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PYTHON-BASED STATISTICAL ANALYSIS OF THE ECOLOGICAL VARIABLES IN THE ITALIAN ALPS

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Abstract: *The high Alpine region of northern Italy is characterized by unique ecosystems, a complex hydrogeological setting, steep topographic gradients, variety of vegetation types and landscape patches, and varied in climatic and meteorological factors. Alpine ecosystem is even more complex when the vegetation composition is dominated by coniferous trees, since underground flow conditions and directions have unpredictable water quantities. Modelling such ecosystems requires advanced tools of programming and computing approaches, such as Python. This article is focused on the distributed water balance modelling in alpine catchments. The area is dominated by the coniferous forests (spruce, pine) with trees of different age (old >200 years and young, <30 years). Selected trees are covered by epyhytes (lichens). For effective planning and management of the use of water resources, Python-supported estimations and statistical modelling are a necessary approach for environmental forest monitoring. In particular, the highest suitable spatial resolution that can be achieved in water balance estimations is evaluated in a complicated topographical setting of South Tyrolean Alps with limited knowledge of physiographic factors of forest and meteorological variables (precipitation, temperature, air humidity).*

Keywords: *Python, modelling, environmental monitoring, climate, statistics, data analysis*

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1. Introduction

1.1. General background

The protection of biodiversity and sustainable development in the Alpine and mountainous regions of Europe is facing significant problems due to climate change (Kadereit et al., 2008; Klaučo et al., 2013; Remias et al., 2018). Climate change affects diverse aspects of the environmental, including nature and society (Ausserladscheider, 2024; Klaučo et al., 2017; Lemenkova, 2024a, 2025; Keiler et al., 2012; Kruse & Pütz, 2014). Climate change, for instance, is responsible for alterations in rainfall and snowmelt patterns brought on by rising temperatures. In turn, they affect the dynamics of drought in Alpine mountain catchments or, in contrast, cause floods (Laghari et al., 2012; Lemenkova, 2024b). Furthermore, decreased snowmelt is causing droughts in high-altitude regions more frequently, which has a significant impact on downstream

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water flow and availability (Bilish et al., 2020). For ecosystems, climate change can endanger lichens and epiphytic bryophytes, whose eco-physiology is highly dependent on ambient temperature due to their nature (Joly et al., 2009). These examples, among many others, well illustrate the strong linkage between climate and environment.

To reveal the correlation between diverse environmental and climate parameters, the advanced computing methods are needed. These include, for instance, statistical methods of data processing by libraries of Python or R (Karssenberg et al., 2007; Lemenkova, 2019a, 2019b, Mehlhase, 2013). The effectiveness of these tools is proved by diverse publications where the applications of programming tools are reported (Persson & Khojasteh, 2021; Lemenkova, 2019c; 2022a 2025b; Bilina & Lawford, 2012). The advanced tools of modelling are also successfully applied in diverse branches of engineering and geology (Lindh, & Lemenkova, 2023a, 2023b; Memmott et al., 2021; Miftari et al., 2023). Following these examples, in this study, we modeled the response of epiphytes to temperature changes using programming Python libraries. The aim is to reveal the linkage between species occurrence data along severe elevational-temperature gradients within the range of forests dominated by Alpine spruce using advanced modelling. Numerous spruce and pine species found in northern Italy's subalpine forests are at risk of changing their land cover in the near future as a result of deforestation. By identifying the most important species and the areas where their conservation is anticipated to be most successful, a local assessment of the existing altitudinal range of species may offer a method to monitor the consequences of warming.

Alpine highlands and mountains supply large amounts of water, with the latter serving as a vital resource for the lowlands. These amounts of water run-off are observable in river systems at the larger scale and play a major role in the global water supplies. In mountainous areas, such as Alps, these regions should also receive special attention when it comes to management initiatives on nature conservation, forest restoration, as well as ecological and hydrological analysis of response of vegetation to climate change. The specifics of water supplies that come from coniferous mountains are still up for debate, while being widely understood in theory. The capacity of the hydrological cycle for dampening the increasing radiative forcing due to climate change is challenged in the last years, as an increasing land surface area is becoming water limited. Understanding and quantifying sources of water in terrestrial ecosystems, and the role of the different structural properties of the vegetation canopy in the response to climate forcing is urgently needed.

1.2. Objectives and goals

1.2.1. General objective

The general purpose of this research is to apply the advanced computing tools of statistical analysis of Python to modelling the environmental dataset that shows correlation between the climatic variables and vegetation responses in Alps.

1.2.2. Specific objectives

- To reveal correlations between the transpiration from sap flow data, evapotranspiration and net ecosystem exchange,
- To ascertain if the forest trees with old (>200 years old) and young (<30 years old) forest stand in South Tyrol have distinct phytological characteristics that result in response to meteorological variables,
- To find out if throughfall fraction differs for old and young coniferous forests

– To detect correlations between the transpiration from sap flow data, evapotranspiration and net ecosystem exchange in the coniferous trees (dominated by spruce and pine),
– To model meteorological data in order to track trends between the variables in the dataset (monthly precipitation as sum and maximum daily sum) and temperature (monthly average and average daily max and min) in order average.

To answer these questions, in this paper, a statistical modelling method has been presented that uses Python tools for data processing. Based on the data processing the results illustrated response of trees to climate changes and water balance in a spatially dispersed way for the area of South Tyrol, Italian Alps.

1.3. Study area

This study evaluates a number of elements that constitute water balance in Alpine catchments of South Tyrol, including precipitation, evapotranspiration, runoff, and storage variations, using a hydrological model. Precipitation (P) is the primary way that water enters terrestrial ecosystems in the hydrological cycle. Although evapotranspiration (ET) contributes about 60% of the yearly terrestrial P, its proportional significance varies greatly among biomes and ecosystems, ranging from 55% to 80% of incoming P. This water exits terrestrial ecosystems as stream runoff (Q) or evapotranspiration (ET) back into the atmosphere. This interaction is important for understanding of the hydrological processes within the forest ecosystems. Since the difference between entering P and ET represents the amount of water accessible in terrestrial ecosystems, it is crucial to model this ratio and analyse how much water remains in the ecosystems after ET. This variation has influences water availability in ground waters, preventing droughts and dryness, and thus supporting normal vegetation growth, on stream flow, groundwater recharge, and the carbon cycle of the ecosystem.

The site is placed at 1730 m a.s.l. in the mountains dominated by the coniferous forests with the uneven aged species mainly composed by spruce, Figure 1. The study emphasizes how the water balance is impacted by tree height, age, land use, altitude, and climate variability. By contrasting the model's output with actual data, it becomes clear how various elements interact and differ among Italian Alps catchments. A study includes different contribution of young (30 years) and old (200 years) subalpine forest. Water cycle was analysed in the Italian Alps.

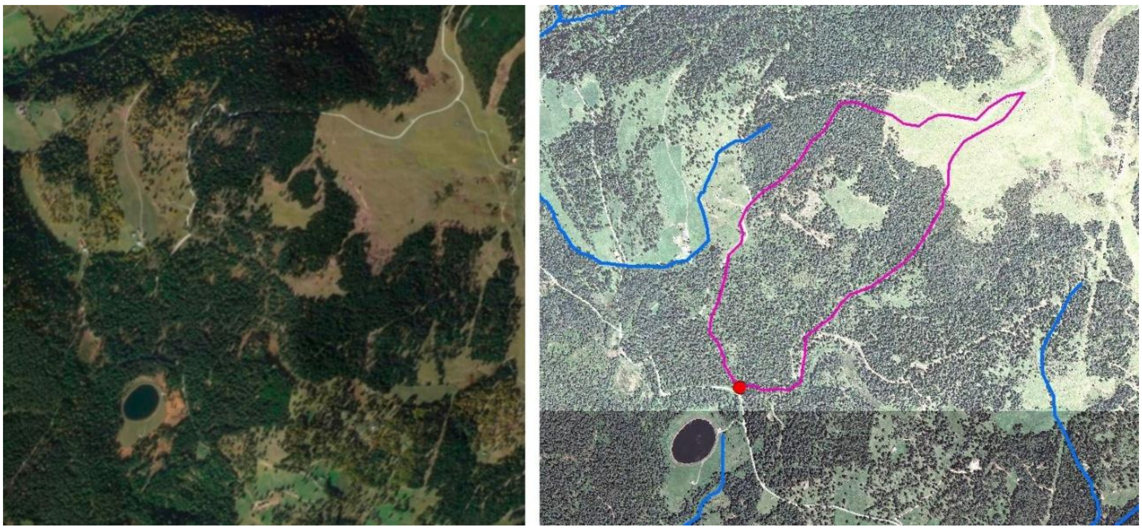

Figure 1. Map of the catchment area where the fieldwork was performed for data collection Left: aerial image; right: catchment area (purple-colored contour).

2. Methods

The methodology includes different statistical approaches which were applied including eddy covariance, sap flow, fog deposition and canopy interception information on trees. In particular, the data were analyzed using a variety of spatiotemporal discretizations, ranging from annual to daily (or shorter) time-steps in the temporal scale and from lumped to dispersed in the geographical scale, Figure 2.

Modelling using Python was performed to analyse structures to the hydrological cycle. This enabled to compare the results of the water balance modeling in a South Tyrolean watershed across species with different age and height, as well as presence or absence of lichens on the truncs. The estimation of the water balance in high Alpine terrain was done using Matplotlib modelling technique using statistical analysis (boxplots and graphs) for distributed analysis. Models using libraries of Python were used to assess the throughfall proportion of water for both young and old coniferous forests in order to ascertain the distribution of water balance components throughout time and space. The climatic variables were measured using the equipment. The square root of the sum of the equipment's squared systematic errors and the standard deviation of the mean values during the analyzed periods was used to get the absolute error per measured component.

The water partitioning at the catchment level was estimated for the old and young stand (of and yf, respectively) for five months during the growing season of 2019 (30/5/2019 (DOY 150) to 07/11/2019 (DOY 311)). Total precipitation (P) was split into rain (Pr, mm) and mixed precipitation (Pm, mm) (only 9 days with fog-only during 2019, Table 2), canopy interception (I, mm) was calculated as P - throughfall (Tf) - stemflow (Sf), Equation 1:

$$P = Pr + Pm + F = Tf + I + Sf. \tag{1}$$

Total forest evapotranspiration (ET_EC) was considered to be the sum of tree transpiration (T), evaporation of intercepted water (I), transpiration of the understory (Tu), and soil evaporation (Es), Equation 2:

$$ET_{EC} = T + I + Tu + Es. \tag{2}$$

ET_EC was measured for the whole forest using eddy covariance, T for trees of the two stands using sap flow sensors, and I was considered to be equal to tree interception (as intercepted water will eventually evaporate) calculated from precipitation balance. Thus the sum of understory evaporation plus soil evaporation (Esu) could be calculated as the residual of ET_EC - T – I, Equation 3:

$$Esu = ET_{EC} - T - I. \tag{3}$$

The Discharge (DC) and change of soil moisture (dSWC) were also measured for the whole forest. The annual water balance was calculated for the same period and the whole 2019 following Equation 4:

$$Pr + Pm = ET_{EC} + dSWC + DC + DPe. \tag{4}$$

where all acronyms are listed above except for DPe, which is deep percolation (unmeasured, likely negligible). These terms were expressed in mm (1 mm = 1 kg m^{-2} of water).

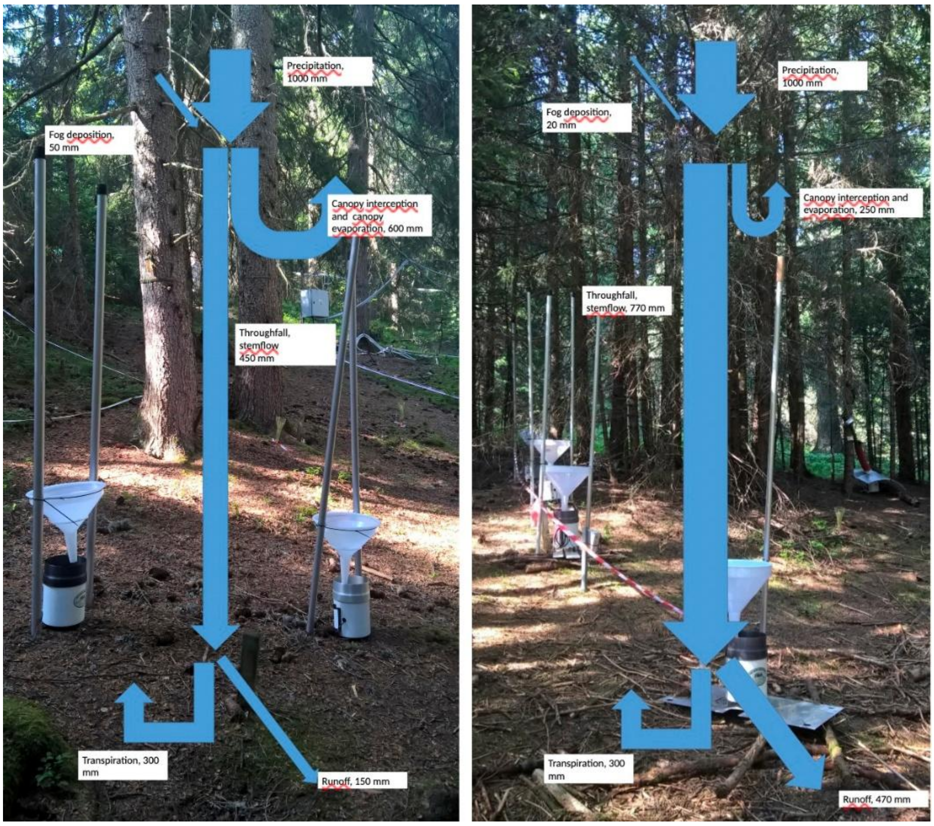

Figure 2. Forest showing old (>200 y. old) and young (<30 y. old) stands, South Tyrol

In Python, the data were processed using Matplotlib library. The advances of Python for data processing consists in model optimization. Thus, the majority of the parameters in the conceptual model are derived a priori from catchment physiography to prevent an automatic model calibration. Such approach contributes to the low model complexity and better adjustment to the actual dataset. Monthly data on trees with or without lichens is used in the first model, whereas semi-distributed discretization and daily data on old and young trees are used in the second model. The inputs for both models are temperature and precipitation data. In particular, we provided a comparative case study in which we used several spatiotemporal discretization carried out with Python scripting tools to analyze the simulation results of two conceptual water balance models. Assessing whether various models with various discretization can still produce comparable outcomes in spruce, Swiss pine, and other species of the coniferous trees, Figure 2.

Existing statistical approaches are integrated in the methodology of the modeling process. The optimized approach for taking into account every step of water balance estimate, from the creation of input data to model parameterization and water balance simulation, has been adopted to employ spatial disaggregation into subregions with comparable meteorological and topographic characteristics of the catchment area, Figure 2. The mountainous watershed is the primary study area located in the northern Italy.

3. Results

The findings support species-specific and differentially shaped tree species-temperature interactions. The results suggest that community composition is likely to be influenced by how susceptible individual tree species with varying heights and ages are to climate change. Specifically, the results show that a marked difference exists between young and old forest structures: Young forest: 550 mm yr-1 back to the atmosphere as ET (LE ~ 25 kW m-2). The larger part is given by transpiration. Old forest: 900 mm yr-1 back to the atmosphere as ET (LE ~ 40 kW m-2). The larger part is given by direct evaporation from the wet canopy. This highlights that old forests, mainly due to their physical characteristics, are much more efficient in contrasting the global change, by sustaining more efficiently local and global hydrological cycle. Whiskers showing canopy throughfall fraction of precipitation of the two forest ages, Figure 3.

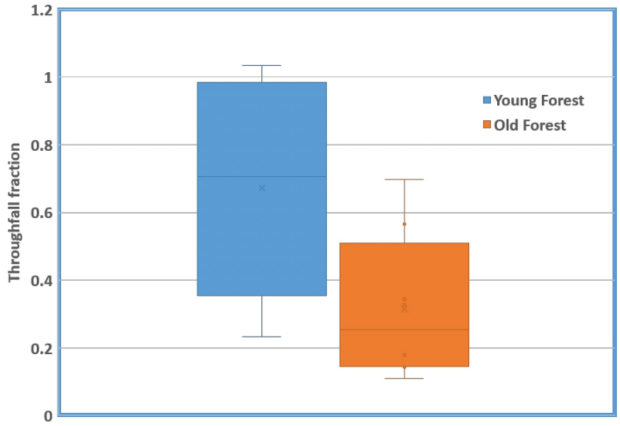

Figure 3. Throughfall fraction for old and young coniferous forests

The trees located within the watershed catchment area were evaluated by calibrated daily model's parameters using meteorological data. To determine the water balance of the Italian Alps, the monthly model's distributed parameters were approximated regionally and locally.

Simulations of throughfall fraction were done for old and young coniferous forests and show the identical performance from both models. The models perform well when simulating temporal dynamics for the primary inputs and outputs of ecosystem. Nevertheless, they have poorer agreements for sub-components, e.g., presence of lichens at trees of different age. Differences in relation between the transpiration from sap flow data, evapotranspiration and net ecosystem exchange were obtained from eddy covariance data and modelled using Python, Figure 4. The evapotranspiration is the important eco-hydrological parameter that indicates the health of vegetation within the context of water cycle (Lemenkova, 2022b; De Niel et al., 2019).

The uncertainty in data classification and modelling is associated to the distribution of environmental variables to target parameters (temperature, precipitation, occurrence of fog in selected days and tree height and age). The datasets was analysed in this work and the weather conditions might affect the overall results of data processing (rainy days or dry days). Since this is related to monitoring habitat and vegetation over time, spatial uncertainty should be estimated to avoid biased conclusions.

In Python, a solution evaluate accuracy is proposed by the modelling which plots the graph (see Figures 3–6) which demonstrates the threshold results in environmental parametrization. Technically, it is realized using scripts with the plotting and statistical libraries of Python (Matplotlib and auxiliary ones).

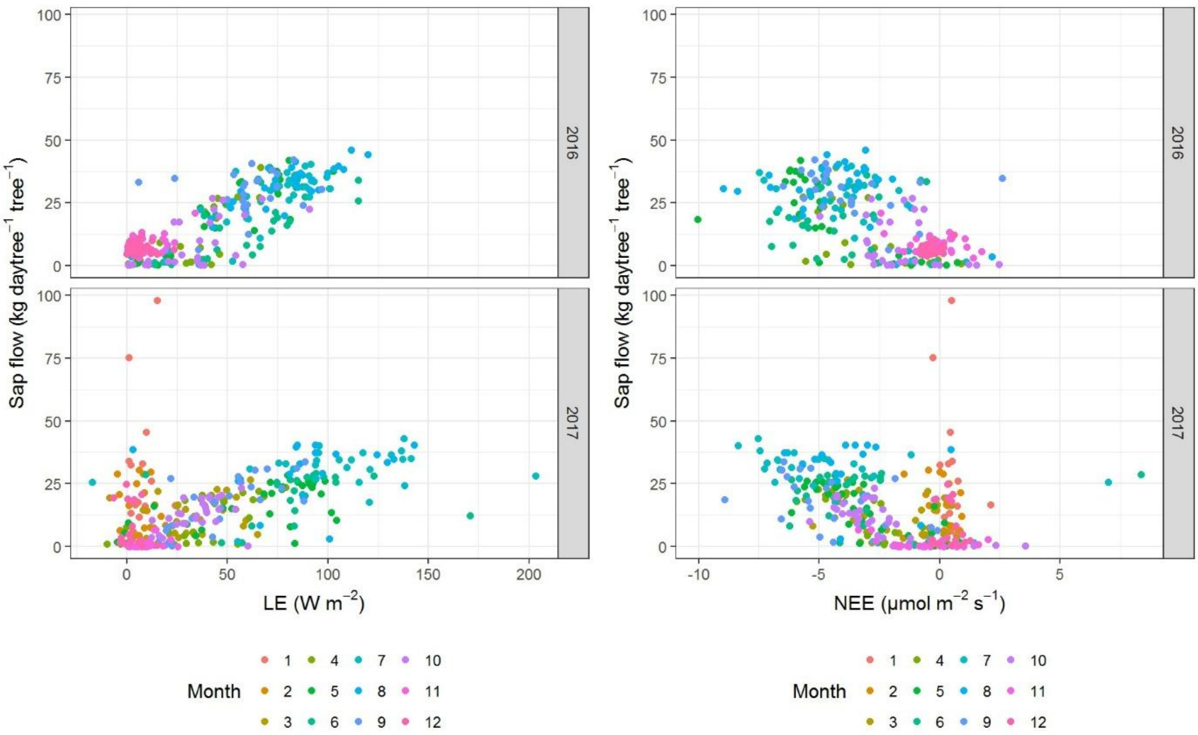

Figure 4. Python-based models showing the relation between the transpiration from sap flow data, evapotranspiration (a) and net ecosystem exchange (b) from eddy covariance data

The statistical plots visualising these data show the calculated correspondence for each classified parameter in the classified dataset (see Figures 4-6). The variations are mainly related to different calibration approaches and are not dependent on the spatio-temporal discretization of spruce and pines. Overall, the two water balance models yield consistent results, suggesting that the usage of monthly meteorological and climate data is effective to the usage of daily data on the watershed areas, Figure 5.

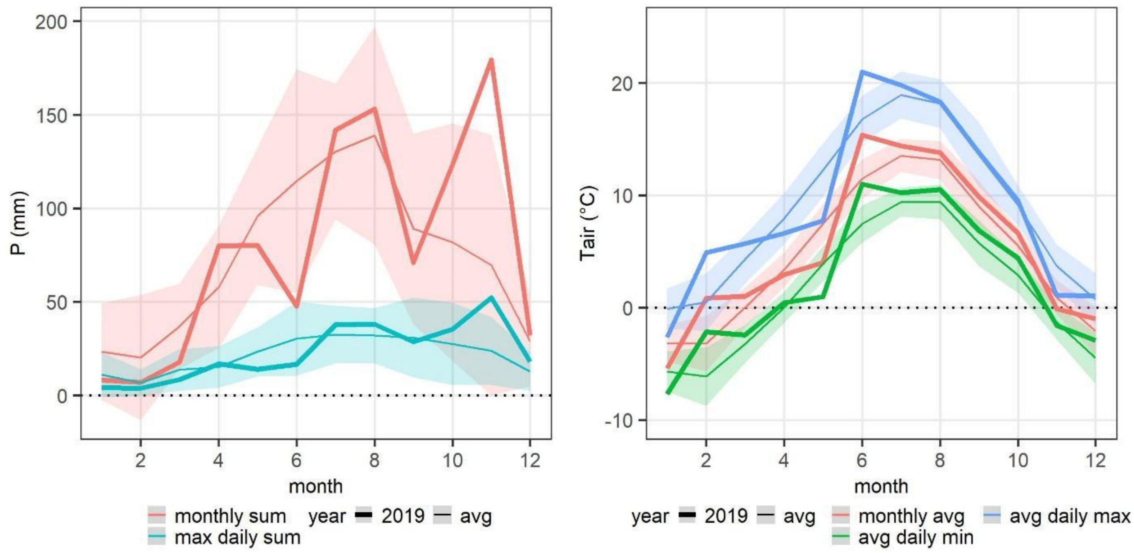

Figure 5. Python-based models showing average monthly precipitation (monthly sum and maximum daily sum) and temperature (monthly average and average daily max and min) for 2019 (thick line) and for the period from 1999 – 2019)

Three meteorological drivers and the kind of precipitation were found to be related by the Python-based modeling. The occurrence of fog and mixed precipitation throughout the 2019 study period was then predicted using these data. These forecasts were contrasted with fog observations from a public camera situated 300 meters below the study site and 3 kilometers away. For the purpose of studying meteorological conditions (global radiation: total global radiation in the top row, diffuse global radiation in the middle, ratio of diffuse global radiation to total global radiation, temperature, and relative humidity) in greater detail during dry, fog, and precipitation periods as well as times with mismatches between observed and predicted fog, three representative time periods were chosen for 2019: late May to early July, mid-July to early September, and mid-September to early November.

Figure 6 shows the correlation between the environmental data. The graph above shows time course of daily precipitation (P, top left in continuous line for clarity) as well as daily evapotranspiration measured with eddy covariance (ET) and daily transpiration for the old (Tof) and young (Tyf) forest upscaled from sap flow measurements (top right). Below: Correlation of daily ET, Tof, and Tyf with daily P (bottom left) and correlation of daily Tof and Tyf with daily ET. For both 2015 and 2019, the number of days with dry weather, fog, precipitation (rain or snow), and mixed precipitation was computed and discussed. In order to evaluate the accuracy of our forecasts, we included both the observation (obs) and prediction (pred) periods for datasets from 2015 and 2019 and compared the periods marked by dry weather, fog, and rain.

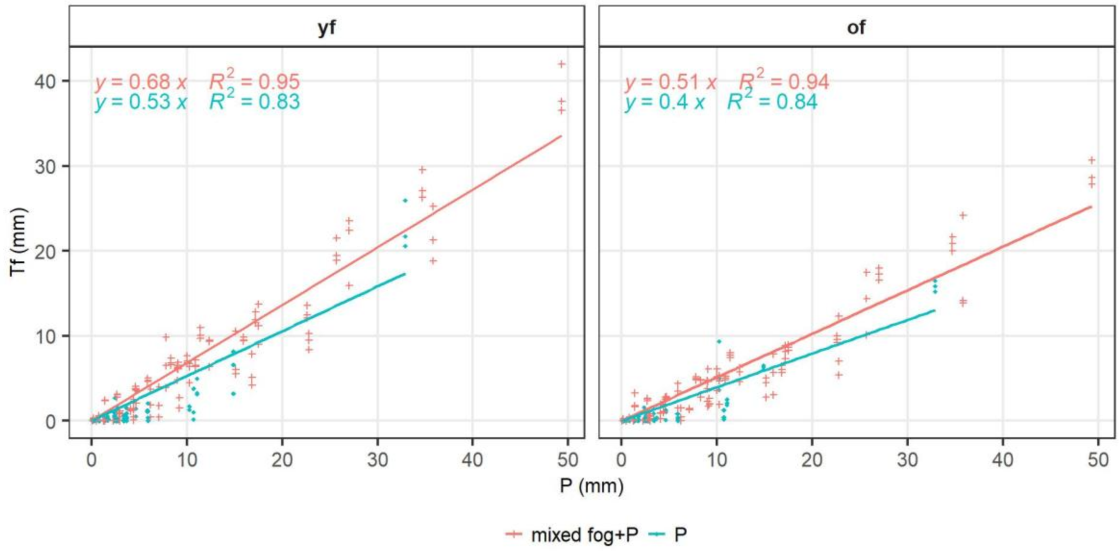

Figure 6: Python-based models showing correlation between the environmental data

The aim of Python-based modelling is to determine the confidence level at which each parameter is categorized correctly and accurately associated to another variable (temperature and precipitation, transpiration from sap flow data and evapotranspiration, as well as net ecosystem exchange). It is the correlation maps that enable to reveal the linkage between these parameters. Systematic assessment of the effects on water-soil content are useful not only in environmental monitoring, but also in practical technical solutions such as civil engineering (du Toit, et al., 1997; Lindh & Lemenkova, 2022, 2023c, 2023d; Zeng et al., 2011).

3. Conclusion

In this article, the European Alps, with special reference to South Tyrol, are used as an example to illustrate the components of the water balance—precipitation, runoff, evapotranspiration, and storage change—as well as their interactions and unique characteristics in the forest mountains with dominating coniferous species (Swiss pine, spruce). The study revealed that strong temporal and spatial differentiation of the Alpine climate has a significant impact on the water cycle. The suitability of several Python-based methods for the spatial interpolation of temperature point measurements, responses of trees, presence of lichens on thee trunks and precipitation is assessed with respect to their suitability for hilly terrain, and external statistical evaluation is determined to be the most appropriate.

The Python programming and statistical tools used in this research presents a powerful tools to modeling datasets. The effectiveness is achieved by processing variables and visualizing correlations between the environmental parameters (temperature, precipitation, fog occurrence, and evapotranspiration). The comprehensive and integrated nature of the data processing supported by Python, along with the diverse libraries (Matplotlib, NumPy, SciPy, Pandas, etc), allows for visualization and plotting datasets with diverse variables. This enables to get valuable insights into various climate-environmental aspects of the forest ecosystems such as response of vegetation to meteorological settings (e.g., higher or lower temperature leading to droughts or dryness), evaluate possible trends and ecological dynamics in the future and evaluate ecosystem health (age and height of trees).

In order to calculate monthly and regional distributed differences in forest phenology, a water balance model for an alpine watershed that can integrate main hydrological processes is presented. These strengths underscore the potential of Python and other programming tools (R, Octave or Matlab) to advanced environmental analysis and enhance decision-making in landscape monitoring and land management. Nevertheless, it is also essential to acknowledge the limitations identified in the statistical modelling, such as the limited sample size and geographic constraints, which might explain the correlation between the given parameters of the findings. Therefore, in future studies, it is recommended to extent study area to further regions of South Tyrol in order to evaluate the distribution of the species in subalpine forests (spruce, pine, broad-leaved trees) and their response to the climatic processes.

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