Final Report for Project **1480**

Project title: **Fork-to-farm agent-based simulation tool augmenting BIOdiversity in the agri-food VALUE chain**

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1. Purpose and overview of the project results

The BioValue project investigates the complex interactions between biodiversity, the food and agriculture industry, environmental factors, consumer tastes, and health outcomes. The project develops the BioValue Tool, a flexible tool for analyzing biodiversity in the agri-food value chain, to model, evaluate, breed, produce, and promote genetically diverse, underutilized crops like cereals, legumes, and vegetables in seven pilot sites countries (Cyprus, Estonia, Germany, Greece, Spain, Italy, Turkey, and Norway). These crops are integrated into market-ready food products, enhancing agro-biodiversity and appealing to consumers. The project also aims to deliver a user-friendly framework to assess policy effectiveness, environmental progress, and regulatory compliance.

We examine the impacts of climate change on European agriculture, focusing on how increasing climate variability challenges agricultural productivity and management. As climate extremes such as heatwaves, droughts, and shifts in seasonal precipitation become more frequent and intense, the work supports the development of adaptive strategies using high-resolution climate model data. These simulations improve the understanding of climate-driven risks affecting crop production. To this end, we employ advanced CMIP6 Earth System Models (EC-Earth3, CNRM-CM6-1-HR, and MPI-ESM1-2-HR) under the SSP5-8.5 high-emission scenario to represent potential mid-21st-century conditions in Europe. This scenario highlights the urgency of identifying suitable agricultural adaptations under strong warming pressures. Because EURO-CORDEX CMIP6 simulations were not available at the time of the project implementation or were only scarcely available, alternative high-resolution ESMs (mentioned above) were selected and tailored for agricultural applications.

To obtain precise regional projections, we apply two statistical post-processing techniques: downscaling using the Perfect Prognosis (PP) approach and bias correction using Quantile Delta Mapping (QDM). The PP method translates large-scale atmospheric predictors into local climate variables, providing refined spatial and temporal information for the pilot sites. QDM adjusts model outputs to better match observed distributions while preserving projected trends, ensuring applicability for impact assessment and local agricultural planning. The combined procedures enable downscaling to spatial resolutions approaching 1 km, depending on latitude, producing geographically and temporally detailed climate information suitable for operational use. The methodology follows the recommendations of Galmarini et al. (2019) and the BAD-JAM framework and yields consistent, high-resolution projections. The resulting datasets provide refined temperature and precipitation information necessary to characterize local climate extremes and support climate-informed agricultural planning by the BioValue partners.

We produce detailed climate atlases for each pilot site, delivering daily, monthly, and seasonal projections for selected crops under present and future conditions. In parallel, we compile a comprehensive table of agriculture-relevant indicators to evaluate regional climate risks. This includes drought indicators, heat stress metrics, and compound event measures such as the Standardized Precipitation Index (SPI), Heat Magnitude Day (HMD), and Combined Stress Index (CSI). Together, the atlases and indicator framework support evidence-based adaptation planning and risk management and improve preparedness for climate-induced agricultural stress at regional and farm scales.

Then, we assess the potential impacts of compound climate events on European agriculture, particularly sequences such as dry winters followed by hot summers. These conditions can strongly affect crop development and increase the likelihood of yield losses. By analysing such patterns, we identify key climatic stressors affecting agricultural systems and provide information needed to adapt management practices and maintain production stability under increasingly variable climate conditions.

In conclusion, we highlight that ongoing climatic changes are expected to substantially alter the conditions under which European agriculture operates. Increasing temperature variability, more persistent drought episodes, and shifts in seasonal precipitation patterns will progressively affect crop suitability, yield stability, and water demand. Under high-emission pathways such as SSP5-8.5, these pressures are projected to intensify, making forward-looking planning essential. Reliable planning therefore depends on regionally resolved climate information, as agricultural responses must be tailored to local conditions rather than broad continental trends.

The analysis also underlines that agricultural vulnerability is unevenly distributed across Europe. Southern regions are likely to face heightened aridity and increased irrigation pressure, whereas northern regions may encounter excess moisture, soil saturation, and erosion risks. In central European areas, transitional conditions may lead to unstable growing seasons and increased exposure to late-season drought. Anticipating these spatial contrasts enables adjustments in crop selection, timing of operations, and water management strategies.

To support decision-making, the use of targeted climate indicators provides practical guidance for risk assessment. Metrics capturing precipitation deficits, heat accumulation, and combined stress conditions allow stakeholders to interpret complex climate signals in operational terms. Such indicators help translate climate projections into actionable information for farm management, seasonal preparedness, and medium-term planning.

Finally, the findings stress the need for coordinated adaptation strategies that integrate climate knowledge into agricultural management and policy frameworks. Effective responses will require alignment between climate information services, farm-level practices, and regional planning measures. By linking localized projections with practical management options, we demonstrate how proactive adaptation can reduce exposure to climate risks and maintain production stability under increasingly variable environmental conditions.

2. Downscaling and bias-correction

In the pre-processing phase, the CMIP6 model data, observation data (EMO1), and ERA5 reanalysis data were used. This procedure was carried out individually for each BioValue pilot site country and tailored to their respective months, as identified by the pilot sites and for each crop. The historical period covers 1990–2014, while the future scenario under SSP5-8.5 extends from 2015 to 2050.

The statistical downscaling approach combines the Perfect Prognosis (PP) framework with the analog method, specifically applying method M6 as described in Bedia et al. (2020). Predictors for precipitation include specific humidity at 700 and 850 hPa (hus700, hus850), mean sea-level pressure (mslp), 500 hPa geopotential height (zg500), and 850 hPa air temperature (ta850). For temperature variables (ta, tn, tx), only zg500 was used as a predictor. The predictand observational data were based on the European Meteorological Observations at 1 arcmin (EMO-1) daily dataset (1990–2014) (Thiemig et al., 2022), while ERA5 reanalysis data (Hersbach et al., 2017) served as the perfect predictors.

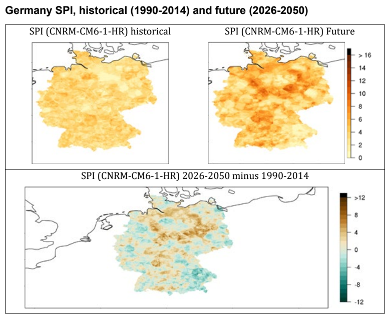
Following the downscaling process, bias correction was applied using the Quantile Delta Mapping (QDM) method (Cannon et al., 2015) to correct systematic deviations between model outputs and observations while maintaining the projected climate trends.

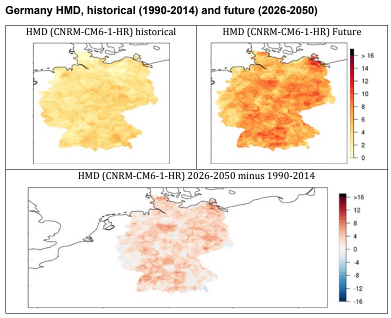
The post-processed simulations were produced at daily resolution. To facilitate analysis and data handling by end users at the pilot sites and the BioValue Tool, the dataset was additionally aggregated to a weekly scale, using non-overlapping 7-day blocks. For precipitation, 7-day sums were calculated, and for temperature variables, 7-day means.

The obtained dataset of high-resolution climate variables: pr: Precipitation total (7-day sum, unit: mm), ta: Mean air temperature (7-day mean, unit: °C), tn: Minimum air temperature (7-day mean, unit: °C), tx: Maximum air temperature (7-day mean, unit: °C) is freely available in the institutional repository of Justus-Liebig-University Giessen (https://doi.org/10.22029/jlupub-19887.2)

3. Climate indices for agricultural sector

The resulting high-resolution datasets form the basis for multiple analyses, including the calculation of extreme climate indices such as the Standardized Precipitation Index (SPI), Heat Magnitude Day (HMD), and Compound Stress Index (CSI) (see Figure 1 for selected pilot site countries). These products enable detailed assessments of regional climate risks, the evaluation of compound climate events, and the development of data-driven adaptation and mitigation strategies to safeguard biodiversity and agricultural productivity under future climate conditions.

a) 

b) 

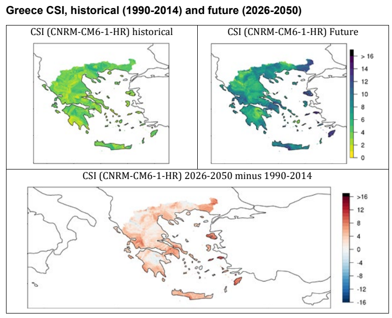
c) 

Figure 1. Spatial distribution of climate indices for the historical period (1990–2014) and a future climate scenario (CNRM-CM6-1HR 2026–2050). (a) Standardized Precipitation Index (SPI) over Germany; (b) Head Magnitude Day (HMD) over Germany; and (c) Compound Stress Index (CSI) over Greece.

4. Summary

In this project statistical downscaling combining the perfect prognosis and the analog method, and bias-correction using the quantile delta mapping on climate simulations from three high-resolution models: MPI-ESM1-2-HR, EC-Earth3, and CNRM-CM6-1-HR. The resulting dataset provides key climate variables (precipitation, mean, maximum, and minimum temperature) for eight countries in the extended European domain. The climate variables were used to compute three climate and compound stress indices (SPI, HMD, and CSI). All variables and indices were generated for a defined historical period (1990–2014) and for the high-end future emissions scenario (SSP5-8.5).

5. References

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