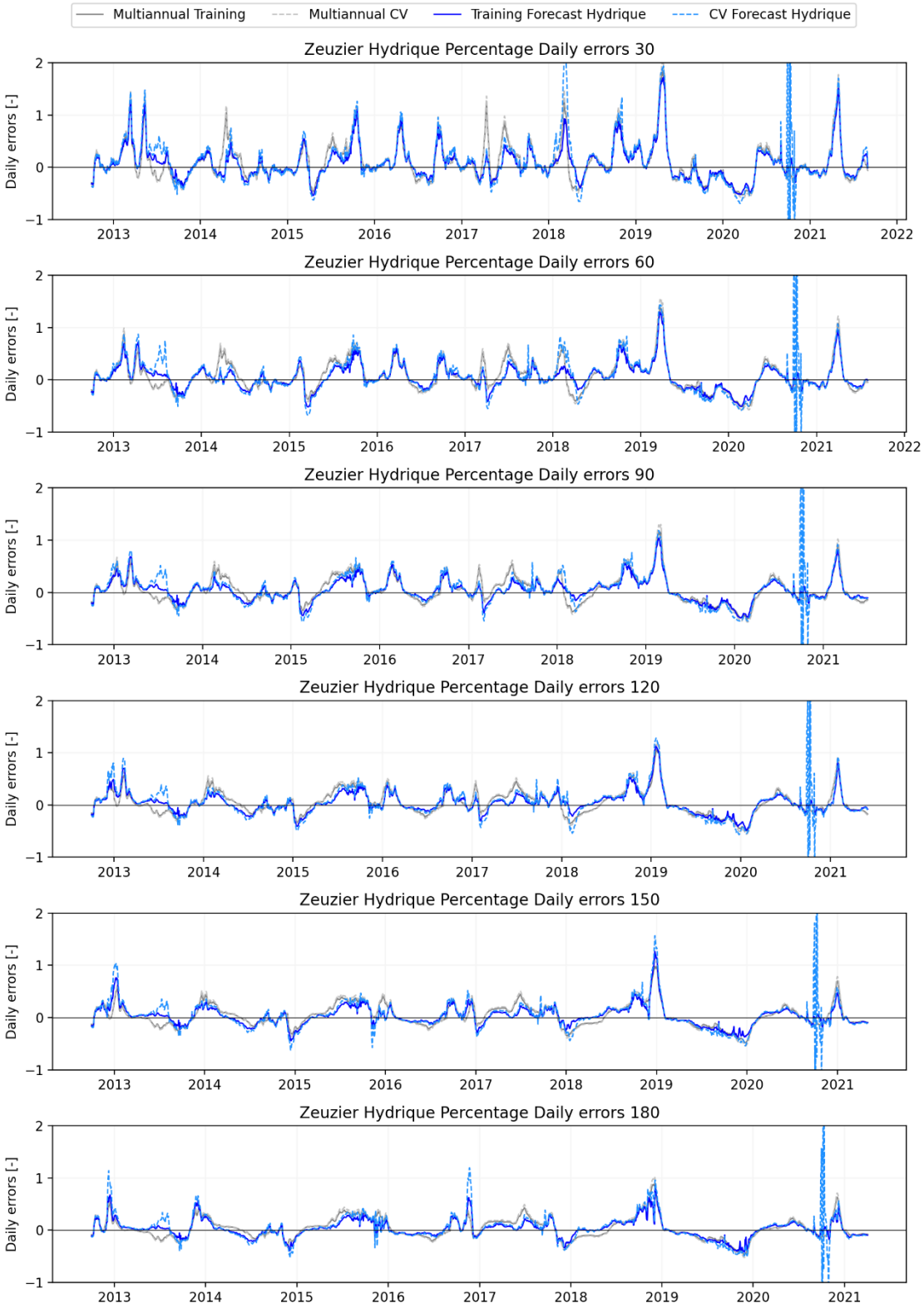
ooo. Kummenbord, MAPE, Hydrique + Wegaw, training



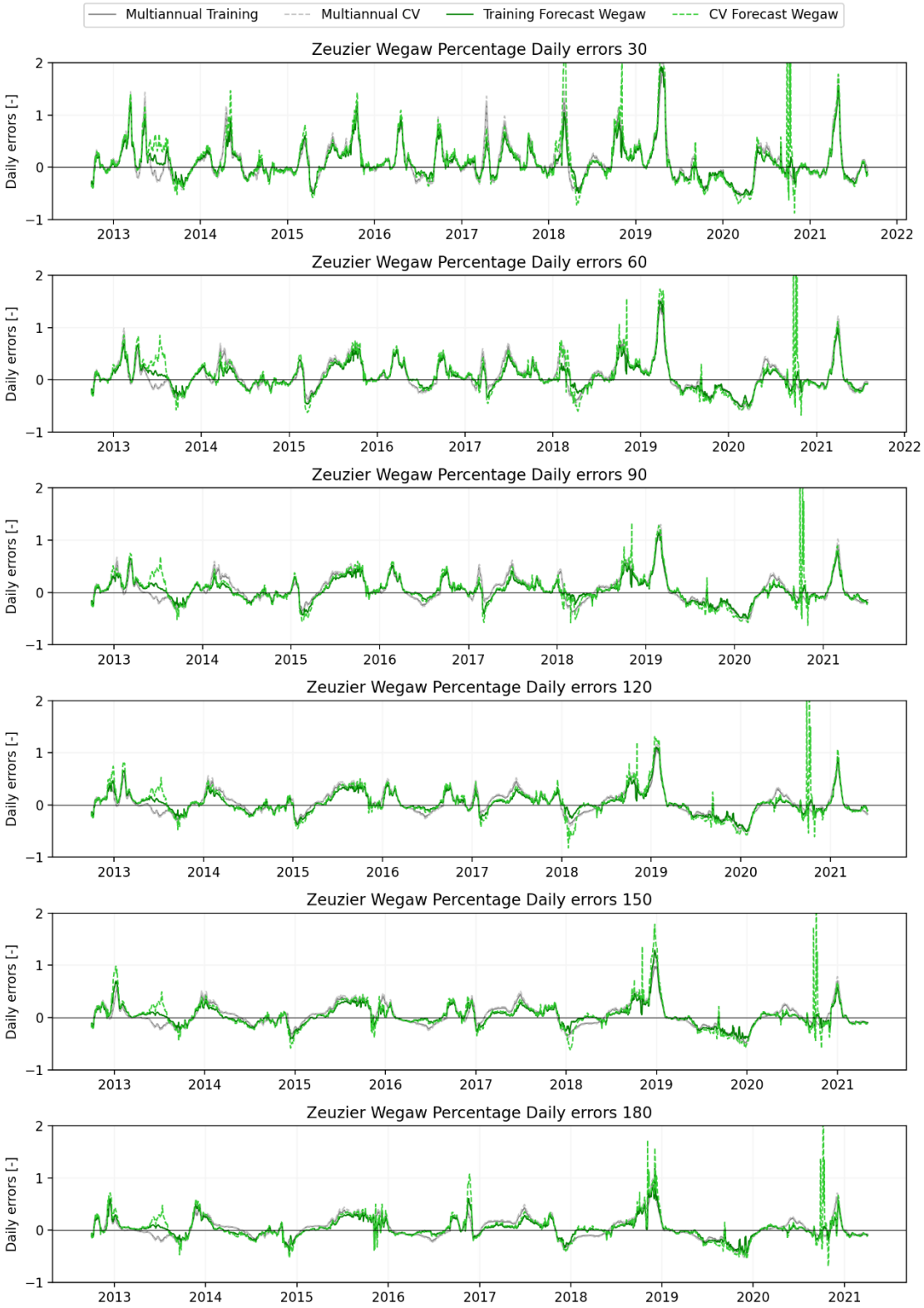
ppp. Kummenbord, MAPE, Hydrique + Wegaw, cross-validation



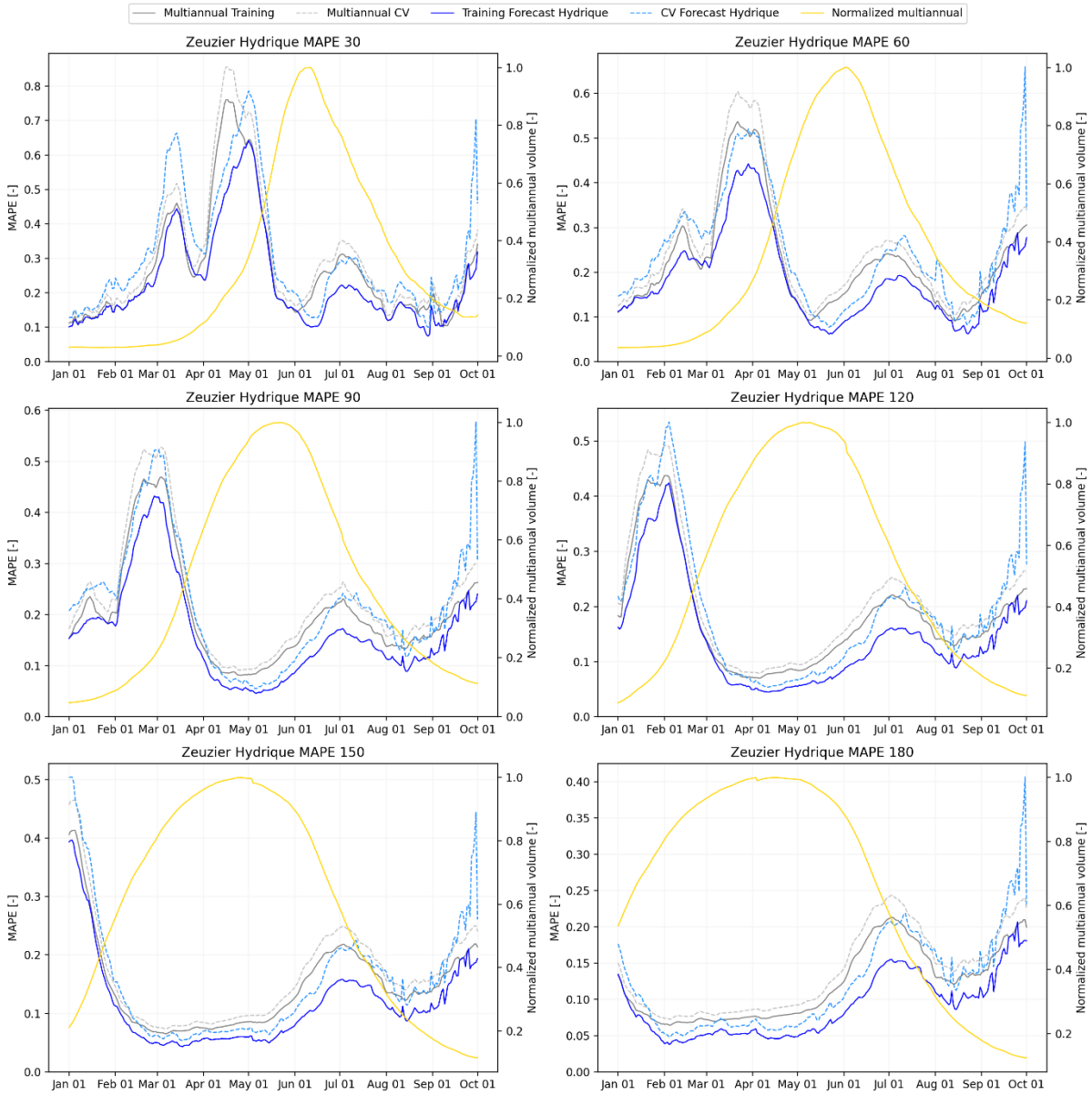
qqq. Zeuzier, daily errors, Hydrique SWE, training+cross-validation



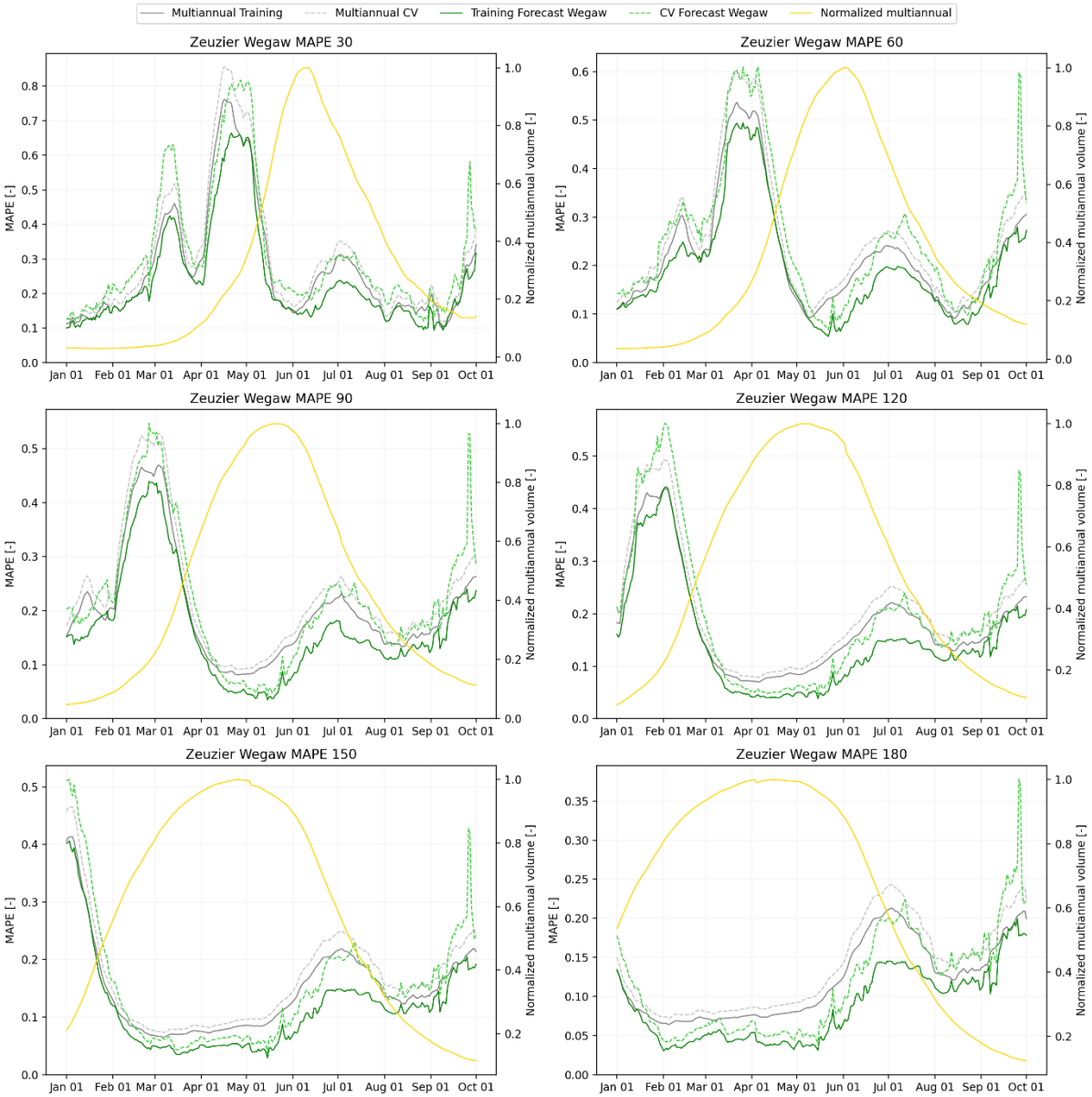
rrr. Zeuzier, daily errors, Wegaw SWE, training+cross-validation



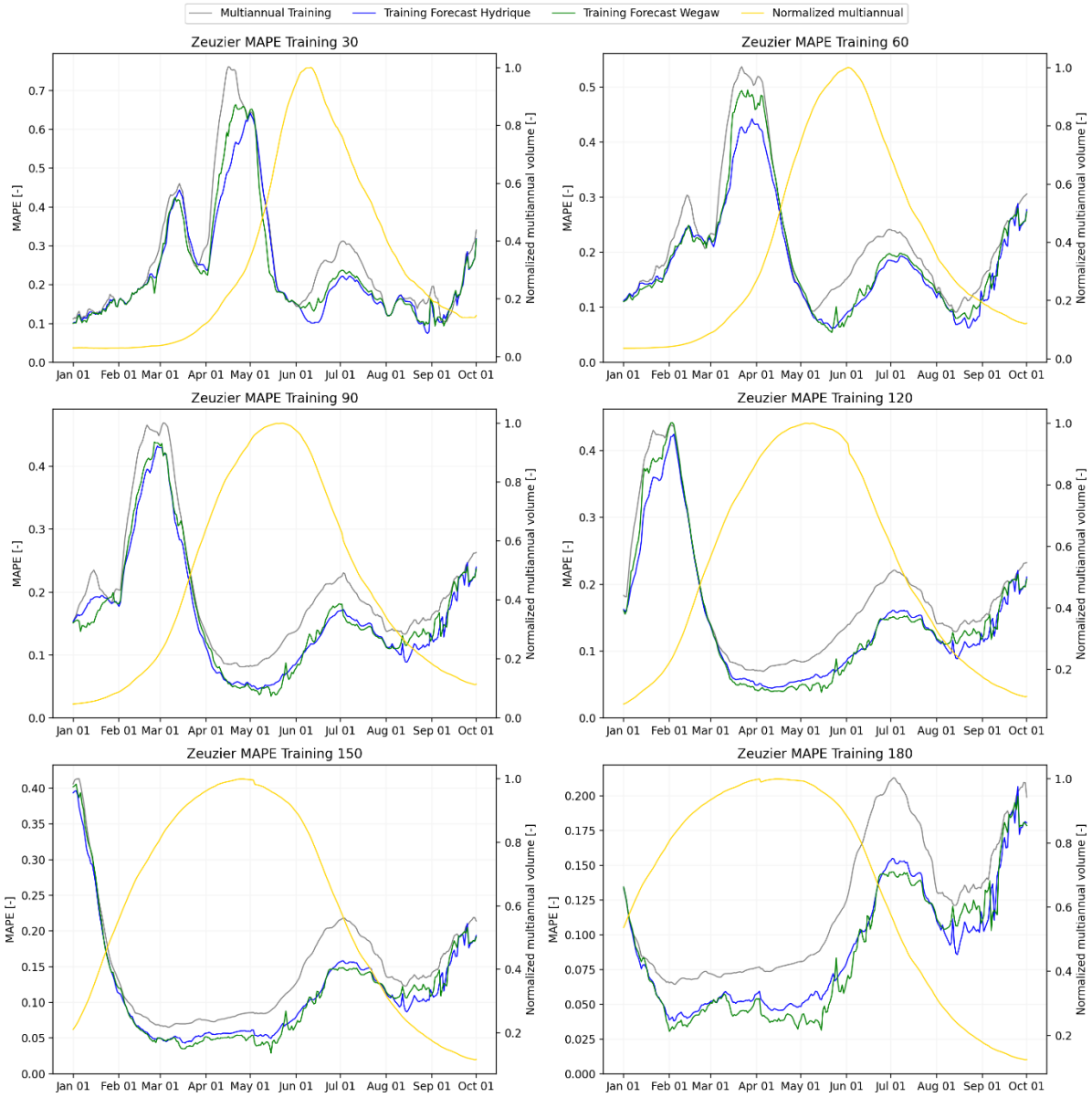
sss. Zeuzier, daily MAPE, Hydrique SWE, training and cross-validation



ttt. Zeuzier, daily MAPE, Wegaw SWE, training and cross-validation



uuu. Zeuzier, MAPE, Hydrique + Wegaw, training



vvv. Zeuzier, MAPE, Hydrique + Wegaw, cross-validation

