Final Preport for Project **1245**

Project title: **Weather and climate modules of the AI-based early warning system DAKI-FWS**

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1. Purpose and scientific overview

The DAKI-FWS project (Data and AI-supported Early Warning System to Stabilize the German Economy), funded by the German Federal Ministry of Economic Affairs and Climate Action, aimed to develop an innovative early warning system with a seasonal time horizon to support the protection of lives, infrastructure, economic activities and environmental systems. Within this framework, the weather and climate modules focused on improving the usability of seasonal forecasts through preprocessing, artificial intelligence approaches, hydrological modelling and impact-related applications.

The scientific work addressed a key limitation of seasonal forecasts, namely their coarse spatial resolution and systematic biases, which restrict their direct use for regional climate risk assessment. To address this challenge, the project developed an integrated modelling workflow combining seasonal forecast preprocessing, AI-based downscaling and bias correction, extreme-event detection, hydrological modelling and climate-sensitive applications such as tick distribution modelling.

A key scientific contribution of the project is the demonstration that these components can be combined into a consistent workflow linking climate prediction with impact modelling. This integrated approach allows seasonal climate information to be translated into application-relevant indicators for early warning purposes (Figure 1).

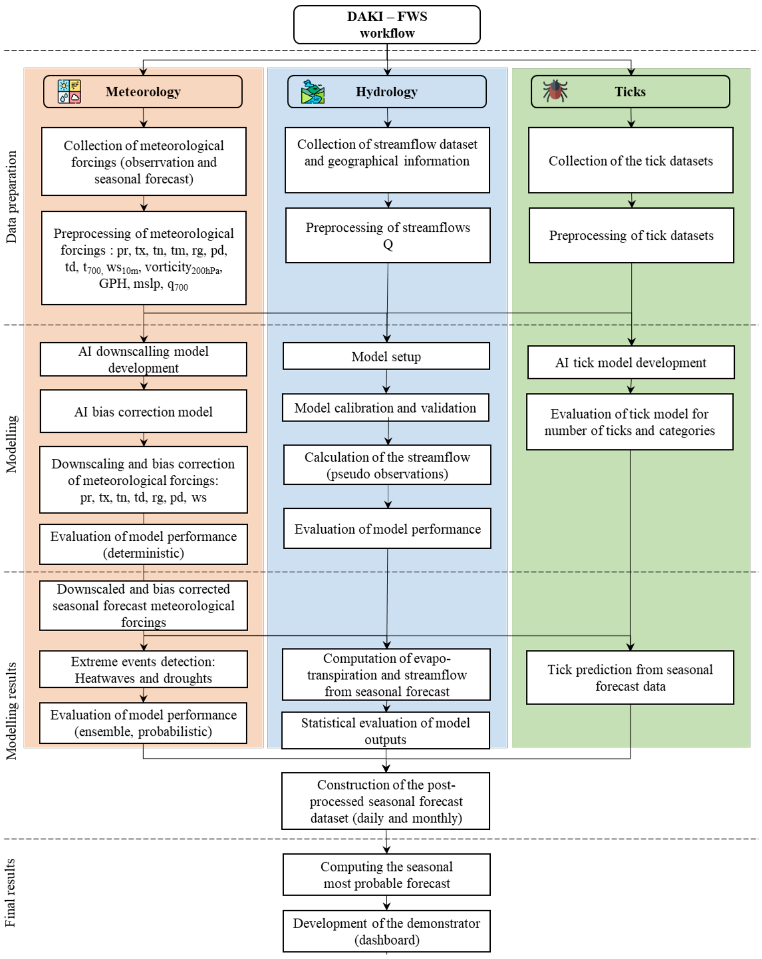

Figure 1: *Workflow of the DAKI-FWS early warning system*

2. Seasonal forecast preprocessing, downscaling and bias correction

A major scientific component of the project was the development of bias-correction and downscaling approaches to increase the spatial resolution and reliability of seasonal forecasts. The work included the testing and implementation of multiple machine-learning approaches, including deep neural networks, Gaussian mixture models, support vector machines, random tree methods and convolutional neural networks.

The downscaling framework was based on relationships between large-scale atmospheric circulation predictors and high-resolution observational predictands. Data preprocessing included nonlinear principal component analysis and analog search approaches to improve predictor selection and training data structure.

The implementation of Residual Convolutional Neural Networks represented an important methodological development. The results demonstrated the capability of the models to significantly increase spatial resolution while maintaining good agreement with observations. The downscaled temperature fields showed strong similarity to observational datasets and reduced bias across most of the study domain (Figure 2a).

The performance of the downscaling system was further improved by using analog search on multiple geopotential-height levels, which increased predictor consistency and improved model robustness. The final assessment demonstrated systematic improvements compared to raw seasonal forecasts, including improvements in spatial structure and probabilistic forecast skill.

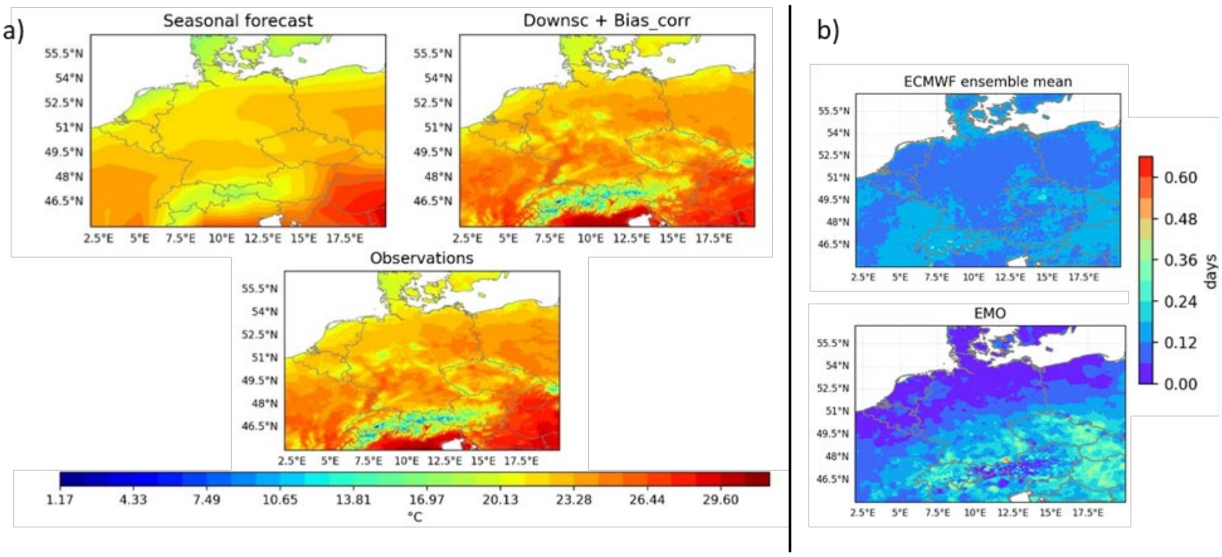

Figure 2: *a) Maximum temperature for June-July-August (2012-2015): raw seasonal forecast (left), downscaled to 1 arcminute and bias corrected (centre), and observations (right). b) Heat wave duration averaged over the test period (2012-2015): model output (upper panel), and observations (bottom panel).*

3. Detection of heatwaves, droughts and concurrent extremes

The detection and characterization of extreme events represented another key scientific objective. The project developed AI-based approaches to detect heatwaves and droughts using long-term observational datasets, seasonal forecasts and large-scale circulation indicators such as ERA5 temperature fields, geopotential height and NOAA sea surface temperatures.

Heatwaves were identified using percentile-based thresholds and characterized by duration, intensity and cumulative intensity. The work also included regional analysis across multiple European subregions and probabilistic detection across seasonal forecast ensembles (Figure 2b).

In addition to individual hazards, the project developed a non-stationary detection tool for concurrent extremes based on the inhomogeneous J-function from point-process theory. This tool enabled analysis of dependencies between extreme events while accounting for non-stationary changes in event frequency. The methodology involved Monte Carlo simulations and AI-based classification approaches using support vector machines, random forests and deep learning.

These developments demonstrate the capacity of the project to move beyond single-hazard analysis toward compound risk assessment.

4. Hydrological modelling

Hydrological modelling formed a central component of the project, providing the link between seasonal meteorological forecasts and water-related impacts. The LISFLOOD hydrological model was implemented for German and transboundary river catchments and calibrated using meteorological forcings and hydrological observations.

The modelling workflow included preparation of meteorological inputs, computation of potential evapotranspiration using LISVAP, model calibration, and evaluation using the KGE performance metric. Streamflow simulations were conducted for major river basins including the Weser, Rhine, Danube and Oder.

A major achievement was the integration of AI-downscaled seasonal forecast data as inputs to the hydrological model. This enabled seasonal streamflow simulations based on multiple ensemble members and lead times. The results demonstrate the successful coupling of AI-enhanced meteorological forecasts with process-based hydrological modelling (Figure 3a,b).

The project also developed a demonstrator (Figure 3c) allowing exploration and visualization of downscaled meteorological variables, heatwaves, simulated streamflow and climatic water balance, supporting the transition from methodological development to application.

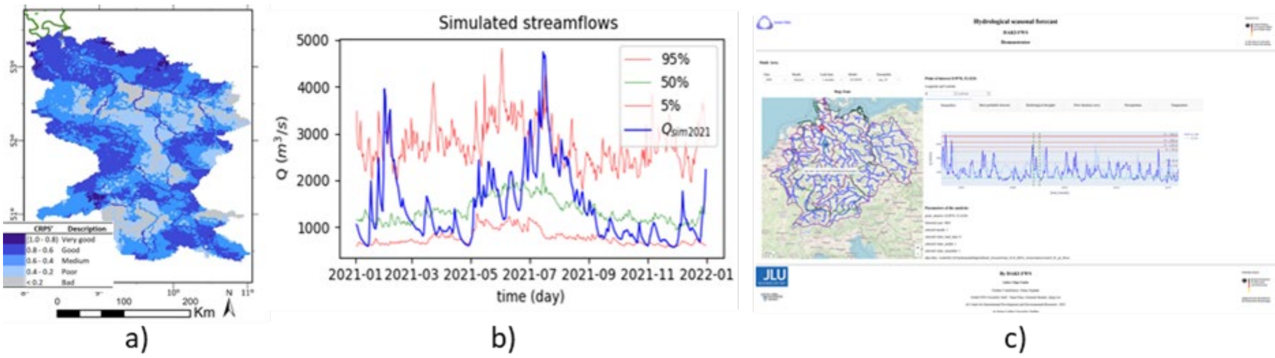

__Figure 3__: a) Performance of the seasonal forecast for the reforecast period. b) Example of the simulated streamflow for the Weser catchment. c) Overview of the demonstrator.

5. Tick modelling and climate-sensitive applications

An additional component of the project addressed climate-sensitive ecological risks through modelling of tick occurrence. The work was motivated by the influence of meteorological and climatological conditions, including extreme events, on tick habitats and the associated risk of tick-borne diseases.

Tick occurrence datasets were compiled from sources including the European Centre for Disease Prevention and Control and the Global Biodiversity Information Facility. The data were preprocessed to identify spatial patterns and support predictive modelling (Figures 4, 5; Table 1).

Machine-learning approaches including random forests and neural networks were developed to predict tick distribution using meteorological variables, elevation and land use as predictors. Model evaluation using RMSE, ROC curves and AUC values showed that the models could reproduce general spatial patterns but had limitations in reproducing extreme values.

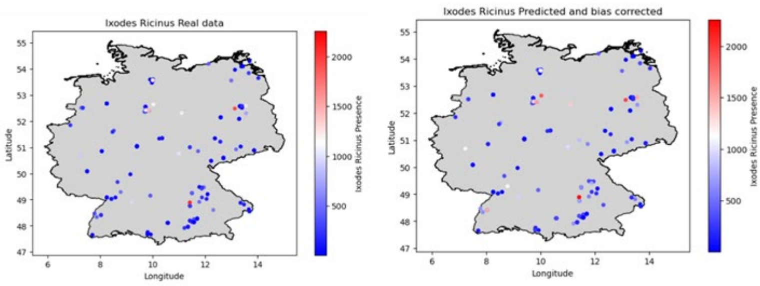

__Figure 4__: Ixodes Ricinus: (left) observed data vs (right) predictions for the testing period

Table 1. Tick risk classification

Classification	Logarithmic Scale Range
1 - Low Risk	0 – 2
2 - Middle Risk	2 - 2.8
3 - High Risk	2.8 - Inf.

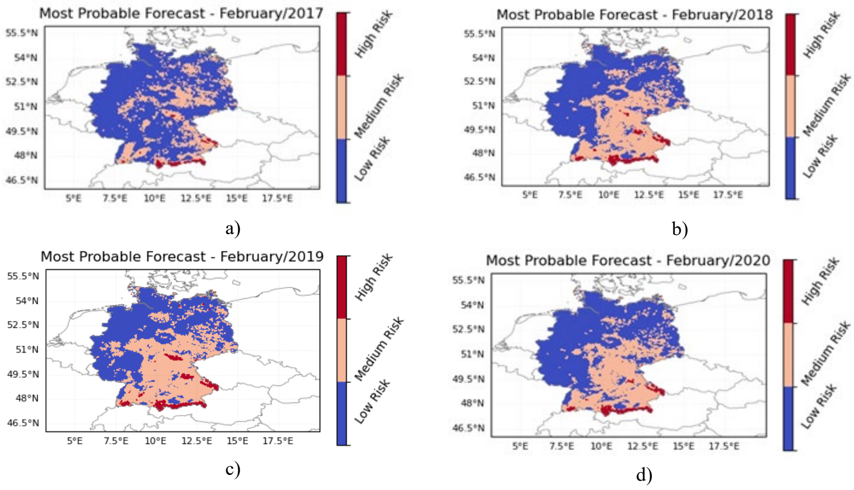

Figure 5*: Ixodes Ricinus: Most probable forecast; February 2017-2020*

This work demonstrates the broader applicability of the DAKI-FWS framework beyond meteorological hazards toward ecological and public-health applications.

6. Overall scientific achievements and conclusions

The DAKI-FWS weather and climate modules achieved significant scientific progress in improving the usability of seasonal forecasts through AI-based preprocessing and their integration into impact-oriented modelling applications. The project demonstrated that bias correction and downscaling using advanced neural-network approaches can significantly improve the spatial representation and forecast skill of seasonal predictions.

The improved meteorological information was successfully integrated into hazard detection, hydrological modelling and ecological applications, demonstrating the feasibility of a fully integrated climate-service workflow. The final verification confirmed improvements of AI-processed forecasts compared to raw seasonal forecasts based on multiple deterministic and probabilistic verification metrics.

Overall, the project demonstrates the value of combining climate science, artificial intelligence and impact modelling within a unified early warning framework. The results provide a scientific basis for the further development of climate-informed early warning systems using seasonal forecast information.