European Decadal Climate Outlook Technical Appendix

METEO unit

Institute for Environmental Research and Sustainable Development,
National Observatory of Athens, Athens, Greece

contact: Georgios Fragkoulidis (geofrag@noa.gr)

1. Introduction

The climateoutlook.eu web platform has been developed by the METEO unit of the National Observatory of Athens (NOA), Greece, within the framework of the Augures! research program funded by the European Climate Foundation. It delivers high-resolution decadal climate forecasts specifically tailored for the European agriculture sector, bridging the critical gap between seasonal forecasts (1-9 months ahead) and climate projections (20-100 years ahead). This medium-term forecasting is essential for society, providing crucial data for planning and risk management in vital sectors such as agriculture, water resources, energy, fisheries, and public health.

The climate of the coming years and decades is shaped by the anthropogenically forced global warming, the naturally occurring (i.e., intrinsic) climate variability (as this manifests in aperiodic fluctuations at annual-to-decadal time scales or quasi-periodic phenomena like the El-Nino Southern Oscillation), and natural external forcings (e.g., volcanic and solar activity). Climate change projections start from randomly selected preindustrial states and aim to unveil the effect of the first factor (anthropogenically forced global warming) for specific scenarios of greenhouse gas emissions. In terms of external natural forcings, the timing of major volcanic eruptions is unpredictable and the solar activity variations have a known and rather limited role on climate. Regarding the intrinsic variability, a new endeavor by the climate science community was initiated about 20 years ago in order to explore the ability of climate models to simulate the intrinsic climate variations of the coming years given the current state of the oceans and the atmosphere (Meehl et al., 2009). This gave rise to the field of decadal climate predictions. These are predictions of the next 1-10 years that are issued every year and aim to fill the gap between seasonal forecasts (1-9 months ahead) and climate change projections (20-100 years ahead).

Decadal climate predictions combine aspects of both a forced and an initial condition problem, as illustrated in Fig. 1. At daily-to-annual time scales the evolution of the climate system is largely modulated by the conditions of the initial (observed) state (internal unforced variability), while at multidecadal time scales external forcings prevail. On annual-to-decadal time scales, initial conditions (mainly those in the ocean) and external climate forcing (greenhouse gases, solar variability, volcanoes, aerosols) are — in principle — equally important factors.

Taking the above into account, “initialized” decadal climate predictions (i.e., starting from conditions that describe the current status of the climate system) are needed in order to capture any predictable signals in the climate variations of the next 10 years. These special predictions have been found to be more skillful for these lead times compared to the typical climate projections, the main objective of which is to capture the

long-term effects (i.e., 20 years out to a century ahead) of external forcings (Boer et al. 2013, Solaraju-Murali et al. 2019).

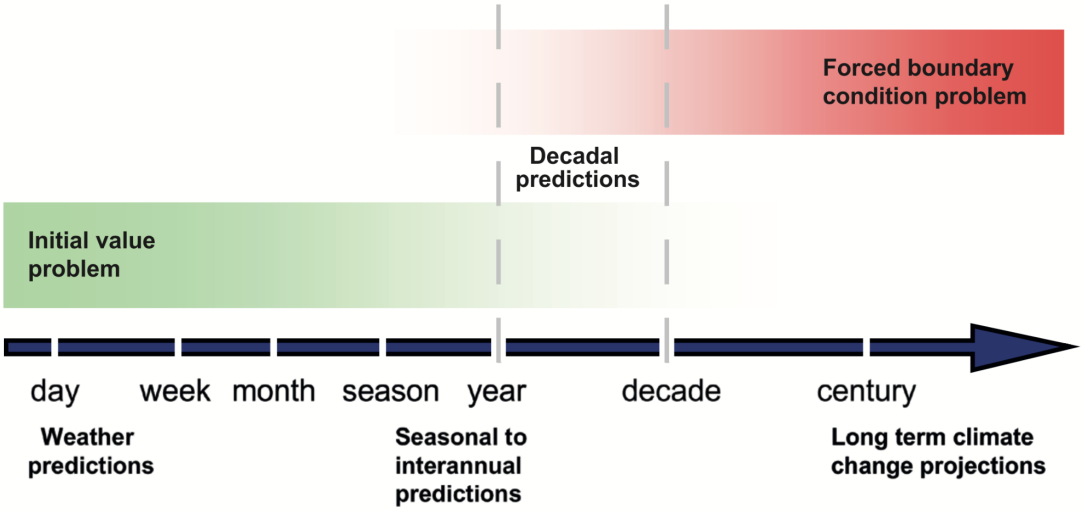

Figure 1: *A schematic illustrating the progression from an initial-value based prediction at short time scales to the forced boundary-value problem of climate projection at long time scales. Decadal prediction occupies the middle ground between the two (Source: IPCC AR5, 2013; adapted from Meehl et al., 2009)*

As with seasonal forecasts, decadal climate predictions **are neither able nor built to predict the weather of particular days in the years ahead.** Their objective is to accurately simulate the climate tendencies over long periods (e.g., 1-5 year means) and over large areas. This is possible to the extent that the slowly evolving properties and processes of the land surface, sea ice and oceans collectively have a noticeable effect on the interannual evolution of the entire climate system.

2. Decadal Prediction Models

Several research groups across the world are working on near-term climate predictions under the coordination and guidelines of the Decadal Climate Prediction Project (DCPP) of the World Climate Research Programme. To account for the chaotic nature of the climate system and the structural differences between individual models, our platform utilizes a multi-model ensemble approach. The currently available predictions rely on the average output of two state-of-the-art models:

- HadGEM3 (Met Office Hadley Centre, UK; Hermanson 2020)
- NorCPM1 (Bjerknes Centre for Climate Research, Norway; Bethke et al. 2025)

Both centres issue 10 equally-probable ensemble members, so our multimodel ensemble comprises 20 scenarios for the coming decade. The real-time forecast currently displayed (the DCPP “s2024” prediction) was initialized in November 2024 and issued in the spring of 2025, covering the 10-year horizon through 2034. To communicate the confidence of these predictions, the 10-year average of all parameters is accompanied by an uncertainty estimate. This is inferred by the spread of our 20-member ensemble, quantified here as the distance between the 5th and 95th percentiles.

3. AI-based Downscaling

Global climate models, such as the ones used for decadal predictions, typically run at a horizontal resolution of approximately 100km, which is too coarse for precise impact modeling in the agriculture, energy or other sectors. To bridge this gap, we have developed a data-driven downscaling model utilizing a deep learning framework based on a multivariate Residual U-Net architecture (Fragkoulidis et al., 2026).

While the broader European domain is presented at a 0.5° resolution, focus regions including Greece, France, and Romania are downscaled to an ultra-high resolution of 0.05° (approximately 5 km). The deep

learning model is trained on the Copernicus European Regional Reanalysis (CERRA) dataset. By utilizing daily maximum/minimum temperature, precipitation, mean sea level pressure, and downward surface solar radiation as meteorological predictors alongside static topographic variables like elevation, the deep learning network accurately translates the coarse climate model output into realistic, localized meteorological data. For more details, please see Fragkoulidis et al., (2026).

4. Anomaly Computation and Implicit Bias Correction

When climate models are initialized with observed real-world data, the model physics experience an "initialization shock". As the forecast progresses over the 10-year horizon, the models gradually drift away from the observed initial state toward their own preferred internal climatology. Because of this continuous drift, each "lead month" (the number of months since the forecast started) possesses a unique climate state. To counter this, our platform employs an implicit bias correction methodology:

1. Hindcast Climatology: We compute the model's historical climate for every specific lead month based on the downscaled hindcasts (i.e., retrospective forecasts) covering the period of 1980 to 2018.
2. Anomaly Extraction: For the real-time forecast, we subtract the corresponding lead-month's historical model climatology.

Because we present all agro-meteorological indicators as deviations (anomalies) from the normal period (1991-2020), this subtraction inherently neutralizes the lead-time dependent model drift, resulting in a bias-corrected anomaly.

5. Agro-Meteorological Indicators

The agro-meteorological indicators presented in the application as deviations from the norm (1991-2020) are the following:

- Monthly mean maximum daily temperature
- Monthly mean minimum daily temperature
- Monthly cumulative precipitation
- Number of hot days (maximum temperature above 35°C) in the year.
- Number of frost days (minimum temperature below 0°C) in the year.
- Number of frost days during spring (minimum temperature below 0°C). Late frost risk for early-blooming olives or other crops.
- Duration of longest dry spell (consecutive days with precipitation below 1 mm) in the year.
- Average daily precipitation amount on wet days (days with precipitation above 1 mm).
- Total number of days in the year with precipitation above 20 mm.

The term precipitation refers to any form of water that falls from the atmosphere to the Earth's surface. This includes rain, snow, hail, and sleet.

6. Explicit Bias Correction and Crop Yield Modeling

In upcoming updates, the platform will expand beyond meteorological indicators to feature direct crop yield anomaly estimates (specifically for maize and winter wheat) utilizing the DSSAT crop model (Jones et al. 2003). Because dynamical crop models require absolute daily inputs rather than anomalies, we perform explicit bias correction before the downscaling of the data. This process ensures large-scale systematic errors are accounted for prior to topographic adjustments:

- The bias is quantified as the mean difference between the historical model hindcasts and the upscaled (1°) CERRA observational dataset.
- This lead-month dependent bias is subtracted from the real-time daily forecasts for Tmax, Tmin, solar radiation, and precipitation.
- Physical limits are then enforced: precipitation corrections are applied conditionally to prevent artificial drizzle, and unphysical negative values in solar radiation or precipitation are zeroed out.

The bias-corrected fields are then fed into the crop model to drive the growth of maize and winter wheat. The 1991-2020 (current climate) is then subtracted from the resulting yield estimates, in order to derive the crop yield anomalies of the coming decade that are presented in the platform.

Overall, by linking explicit bias correction, AI-driven downscaling, and sophisticated crop modeling, the Augures! platform aims to provide the European agricultural sector with an unprecedented tool for anticipating and adapting to near-term climate shifts.

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