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Original research article

Seamlessly combined historical and projected daily meteorological datasets for impact studies in Central Europe: The FORESEE v4.0 and the FORESEE-HUN v1.0

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HIGHLIGHTS

- FORESEE is a seamless climate database for Central Europe.
- The two new datasets are based on 14 model and 2 RCP scenarios.
- It enables the ensemble-based quantification of the projected climate change signal.
- Two application examples are presented for probabilistic impact assessment.

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ABSTRACT

The FORESEE is an open access, climatological database for Central Europe containing observed and projected meteorological data for the 1951–2100 period. As a climate service, FORESEE disseminates basic meteorological variables at a daily time step with a $0.1^{\circ} \times 0.1^{\circ}$ spatial resolution including maximum/minimum temperature, precipitation, incoming shortwave solar radiation and daylight vapour pressure deficit. The future climate in FORESEE v4.0 and FORESEE-HUN v1.0 is projected by 14 regional climate models from the EURO-CORDEX database using the Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios. Based on RCP4.5 the country-specific results indicate similar projected mean changes in annual mean temperature (1.5–1.7 °C) but considerable differences in precipitation (from −1.6 to 6.9%) in the region for 2071–2100 relative to 1991–2020. We present two case studies to demonstrate the applicability of FORESEE in climate change impact studies using the ensemble approach. Climate change induced negative weather effect (15.4% and 28.9% mean loss for 2071–2100 according to RCP4.5 and RCP8.5, respectively) might dominate the future winter wheat yields in Hungary that is superimposed to the overall trend determined by other factors. The projections provide consistent results about the mean advance in the start of the growing season for forests in Hungary up to 2100 with ensemble mean of 9.1 days (RCP4.5) and 19.8 days (RCP8.5). We also demonstrate that the representative model selection method might lead to misleading results in impact studies that should be considered. The updated FORESEE is a way forward in the dissemination of policy-relevant essential climate data in Central Europe.

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Practical implications

Studies addressing the impact of climate change on the natural environment, agriculture, society, economy, human health, etc. usually need projected climate data for the future (IPCC, 2013, 2021). However, climate models are far from being perfect and deviations between observations and model results are common, particularly at smaller, regional scales (Christensen et al., 2008). This calls for the bias correction of the model simulations, and the construction of seamless (i.e., smooth; without artefactual discontinuity) combination of the observation-based and bias-corrected projection parts of the dataset. Such corrections are essential if the results of the model simulations are used in impact assessments and decision-making.

To support climate change-related impact studies in Central Europe with observation-based and bias-corrected meteorological data for the future the first version of FORESEE database was created and published in 2015 (Dobor et al., 2015), providing daily gridded data for 1951–2100. However, that version did not address the issue of discontinuity between the historical and future projections parts of the dataset.

In the last few years, an increasing number of research groups recognized the importance of bias-corrected datasets. Several studies were built on the previous versions of the FORESEE database focusing on plant development, hydrology, biodiversity, and other issues. One of the most important applications of the FORESEE database is to directly provide meteorological input data to the Biome-BGCMuSo biogeochemical model (Hidy et al., 2022), that was already used by several research groups (e.g., Fodor et al., 2021; Ostrogović Sever et al., 2021). FORESEE is also embedded in the AGROMO software (https://github.com/hollorol/AgroMo) that is the first Integrated Assessment Modelling software for Hungary focusing on crop production (Fodor et al., 2021). Additionally, the dataset was used for the investigation of different ecosystems' functioning based on remote sensing data (Kern et al., 2017, 2018; 2020, 2021). Besides this, the FORESEE dataset was used in various additional research such as forest phenology (Hlásny et al., 2016; Kostić et al., 2021), vegetation phenology (Dávid et al., 2021), aerosol particle formation (Salma et al., 2021), crop production (Koós et al., 2021; Marton et al., 2020; Bognár et al., 2022), and soil water content modelling (Horel et al., 2022).

Web-based data retrieval is available for FORESEE to enable fast and simple data download. Point-based data query is supported in a simple map-based form (https://nimbus.elte.hu/FORESEE/map_query/index.html). The web application will be extended in the future to simplify data retrieval and to support representative model selection.

In the new versions of the FORESEE database – that is the subject of the present study – discontinuity correction has been introduced to avoid any artefactual discontinuity in the temperature at the beginning of the projections, due to the transition from observation-based data to projections. This is particularly important because of the strong and unprecedented warming in the region after 2000 that was not represented well by the models. Beyond the basic climate variables (maximum and minimum temperature, and precipitation), FORESEE provides additional meteorological variables (daylight incoming shortwave solar radiation, daylight vapour pressure deficit and daylight mean temperature) as well derived from the basic variables. This ensures that the database is intrinsically consistent not only throughout its temporal domain but across the variables as well. The improved FORESEE offers possibilities for diverse scientific and policy-relevant research areas. The exploitation of the database for probabilistic studies and risk assessment is a major application field. Due to the high number of model projections included in the new datasets the usage of the ensemble technique is feasible to describe the projected changes in a probabilistic framework.

This study demonstrates the usefulness of the updated FORESEE database with practical examples for the estimated consequences of the projected climatic changes. We present two case studies for Hungary: i) to estimate the climate change induced weather effect on the winter wheat yield and ii) to estimate the changes in the start of the vegetation season (SOS) for forests using a locally calibrated model. Our results indicate a significant (15.4% and 28.9% mean) weather-induced decline in the winter wheat yield in Hungary for 2071–2100 relative to the period 2000–2016, according to the Representative Concentration Pathway (RCP) 4.5 and 8.5 scenarios. The estimated interannual variability due to the weather effect is expected to increase in the distant future (by ~35%). The second case study points out that projected climate change will result in the advance of the SOS in Hungarian forests with a mean of 9.1 and 19.8 days for 2071–2100, based on RCP4.5 and RCP8.5. The resulting mean trend in SOS of −1.14 days per decade suggests a dramatic shift in forest phenology.

Data availability

The availability (link) to ur data is written in the Manuscript

Introduction

There is a strong societal, economic and political pressure to estimate the potential impacts of the ongoing environmental change in climate-sensitive sectors, and evaluate the possible mitigation options. For this reason, the need for reliable climate data has increased dramatically in the recent decades (Manton et al., 2010; Brasseur and Gallardo, 2016; Findlater et al., 2021). In addition to narrow professional circles, stakeholders and decision-makers are also fundamentally dependent on climate data of adequate quality, preferably available free of charge.

Global and regional climate models are essential tools for estimating the magnitude of the future climate change for selected meteorological variables at high temporal resolution (Taylor et al., 2012; IPCC, 2021). The application of global climate models (GCMs) at a regional or smaller scale is limited due to their coarse spatial resolution. Regional climate models (RCMs) represent physical processes in the atmosphere that are not yet resolved at the coarser resolution, thus providing data at finer spatial resolution useful for regional impact assessments (Wang et al., 2004; Giorgi, 2006; Feser et al., 2011).

Direct use of the RCM results is limited by systematic errors inherently present in the simulated variables as a result of uncertainties in the parameterization and model structure (Varis et al., 2004; Christensen et al., 2008) and errors inherited from the GCMs. Quantification of the expected climate change signal, e.g., in terms of long-term means or frequency of extreme events (IPCC, 2013; Torma et al., 2015; Bartholy and Pongrácz, 2017; Kis et al., 2017), is typically performed by the comparison of the model results for the past and for the future, which means that the systematic model errors are not affecting the results in such a great extent. However, studies addressing the impacts of climate change on the natural environment, agriculture, society, economy, human health, etc. (Dosio, 2016; Hlásny et al., 2016; Giorgi, 2019; Jacob et al., 2020) usually need projected climate data for the future that is free from systematic errors. To satisfy this demand bias correction of climate model results has become a fundamental step before any impact modelling in scientific areas such as hydrology, ecology, biogeochemistry, forestry and agriculture (Teutschbein and Seibert, 2012; Casanueva et al., 2016; Meyer et al., 2019; Chen et al., 2020). The bias correction removes the systematic errors from climate model outputs based on the comparison of the simulation results and observations for a common period assuming that the model errors are stable in time (Ines and Hansen, 2006; Cannon et al., 2015; Cannon, 2018). At present, an increasing number of climate modelling teams are performing bias-correction using public domain RCM data. One major source of the raw RCM data is the CORDEX project (Yang et al., 2010; Gudmundsson et al., 2012; Coppola et al., 2021), which is widely known and exploited by the scientific community (Dumitrescu et al., 2022; Torma and Kis, 2022).

Some of the impact studies do not require daily meteorological data, but instead climatological averages for specific periods in the past and the future (Bobrowski and Udo, 2017). For such purposes, high spatial resolution datasets such as Climate-EU (Wang et al., 2016), ECLIPS (Chakraborty et al., 2021), CHELSA (Karger et al., 2016) and WorldClim (Fick and Hijmans, 2017) offer solutions by using the delta-change method (Moreno and Hasenauer, 2016). The projected climate change signals from GCMs or RCMs are downscaled by interpolation and then applied on a high-resolution observation-based map bypassing the need for bias correction. However, such datasets are not applicable for impact models that are driven by daily resolution data. They call for a consistent combination of observation-based data and RCM simulations that are free from systematic errors. The creation of such datasets is challenging since joining data from different sources could cause discontinuities and inconsistencies.

The availability of ready-to-use meteorological datasets, tailored for the needs of climate change impact modellers, is limited in Central Europe. To overcome the issues outlined above, the first version of the FORESEE (Open Database FOR ClimatE Change-Related Impact Studies in CEntral Europe) database was developed in 2015 (Dobor et al., 2015). The core logic of FORESEE is the seamless combination of freely available, observation-based, gridded historical datasets with projections, derived from available climate model results of selected RCMs.

The original FORESEE provided daily meteorological data for the Carpathian Basin covering the 1951–2100 period using results from 10 bias-corrected RCMs driven by the A1B scenario (Dobor et al., 2015). FORESEE has been continuously updated by extending the observation part. The FORESEE v3.2 (Kern et al., 2019) were the latest versions of the database that were constructed with the original concept. The new FORESEE v4.0 based on E-OBS v22.0e (Cornes et al., 2018) covers larger area with finer spatial resolution, while FORESEE-HUN v1.0 is based on a Hungarian dataset (HMS, 2022), therefore provides data only for Hungary. Both datasets include future projections based on RCP scenarios. Due to methodological refinements and the current user demands, the development of FORESEE is continuously evolving.

The main objectives of our study were (i) to present the new versions of the FORESEE datasets with a detailed description of the construction and methodological developments; (ii) to support climate model selection for impact studies by the detailed description of the FORESEE database; (iii) to quantify the expected future climate of the countries within the FORESEE domain using an ensemble approach; and (iv) to demonstrate the applicability of the ensemble method by estimating the expected climate change induced weather effect on winter wheat yield and the possible shift in the start of the growing season of Hungarian broad-leaved forests also addressing the representative model member selection.

Materials and methods

Construction of the FORESEE database

FORESEE was designed to provide freely available daily minimum temperature (T_{min}; °C), maximum temperature (T_{max}; °C) and precipitation sum (*Prec*; mm) data for the past based on observations and consistent bias-corrected climate projections for the future on a regular grid for the wide region of the Carpathian Basin (Dobor et al., 2015). Additional derived climate variables (see Materials and Methods) are also supplementing the database. Table 1. shows the summary of the FORESEE v4.0 and FORESEE-HUN v1.0 datasets.

Spatiotemporal coverage of the new FORESEE datasets

The FORESEE v4.0 provides data for 1951–2100, while FORESEE–HUN v1.0 provides data for 1971–2100. Compared to previous FORESEE database versions, the geographical coverage of the FORESEE v4.0 was extended (Fig. 1), encompassing the entire territory of 11 countries: Austria, Bosnia and Herzegovina, Croatia, Czechia, Hungary, Kosovo, Montenegro, Romania, Serbia, Slovakia, and Slovenia, and the majority of Moldova and Bulgaria. The FORESEE-HUN v1.0 contains data exclusively only for the area of Hungary.

Table 1
Characteristics of the new FORESEE datasets.

Dataset versions	FORESEE v4.0	FORESEE-HUN v1.0
Spatial coverage	41.5–51.5°N, 9.0–30.0°E	Hungary
Spatial resolution	0.1° × 0.1°	
Temporal resolution	Daily	
Basic variables	*Tmin* [°C], *Tmax* [°C], *Prec* [mm]	
MT-CLIM derived variables	VPD_{DL} [Pa], Rad_{DL} [W m^{-2}], T_{mean_DL} [°C], LD_{DL} [sec]	
Observation-based part		
Temporal coverage	1951–2020	1971–2021
Base dataset	E-OBS v22.0e	HUCLIM
Future projection part		
Temporal coverage	2021–2100	2022–2100
Model sources	EURO-CORDEX	
Number of model simulations	14	
Scenarios	RCP4.5 & RCP8.5	

Both datasets have a regular latitude/longitude (Gaussian) grid with 0.1° × 0.1° spatial resolution (hereafter referred to FORESEE grid). In the FORESEE v4.0 the target area is covered by 211 × 101 grid cells between 41.5–51.5°N and 9.0–30.0°E, consisting of 19 187 inland grid points. In the case of the FORESEE-HUN v1.0 the data are stored on a 69 × 31 regular grid between 45.7–48.6°N and 16.1–22.9°E, with 1233 grid points fully covering the area of Hungary. The reference geographic coordinate system of the stored data is WGS 84. The elevation dataset was obtained by resampling the Shuttle Radar Topography Mission (SRTM) Digital Elevation Database (DEM) v4.1 (Jarvis et al., 2008) to the FORESEE grid (Fig. 1).

Observation-based data

The observation-based part of the FORESEE v4.0 dataset covers the 1951–2020 time period, based on the daily E-OBS v22.0e dataset with 0.1° × 0.1° spatial resolution (Cornes et al., 2018). The downloaded T_{min}, T_{max} and *Prec* data (C3S, 2022) were spatially resampled using the SRTM elevation data to match the FORESEE grid (which is shifted by 0.05° × 0.05° relatively to the grid of the E–OBS database), based on the methodology of Kern et al. (2016).

In the case of FORESEE-HUN v1.0 the observation-based part (1971–2021) was constructed using the high-quality, gridded, daily HUCLIM dataset created and maintained by the Hungarian Meteorological Service (HMS, 2022). The HUCLIM database is constructed from the homogenized data of a dense meteorological observation network in Hungary with the method used in the construction of the CarpatClim database (Szalai et al., 2013). The gridded temperature fields in the HUCLIM dataset were created from the measurements of 55–112 stations, while in the case of precipitation data 500 stations were used (HMS, 2022). In contrast to this, E-OBS data are created including only 16 stations in Hungary (C3S, 2022). We downloaded T_{min}, T_{max} and *Prec* from the Open Data Policy service of the Hungarian Meteorological Service (HMS, 2022).

The FORESEE database was created to contain uniformly 365 days per year (i.e., no leap years). Accordingly, from both observation-based datasets the last days of the leap years were systematically removed. The rainfall amounts on 31st of December in the leap years were added to the previous day in order to preserve the hydrological balance.

Projected climate

The projected part (2021–2100 for FORESEE v4.0 and 2022–2100 for FORESEE-HUN v1.0) is represented by 14 bias-corrected RCM

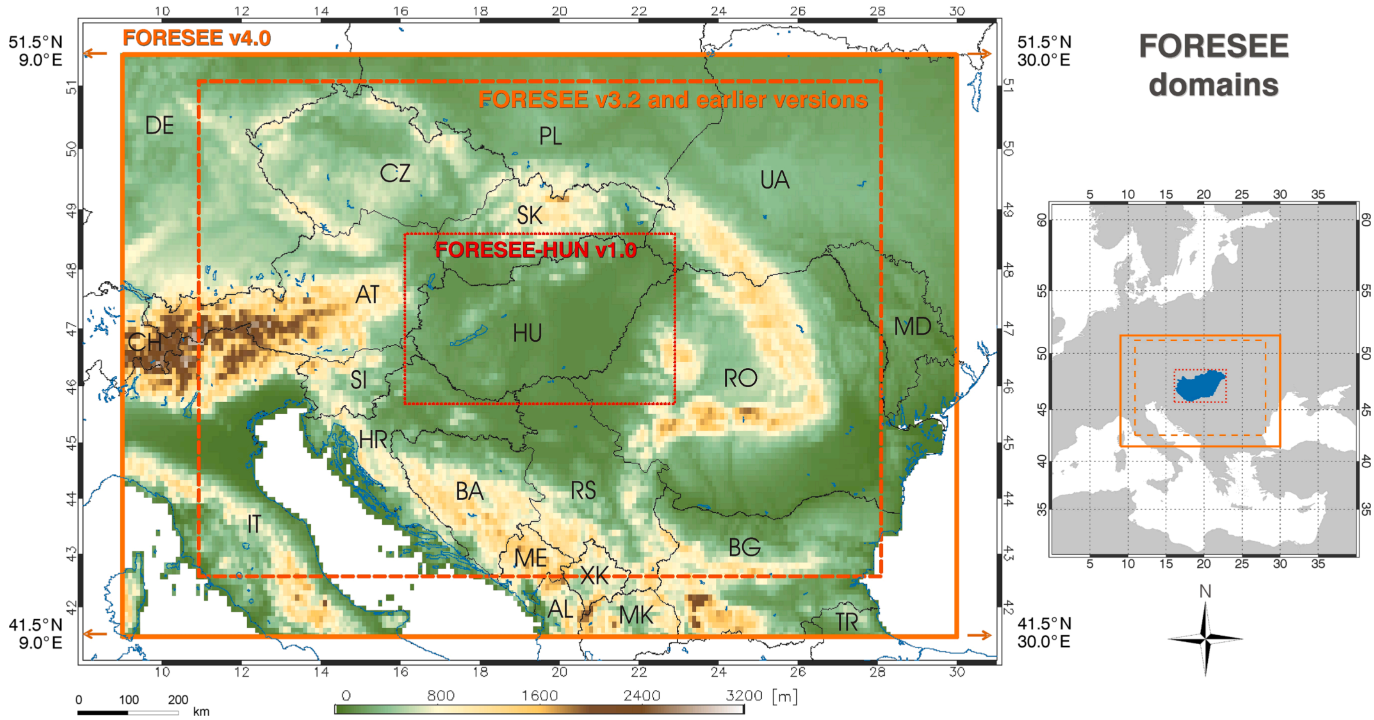

Fig. 1. Map of the spatial coverages of the different FORESEE datasets. Note that FORESEE-HUN v1.0 provides data only for Hungary. Topography is based on the resampled SRTM DEM data.

simulation results for two RCP scenarios (Table 2). We used RCM simulation (hereafter referred to as 'model') results from the EURO-CORDEX initiative (Jacob et al., 2014) driven by two different Representative Concentration Pathway (RCP) scenarios (RCP4.5 and RCP8.5). The model selection was based on the data availability of all 3 basic variables (T_{min}, T_{max}, *Prec*) with daily time-step for the selected RCP scenarios. The starting year of the projections in EURO-CORDEX is uniformly 2006, while the beginnings of the historical simulations are rather diverse (Table 2). The presented FORESEE datasets include projections from 2021/2022. We used projections during 2006–2020 to the baseline period of the bias correction (see below).

Leap years were handled similarly to the observation-based data. In the case of HadGEM2 model outputs (which contain data only until 2099, and only 360 days per year), the last 5 days in every year and the last year (2099) were repeated to create the uniform 365 days per year until 2100. In all cases, the original model data with $0.11^\circ \times 0.11^\circ$ spatial resolution were resampled to the target grid of $0.1^\circ \times 0.1^\circ$ using bilinear interpolation.

Bias correction

We used the cumulative distribution function (CDF) fitting technique (also known as quantile mapping, Ines and Hansen, 2006) at monthly level for each grid point in the target area (see Dobor et al., 2015 for details). Raw climate model data (T_{min}, T_{max} and *Prec*) have been bias-corrected using observations and RCM simulations for the 1971–2020 baseline period. E-OBS v22e was used as the observation-based reference in the case of the FORESEE v4.0, and HUCLIM in the case of the FORESEE-HUN v1.0. The climate model data for the baseline period (1971–2020) were constructed from two parts: the historical model runs for 1971–2005 and the first 15 years of the projections for 2006–2020, where the RCP scenarios were handled separately. The reason behind this combined application of the two simulation phases was 1) to use the longest available dataset for every model combination and 2) to include the last decades containing extreme meteorological events in the baseline period. The extension of the historical model dataset with the data of the projections is an accepted approach in the literature (Llopart et al., 2021), even in the case of the baseline periods of the bias correction (Räty et al., 2018).

The differences between the quantiles of the observation-based dataset and the historical model simulations during the 1971–2020 period were used to adjust the daily projected model results, assuming that the systematic biases of the models in the future are similar to the biases in the past. Temperature correction was based on the quantile differences, while precipitation correction started with the correction of the ratio of wet and dry days, followed by a scaling of the quantile's ratio (Dobor et al., 2015).

Precipitation frequency correction was done using the method introduced in Dobor et al. (2015). In the corrected dataset the precipitation frequency is consistent with the observations which is an added value of FORESEE.

To demonstrate the effect of the applied bias correction method at grid point level Fig. S1 in the Supplementary Material presents an example of the raw and corrected time series both for temperature (T_{max}) and precipitation, for a given grid point based on the yearly mean values.

Discontinuity correction of the temperature datasets

Due to the obvious change in the characteristics of different input datasets (change from observation-based data to projections) discontinuity might be present at the beginning of the projections. In order to eliminate the observed discontinuities in the temperature data series after the bias correction, we performed an additional *discontinuity correction* of the temperature datasets using the method proposed by Kis et al. (2020). In the case of FORESEE v4.0 the discontinuity correction was performed based on the mean monthly differences of the observation-based dataset during 2011–2020 and the projection data during 2021–2030. The corrections were applied for the whole projected part of the dataset (up to 2100), with linearly decreasing weight (see Fig. S1 in the Supplementary material), in order to reach (but not to change) the originally projected values by the end of the 21st century. Due to different periods of observational data, the baseline period of the discontinuity correction applied on FORESEE-HUN v1.0 was shifted by

Table 2
List of the model projections in FORESEE v4.0 and FORESEE-HUN v1.0 as combinations of GCM and RCM simulations.

Abbreviation	GCM	ENSEMBLE	RCM	Start year of the historical simulations
CNRM-CCLM	CNRM-CERFACS-CNRM-CM5	r1	CLMcom-CCLM4-8-17	1950
CNRM-ALADIN53	CNRM-CERFACS-CNRM-CM5	r1	CNRM-ALADIN53	1950
EC-EARTH-CCLM	ICHEC-EC-EARTH	r12	CLMcom-CCLM4-8-17	1950
EC-EARTH-RACMO22E-r12	ICHEC-EC-EARTH	r12	KNMI-RACMO22E	1950
EC-EARTH-RACMO22E-r1	ICHEC-EC-EARTH	r1	KNMI-RACMO22E	1950
EC-EARTH-HIRHAM5	ICHEC-EC-EARTH	r3	DMI-HIRHAM5	1951
HadGEM2-CCLM	MOHC-HadGEM2-ES	r1	CLMcom-CCLM4-8-17	1950
HadGEM2-RACMO22E	MOHC-HadGEM2-ES	r1	KNMI-RACMO22E	1950
MPI-CCLM	MPI-M-MPI-ES M-LR	r1	CLMcom-CCLM4-8-17	1950
MPI-REMO2009-r1	MPI- M-MPI-ES M-LR	r1	MPI-CSC-REMO2009	1950
MPI-REMO2009-r2	MPI- M-MPI-ES M-LR	r2	MPI-CSC-REMO2009	1950
NCC-HIRHAM5	NCC-NorESM1-M	r1	DMI-HIRHAM5	1951
CNRM-RCA4	CNRM-CERFACS-CNRM-CM5	r1	SMHI-RCA4	1970
IPSL-RCA4	IPSL-IPSL-CM5A-MR	r1	SMHI-RCA4	1970

one year both in the case of the observation-based dataset (to 2012–2021) and the projections (to 2022–2031).

Deriving additional variables using the MT-CLIM model

Ecological models used for climate change impact assessments typically need additional climate variables such as incoming shortwave solar radiation and some humidity-related quantity (e.g., Hidy et al., 2022). In order to retain intervariable dependencies as much as possible between the meteorological variables in the dataset, the additional variables were estimated based on the bias-corrected temperature and precipitation data directly. In this way, we assure that there is no inconsistency between precipitation, solar radiation and humidity, which is essential for impact modelling.

We used the Mountain Microclimate Simulation Model (MT-CLIM) v4.3 (Hungerford et al., 1989; Thornton and Running, 1999; Thornton et al., 2000) to estimate daylight (*DL*, from sunrise to sunset) average air temperature (T_{mean_DL}; °C), daylight average incoming shortwave radiative flux (in other words global radiation (RAD_{DL}; W m^{-2}), daylight average water vapour pressure deficit (VPD_{DL}; Pa), and the length of the day from sunrise to sunset (LD_{DL}; sec) consistently for the entire 1950–2100 period. MT-CLIM requires daily T_{min}, T_{max} and *Prec* values and site information such as latitude, elevation, slope, aspect, and angles to the east and west horizon at the target point. Given the relatively large pixel size, horizontal (flat) topography was assumed. Flat topography approximation is a common approach in the case of coarse resolution simulations with MT-CLIM (Bohn et al., 2013).

The correction for VPD and global radiation in arid conditions is implemented in MT-CLIM v4.3 using the method proposed by Kimball et al. (1997) in combination with the replacement of annual precipitation with the effective annual precipitation estimated from a 90-day window starting on the current day. A preliminary analysis indicated that the use of the aridity correction within the FORESEE domain results in sudden and widespread discontinuities in the derived global radiation and VPD data. Therefore, we decided not to use aridity correction due to the lack of justification for its applicability in our region.

Statistical evaluation of the FORESEE datasets

The methodology-related results are demonstrated only for Hungary as an example, based on the FORESEE-HUN v1.0 and RCP4.5. Note that presenting area-averaged results for the whole FORESEE v4.0 domain would be misleading due to the differences in the biases within the whole FORESEE domain.

In order to provide a general overview of the new FORESEE datasets, we present the projected changes at the pixel level in the form of maps and at the level of countries in aggregated form. The climate change signal is calculated as the difference between the observation-based datasets (for 1991–2020) and the bias- and discontinuity-corrected projections (for 2071–2100). The estimated future changes are presented in an ensemble (i.e., multi-model) framework quantifying percentiles and mean values, or individually by models for both FORESEE datasets and both scenarios (Tebaldi and Knutti, 2007). Temperature-precipitation diagrams are presented to easily visualize the expected changes in the basic climatic parameters. Those diagrams are also used to select representative model from the ensemble to support simplified impact assessment.

Applications of the FORESEE database

In order to demonstrate the possible applicability of the FORESEE database in an ensemble framework, two case studies are presented using the FORESEE-HUN v1.0 dataset. We also reflect on the issue of climate model selection.

Estimation of climate change effects on winter wheat yield

The first case study focuses on the adverse (or positive) weather effect on winter wheat production in Hungary. Here we focus exclusively on the pure effect of weather on the yield but not on the yield itself. The long-term yield trend is determined by introduction of new cultivars, agrotechnology and atmospheric carbon dioxide level (Marton et al., 2020), which is further modulated by the weather conditions for a given year that is called weather effect by farmers. The weather effect can be considered as the reason for the high-frequency fluctuation of the yield that is studied here.

The starting point for the analysis is a simple but robust linear model for the estimation of country-mean annual yields of winter wheat, based on the country-mean annual nitrogen fertilizer application (used as a proxy for the technological advancements that could explain the trend in the yield data), and monthly anomalies of selected meteorological variables (Kern et al., 2018). The meteorology-induced change in annual winter wheat yield was originally estimated based on the following model which was calibrated and validated for Hungary (Kern et al., 2018):

$$Yield = 1.557 + 0.041^{*}Fertil - 0.989^{*}\Delta T_{min5} + 1.208^{*}\Delta T_{max5} - 0.013^{*}\Delta VPD_5 \quad (1)$$

where *Fertil* is the country-mean annual amount of nitrogen fertilization (kg ha^{-1}), ΔT_{min5}, ΔT_{max5} and ΔVPD_5 are mean anomaly values of minimum and maximum temperature (°C), and VPD (Pa) in May, respectively. The reference period for the anomaly calculation was 2000–2016, in accordance with the period used by Kern et al. (2018) for calibration and anomaly calculation.

Eq. (1) is a simple additive model, where the effects of meteorology are not coupled with fertilization or any other variable for that matter.

This means that the effects of meteorological anomalies on the yield (the last three terms in Eq. (1) can be estimated independently from the assumptions made on fertilizer use (i.e., technological advancement proxy) and reflects only the effect of the weather. Given that the average of any meteorological anomaly in a reference period is zero by definition, the average of the meteorology-driven part of the yield model (Eq. (1) in the reference period is zero. Hence, the meteorology-induced change in the yield ($\Delta Yield_{Meteo}$) with respect to the reference period can be expressed as:

$$\Delta Yield_{Meteo} = -0.989^{*}\Delta T_{min5} + 1.208^{*}\Delta T_{max5} - 0.013^{*}\Delta VPD_{5} \tag{2}$$

We present the expected $\Delta Yield_{Meteo}$ relative to the reference period (2000–2016) in a 30-year moving average to visualize the effect of climate change. The standard deviations of the expected yield fluctuations due to the weather effects were also calculated in a 30-year moving window to quantify the interannual variability.

Estimation of the climate change effects on the start of season (SOS) in forests

In the mid-latitudes, the observed advance of the spring green-up (i.e., start of leaf-unfolding, expressed by the start of the season date, SOS) during the last decades is considered as a major indicator of global warming (e.g., Menzel et al., 2006; Cleland et al., 2007; Peaucelle et al., 2019). To estimate the possible changes in the SOS of the Hungarian broad-leaved forests in the future we applied a simple growing degree-day model optimized and validated for the Hungarian forests (Dávid et al., 2021). In this model, the SOS is estimated based on the cumulative growing degree-day (GDD), where GDD is the cumulative daily heat sum relative to a predefined base temperature (T_{base}). Accordingly, the estimated SOS is the calendar date (*day*) when the GDD standing from only positive daily mean temperature accumulations starting from the 1st of January exceeds a predefined forest-specific threshold value ($GDD_{threshold}$, Eq. (3)–(4):

$$GDD(day) = \sum_{i=1^{st}Jan}^{day} (T(i) - T_{base}), \text{if} T(i) > T_{base} \tag{3}$$

$$SOS = day \text{when} \, GDD(day) > GDD_{threshold} \tag{4}$$

where T is the daily mean temperature, T_{base} is 7 °C and $GDD_{threshold}$ is 112 °C days for the Hungarian forests (Dávid et al., 2021). With the presented GDD model we estimate changes relative to the baseline (1991–2020) period.

The calculation was focused on grid cells with at least 65% share of all broad-leaved forests based on the National Ecosystem Base Map dataset (Tanács et al., 2019; https://alapterkep.termeszetem.hu/), both for the historical and future projections.

Results

Model biases and their correction

At first, we compared the raw RCM results assuming the RCP4.5 scenario to the HUCLIM-based dataset for the reference period of the bias correction (1971–2020) for the Hungarian grid cells. The distributions of the differences between the observations-based data and uncorrected model results clearly show that the ability of the models to reproduce the past climate during the reference period is rather diverse (Fig. 2). The annual differences at grid cell level are in the range from −6.9 to 8.6 °C for T_{min}, from −7.1 to 10.3 °C for T_{max}, and from −1813 to 1195 mm for *Prec*. The model which is associated with the smallest mean deviation from the observations, both for T_{min} and T_{max}, is the IPSL-RCA4 (using Euclidian distance and mean annual deviations), while for *Prec* it is the MPI-REMO2009-r2.

The distributions of the annual differences between the corrected and the uncorrected values during 1971–2020 and 2022–2100 present the model-specific mean magnitude of the applied bias correction for

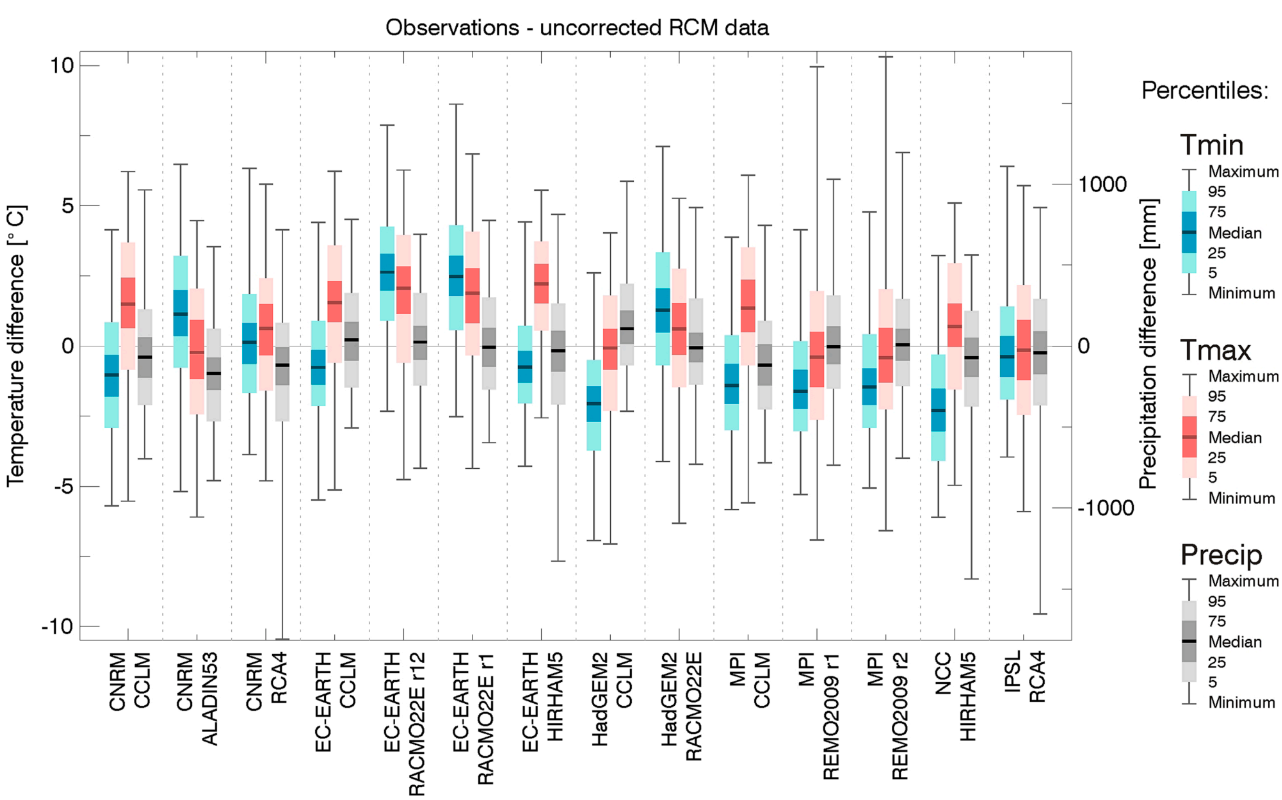

Fig. 2. Model-specific differences between the HUCLIM-based observations and the uncorrected RCM data for the annual T_{min}, T_{max} and *Prec* values at pixel level for 1971–2020, based on the RCP4.5 scenario.

Hungary (Figs. S2–S3). In accordance with Fig. 2, the model that is associated with the smallest bias in the absolute sense with respect to all three variables is ISPL-RCA4.

Next, we compared the Hungarian area-averaged data before and after the applied bias correction using thermopluviograms (i.e., temperature-precipitation diagrams) using mean T_{mean} and *Prec* values both for 1971–2000 and 2071–2100 (Fig. 3). Fig. 3a shows the scatter of the uncorrected models around the observation-based (i.e., reference) values, while Fig. 3b visualizes the same after bias correction. The raw historical model simulations show temperature and precipitation values in a range of 8.2–11.7 °C and 451–743 mm (Fig. 3a). The average T_{mean} and *Prec* of the model ensemble are 10.2 °C and 619 mm, respectively, showing that the ensemble mean T_{mean} is very close (0.1 °C) to the observed values, while the ensemble mean *Prec* deviates to some extent (37 mm). After bias correction, the standard deviation of the projections decreased and the consistency increased in terms of Euclidian distance in the thermopluviograms (Fig. 3c–d). For the period 1971–2000 the observed mean temperature in Hungary was 10.3 °C and the mean annual precipitation sum was 582 mm.

Based on the average monthly temperature differences between the observation-based dataset during 2012–2021 and the bias-corrected model data (assuming RCP4.5) during 2022–2031 without the discontinuity correction, most of the bias-corrected model results show considerably lower monthly temperature values during the period of 2022–2031 compared to the observations during 2012–2021. This indicates the clear need for discontinuity correction. The average monthly temperature differences are presented in the Supplementary Material, separately for T_{min} and T_{max} (Fig. S4).

Observed and projected climate changes based on the FORESEE v4.0 dataset

The observation part of the FORESEE datasets provides strong evidence of the ongoing climate change. Considering the observed changes for 1991–2020 relative to 1971–2000, the investigated countries show a 0.79–1.06 °C mean increase in T_{mean} and −1.3 mm to + 76.9 mm (–0.1% to + 7.9%) change in *Prec* (Table S1–S3) based on FORESEE v4.0. The Hungarian mean annual temperature and precipitation sum increased by 0.91 °C and 21.6 mm (4.3%), respectively.

The spatial distribution of the projected ensemble mean changes in T_{mean} and *Prec* for 2071–2100 relative to the 1991–2020 baseline period indicate substantial differences between the RCP4.5 and RCP8.5 scenarios for the temperature, but less for the precipitation (Fig. 4 and Fig. S5–S6). The projected mean temperature change shows a pronounced elevation gradient (compare Fig. 1 and Fig. 4) with the highest projected increase in the Alps, the Carpathians, and the Balkan mountains (see also Pepin et al., 2015). The projected precipitation change shows a sharp north–south gradient, with a projected increase in the

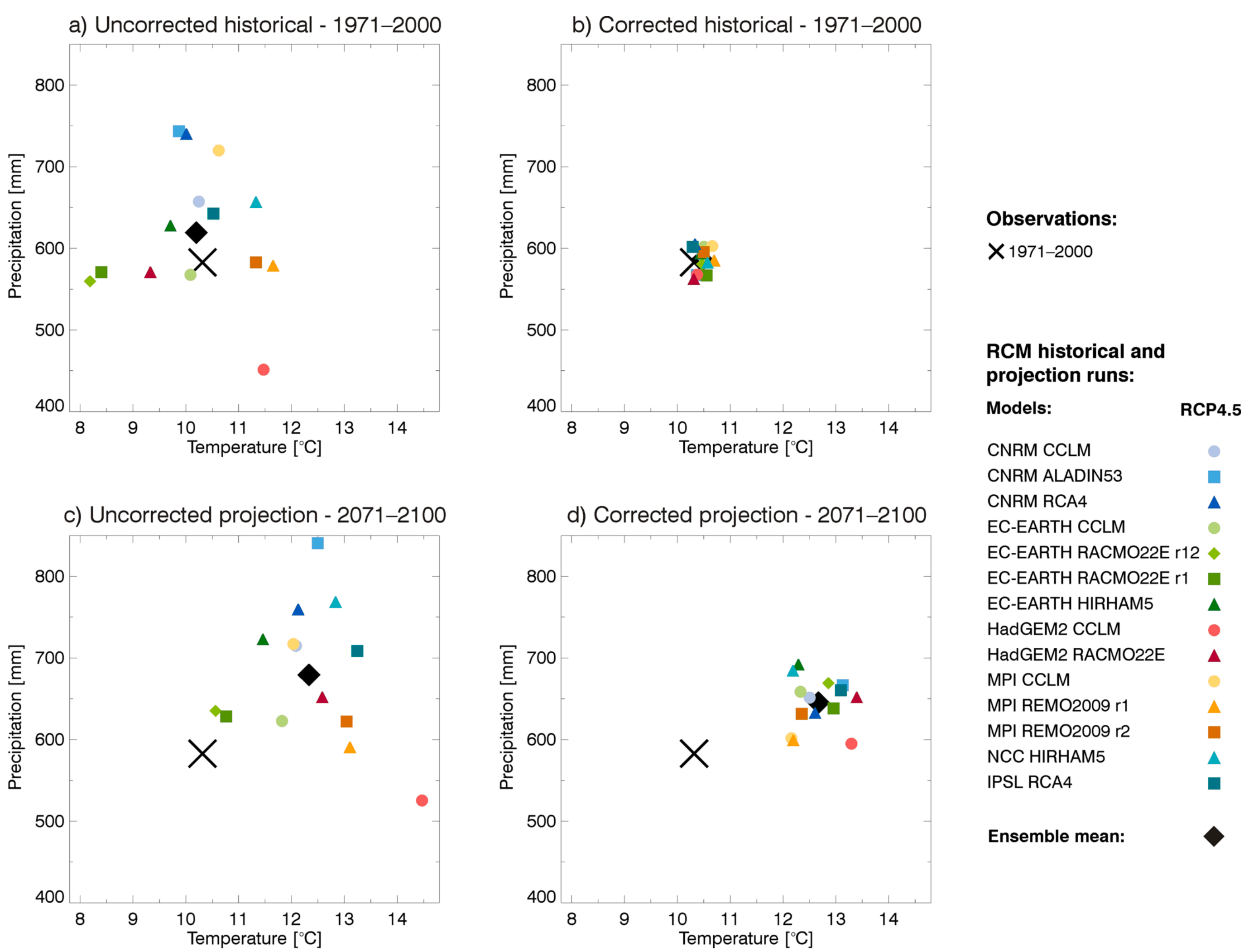

Fig. 3. Thermopluviograms for Hungary based on mean T_{mean} and *Prec* values calculated from the original uncorrected and bias-corrected model runs for 1971–2000 (a and b), and also for 2071–2100 (c and d), based on FORESEE-HUN v1.0 and the RCP4.5 scenario. (Note that the investigated past period differs from the period used for Fig. 2).

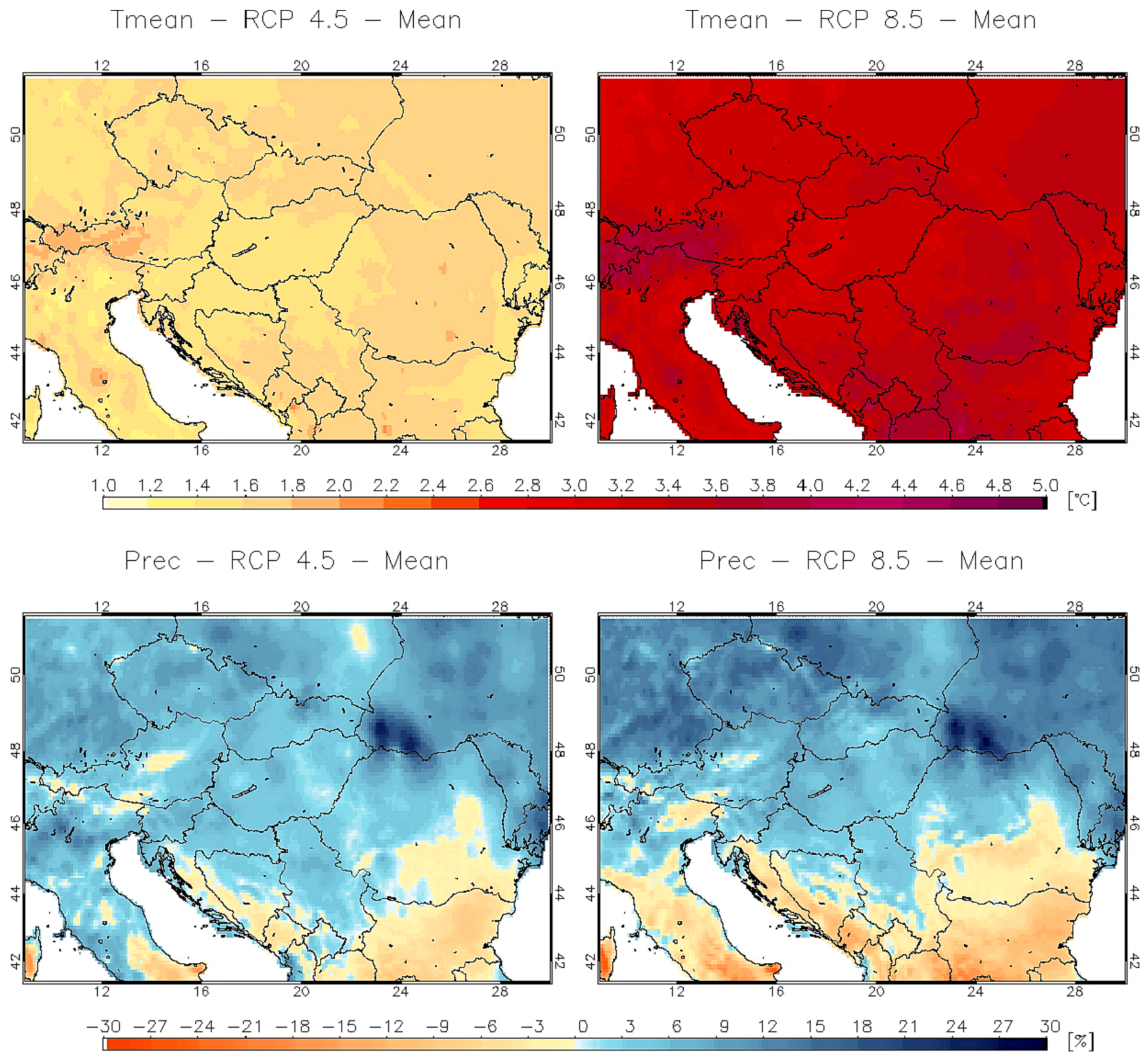

Fig. 4. Maps of the projected long-term mean changes in T_{mean} (expressed in °C, upper row) and *Prec* (expressed in %, bottom row) for the period 2071–2100 relative to the baseline of 1991–2020, calculated as the multi-model mean of the 14 model simulations based on FORESEE v4.0 both for RCP4.5 and RCP8.5.

northern areas and a decrease in the southern areas (Fig. 4). The spatial differences are even more pronounced in the case of the projected seasonal changes (Fig. S7–S10).

Country-specific thermopluviograms are presented in Fig. 5 using the full ensemble. The figure demonstrates that we can identify models which appear to be "coldest", "warmest", "driest" or "wettest", but not unanimously for all of the countries. The thermopluviogram visualizing all countries together (Fig. S11) enables the comparison between different countries, revealing the differences in the observed changes in the past and those projected for the future.

For the application of impact models the thermopluviograms provide essential information supporting model selection (see e.g., Hlásny et al., 2016; Lutz et al., 2016). The end-user might want to select the "wettest"/"driest" model, or the "warmest"/"coldest" and the one that is close to the ensemble mean to save computational time but still capture the range of variability and support uncertainty estimation. The model that is closest to the multimodel mean is usually considered as the one representing the whole ensemble with the most likely trajectory.

Although the climates of the individual countries are rather complex due to their geographical location and diverse orography, a decrease in the projected mean precipitation with latitude can be observed (Fig. 6). For most of the countries the distribution of models' T_{mean} has a negative skew (indicating that some models project exceptional high increase), while *Prec* shows a positive skew (indicating that some models project exceptional high decrease). The RCP4.5 ensemble-mean change of annual T_{mean} for 2071–2100 relative to the 1991–2020 baseline period is projected to be between 1.5 °C (Kosovo) and 1.7 °C (Slovenia), while in the case of precipitation projections of the countries show a more diverse mean change between 1.6% decrease (Montenegro) to 6.9% increase (Czechia). The projected seasonal, country-specific changes are shown in Fig. S12–S13, while the multi-model statistics of the projected changes in *Prec*, T_{min}, T_{max}, and T_{mean} for Hungary are given in Table S4 in the Supplementary Material.

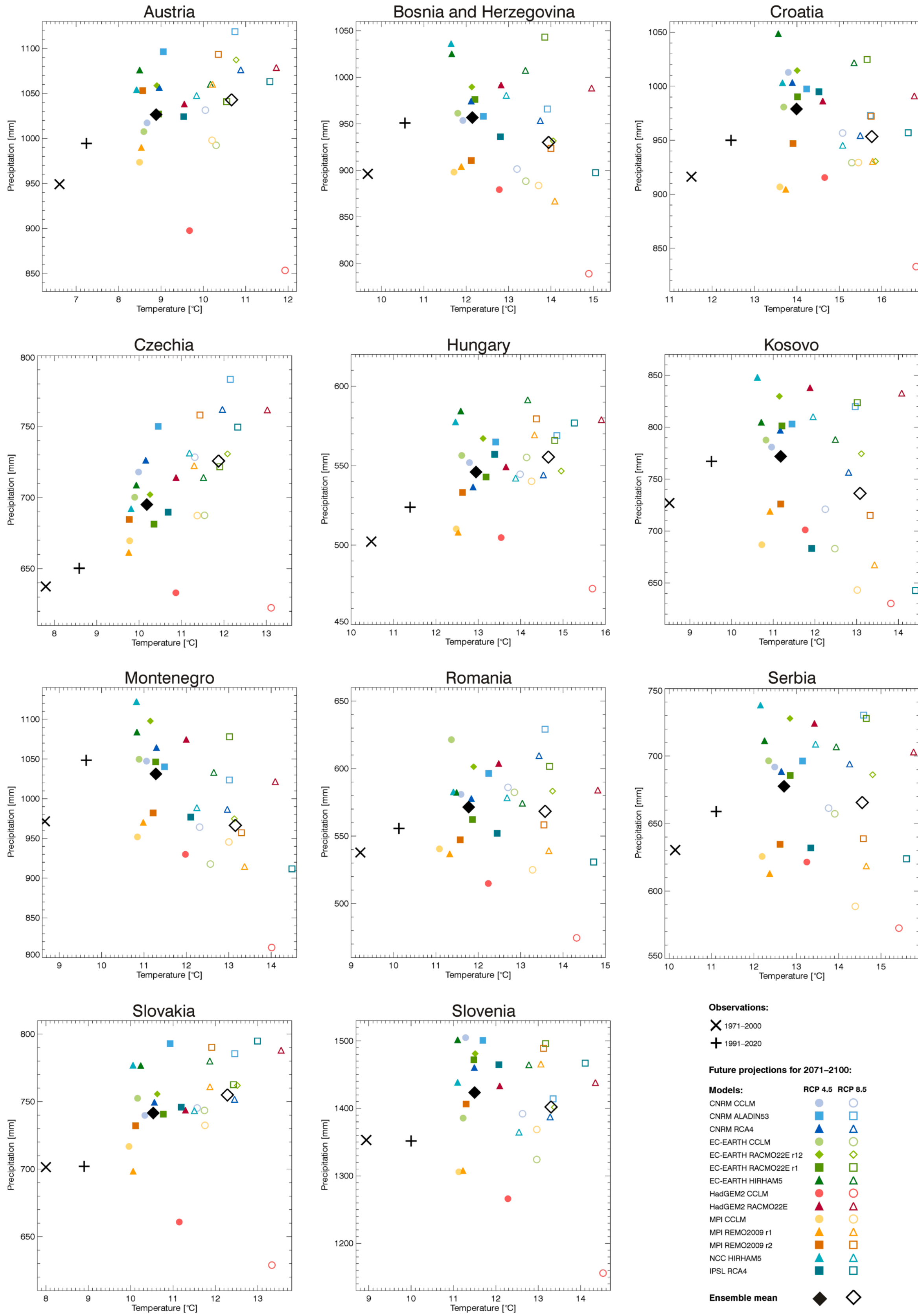

Fig. 5. Thermopluviograms of the observation-based (1971–2000 and 1991–2020) and projected (2071–2100) annual T_{mean} and *Prec* values of the different countries, separately for RCP4.5 (filled symbols) and RCP8.5 (empty symbols) scenarios.

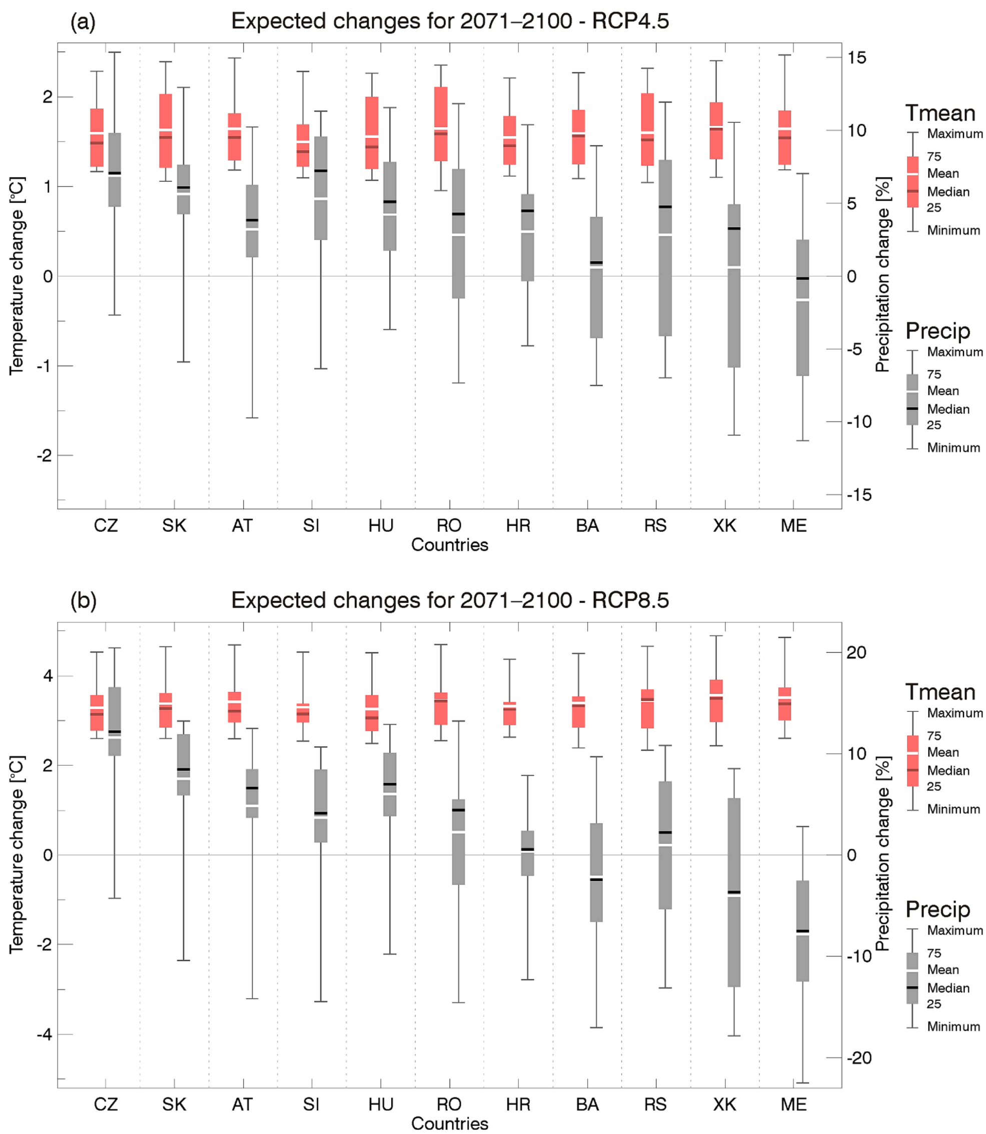

Fig. 6. The projected ensemble statistics of the changes in the country-averaged T_{mean} [°C] and *Prec* [%] during 2071–2100 relative to the 1991–2020 baseline period for the different countries, based on the 14 model projections of FORESEE v4.0, for the RCP4.5 (a) and RCP8.5 (b) scenarios.

Past and projected changes based on FORESEE-HUN v1.0 dataset

FORESEE-HUN v1.0 shows higher area-averaged long-term annual *Prec* (+92 mm), and lower T_{min} (–0.6 °C) for 1991–2020 as compared to FORESEE v4.0 due to the differences between the datasets used in their creation (see Methods). The mean difference for T_{max} is negligible (Fig. S14 and Table S5). Considering the spatial distribution of the differences *Prec* is higher and T_{min} is lower in FORESEE-HUN v1.0 than in FORESEE v4.0 in the majority of the country, while the differences in T_{max} show a diverse pattern (Fig. S14).

Based on the FORESEE-HUN v1.0 database both the Hungarian mean annual temperature and precipitation increased from 1971–2000 to 1991–2020 by 0.78 °C and 33.6 mm (5.8%), respectively (Fig. 7 and Table S6–S7). The ensemble mean of the 14 models projects further warming and an increase in precipitation by the end of the century (2071–2100). The projected long-term mean changes in annual T_{mean} are 1.6 °C (RCP4.5) and 3.2 °C (RCP8.5), and in the annual *Prec* are 4.7% (RCP4.5) and 7.1% (RCP8.5) relative to the baseline period (1990–2020) (Fig. 7 and Table S8). While the long-term mean T_{mean} shows an overall increase in the whole country (Fig. S15), in the case of precipitation the changes are not uniform spatially for all models (Fig. S16).

Considering seasonal changes based on the ensemble mean signal (Fig. 8 and Table S8), the greatest increases in monthly T_{mean} are expected in winter with 2.1 °C (RCP4.5) and 4.0 °C (RCP8.5), while the lowest are expected in summer with 1.3 °C (RCP4.5) and 3.3 °C (RCP8.5). The greatest mean *Prec* changes are expected in winter with 13.6% (RCP4.5) and 24.1% (RCP8.5), while the greatest decreases are expected in the case of RCP4.5 during autumn with −0.4%, and in the case of RCP8.5 during summer with −5.5% (Fig. 8 and Table S8). The direction of the projected ensemble mean seasonal temperature change is uniform for the whole country in all seasons (Fig. S17–19), while the precipitation projections show a uniform increase only during winter and spring (Fig. S20).

The projected seasonal changes in T_{mean} and *Prec* are similar for FORESEE-HUN v1.0 and FORESEE v4.0 (see Table S4), while in the case of the annual values there are slight differences (Table S8).

Changes in the projected monthly T_{mean} and *Prec* data at the country level reveal a high variability between the models for 2071–2100 relative to the baseline period (1991–2020), with up to 3.9 °C (RCP4.5) and 6.2 °C (RCP8.5) monthly T_{mean} increases, and −35% to + 46% (RCP4.5) and −63% to + 56% (RCP8.5) *Prec* changes. Concerning seasonal

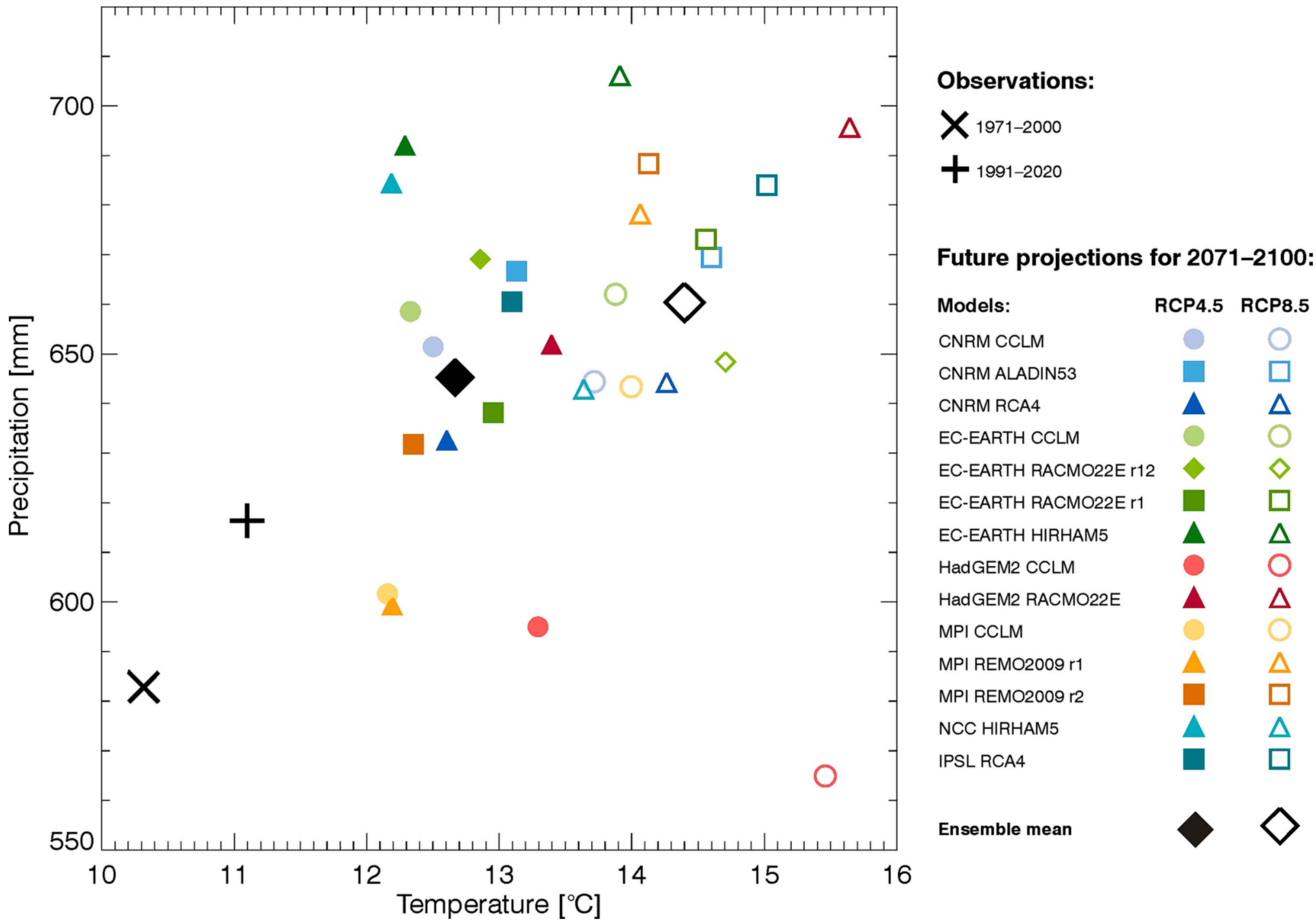

Fig. 7. Thermopluviogram of the Hungarian (area-averaged) climatological means for 1971–2000 and 1991–2020 (black × and + signs, respectively), and for 2071–2100 based on 14 model projections of FORESEE-HUN v1.0 indicated with filled (RCP4.5) and empty (RCP8.5) coloured signs.

patterns, there is no obvious "cold" or "warm", and "dry" or "wet" model throughout the year, but HadGEM2-CCLM can be considered as the "warmest" and the "driest" during summer (Fig. 8). Projected changes in the precipitation frequency based on the mean number of rainy days also present a strong monthly variability with an apparent annual cycle (Fig. S21), where the changes in the monthly mean number of rainy days (when daily precipitation is > 2 mm) range from −40% to + 35% (RCP4.5) and –60% to + 37% (RCP8.5) for 2071–2100.

The application of FORESEE-HUN v1.0 for impact studies

Weather-induced variability in winter wheat yield

Fig. 9 shows the simulated winter wheat yield losses/gains separately for the RCP4.5 and RCP8.5 scenarios. The annual values of the modelled weather effect are also shown for the past, to illustrate the real interannual variability (for the future it is not shown for clarity but instead its variability is plotted in Fig. 9c and 9d). The results suggest tendentious changes in the weather-induced yield variability with a higher negative trend after 2040 (Fig. 9a and 9b). For 2071–2100 this would result in a mean (median) of 0.65 (0.58) t ha^{-1} and 1.22 (1.07) t ha^{-1} yield loss. Note that during 2000–2016 the mean yield was 4.22 t ha^{-1} (HCSO, 2022). The variability of the weather effect between the years (Fig. 9c and 9d) is likely to increase after 2055 and 2051 for RCP4.5 and RCP8.5, respectively, meaning higher interannual variability from 2026 (RCP4.5) and 2022 (RCP8.5). Note that the sudden drop in the standard deviation in 2033 (2004–2033) is the result of the extremely low modelled yield in 2003 (affecting the moving average), due the well-documented heat-wave event in Europe (Ciais et al., 2005).

Focusing on RCP4.5, the results driven by IPSL-RCA4 and MPI-CCLM gave the closest results to the ensemble mean during 2071–2100 (using absolute deviations as metrics). These models are not the ones that are closest to the ensemble mean based on annual T_{mean} (that is CNRM-RCA4; see Fig. 7) where MPI-CCLM is even one of the "coldest" models. In the case of RCP8.5, EC-EARTH-RACMO22E-r1 provides yield loss/gain results that are closest to the ensemble mean during 2071–2100, and it can be considered as an average model based on T_{mean} (but the model that represents the multi-model mean for T_{mean} is CNRM-RCA4). On contrary, the "warmest" models (HadGEM2-CCLM and HadGEM2-RACMO22E) correspond to the greatest negative weather effects. Based on the thermopluviogram the NCC-HIRHAM5 is the coolest model while the most optimistic model results in term of yield loss are provided by EC-EARTH-HIRHAM5. The order of the models with respect to the weather-induced effect on crop yield and the thermopluviogram-based mean T_{mean} increases are not in full agreement.

Expected changes in the timing of start of the growing season

The estimated mean (median) advance of the SOS for 2071–2100 is 9.1 (9.1) and 19.8 (17.3) days for RCP4.5 and RCP8.5 scenarios, respectively, with a range of 3.0–15.0 and 12.5–27.4 days, respectively (Fig. 10). The mean trend is −1.14 and −2.16 days decade^{-1} for RCP4.5 and RCP8.5, respectively.

Focusing on the model selection issue the "coldest" model for RCP4.5 (MPI-CCLM, based on the long-term mean T_{mean}; Fig. 7) is associated

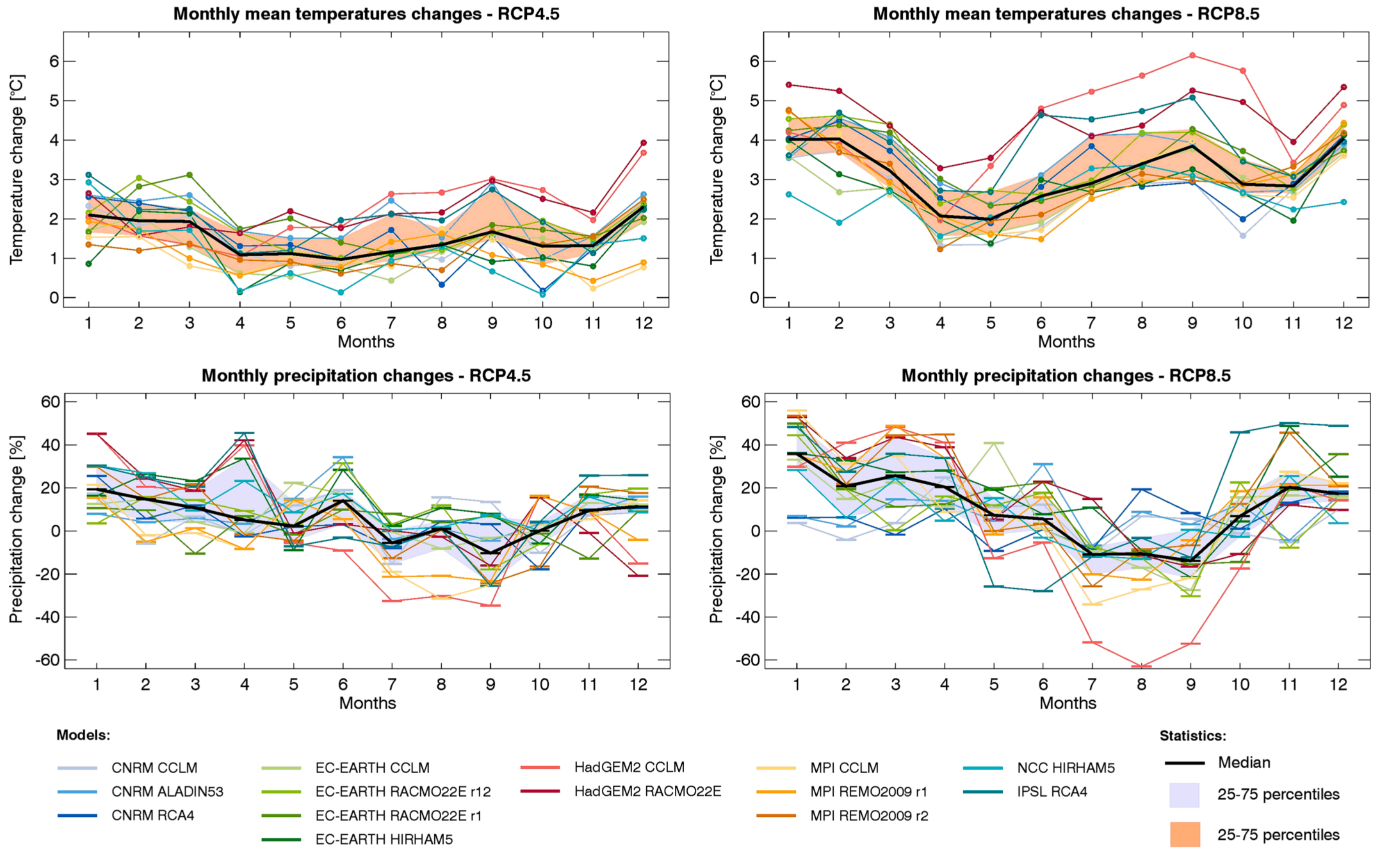

Fig. 8. Changes in monthly T_{mean} and *Prec* for 2071–2100 for the different models relative to the observation-based dataset (1991–2020), based on the RCP4.5 (left) and RCP8.5 (right) scenario (FORESEE-HUN v1.0).

with the smallest advance in SOS (–3.0 days) for the second half of the century. The “warmest” model (HadGEM2-RACMO22E) is not associated with the greatest advance in the SOS (it is associated with −10.5 days shift), but instead the SOS results driven by CNRM-ALADIN53 show the highest shift. CNRM-RCA4 is the closest to the multimodel mean in terms of the thermopluviograms but it is not the one that is closest to the multimodel mean by the end of the century (it is EC-EARTH-HIRHAM5). Based on RCP8.5 projections only the “warmest” model is associated with the greatest change in SOS for 2071–2100 (HadGEM2-RACMO22E), while the coldest model does not correspond to the smallest advance in SOS (NCC-HIEHAM5 using the climate data versus EC-EARTH-CCLM using the SOS results). The representative model for the multimodel-mean temperature changes (CNRM-RCA4) is not the one that provides results closest to the multimodel mean SOS change (HadGEM2-CCLM).

Discussion

Database construction

Although RCMs are continuously improved (Giorgi, 2019), inherent biases are still present in the simulation results. In spite of the fact that bias correction techniques are criticized by some researchers (e.g., Ehret et al., 2012), no reasonable simulation results can be expected by impact models if they are driven by uncorrected climate model results (Teutschbein and Seibert, 2012). Temperature thresholds and tipping points are present in some impact models which means that uncorrected climate data may lead to distorted simulation. Note that, alternative solutions are also proposed by some researchers in hydrology, that include the post-processing of the impact model results instead of the input climate data (Chen et al., 2021), but this is not applicable in other disciplines where the processes are sensitive to the absolute value of the given climate variable.

To avoid issues related to the continuity and interpretability of impact model results based on the temperature for the near future, a so-called discontinuity correction was applied in this study. The sharp discontinuity after 2000 (Fig. S1) is associated with the unexpectedly strong warming in the region that was not represented well by the models in the target domain. To the knowledge of the authors, discontinuity-related issues are not addressed during the construction of similar datasets. Forthcoming studies might use alternative discontinuity correction methods instead of the applied one that is based on linearly decreasing weight by time.

The difference between the FORESEE v4.0 and FORESEE-HUN v1.0 in precipitation (Fig. S14 and Table S5) points to the local limitations of the E-OBS dataset and the importance of the national meteorological networks of observational stations. Open data policies, such as those of the European Union (Directive, 2007/2/EC, Directive 2019/1024/EU), promote data sharing which is essential in the continuous improvement of the observation-based gridded meteorological datasets. A denser observation network contributes to a more realistic gridded datasets, but in the same time it affects the bias correction (Casanueva et al., 2020) with the consequence that the corrected future climate projections also become more accurate.

The added value of FORESEE is the dissemination of radiation- and humidity-related variables. Observation-based, gridded datasets for radiation and humidity are available for potential use, which means that theoretically they could be included in FORESEE. Moreover, RCMs also quantify radiation and humidity which could be used in the projections. However, the implemented bias correction method would inevitably violate the physical consistency between the basic meteorological variables (Dobor et al., 2015), which would hamper the applicability of

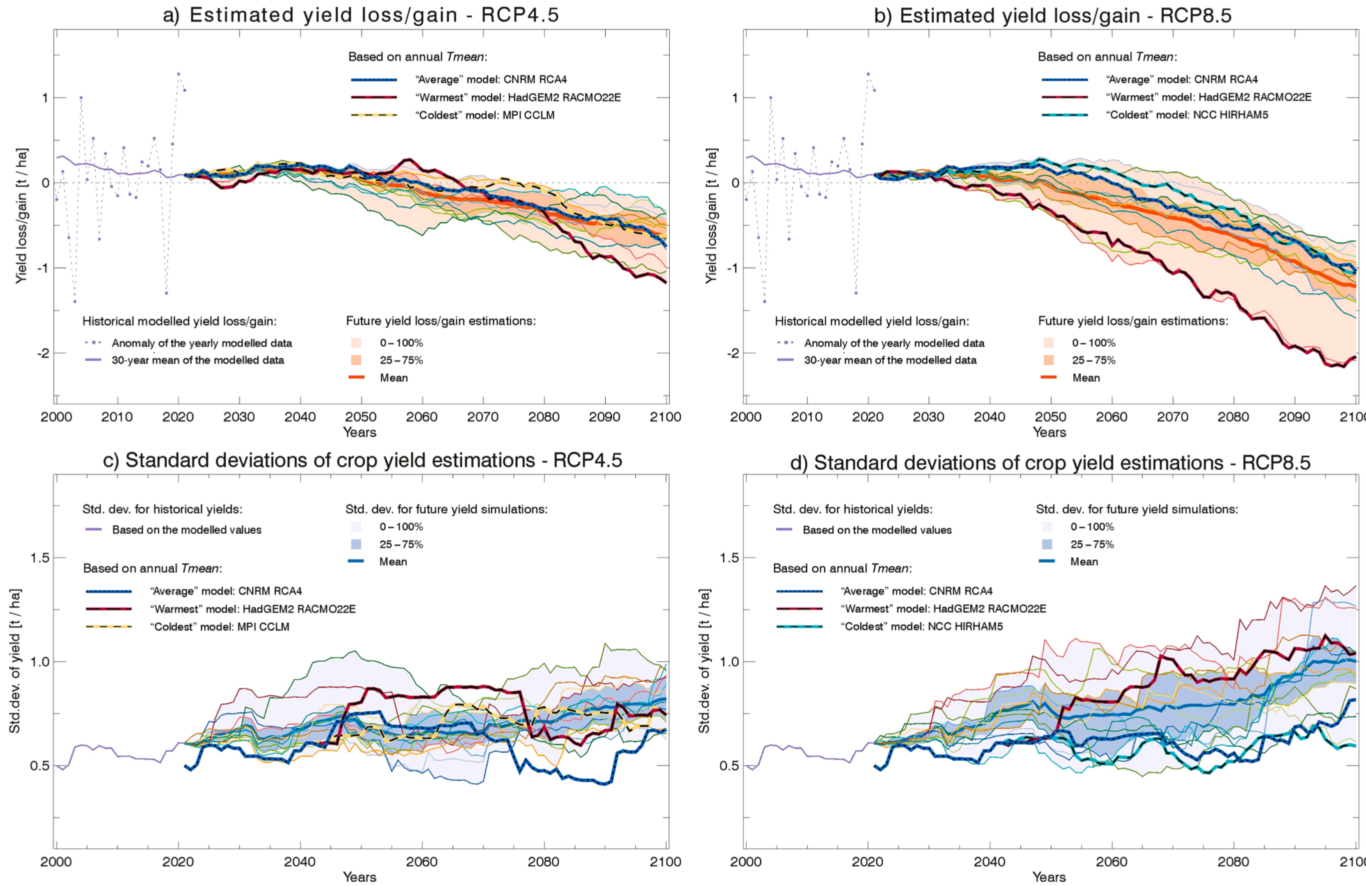

Fig. 9. Simulated climate change-induced shift in the long-term weather effect on winter wheat yield relative to the baseline period (2000–2016) based on RCP4.5 (a) and RCP8.5 (b) scenarios of FORESEE-HUN v1.0. Solid lines indicate 30-year moving averages, where data shown for a given year corresponds to the average yield loss/gain from the previous 30 years. The anomaly of the yearly observed values are also indicated for the period 2000–2021 for illustration. The coloured lines show the individual models, where the colours are in accordance with Figs. 7–8. The corresponding standard deviations of winter wheat yield are also indicated based on RCP4.5 (c) and RCP8.5 (d) scenarios of FORESEE-HUN v1.0.

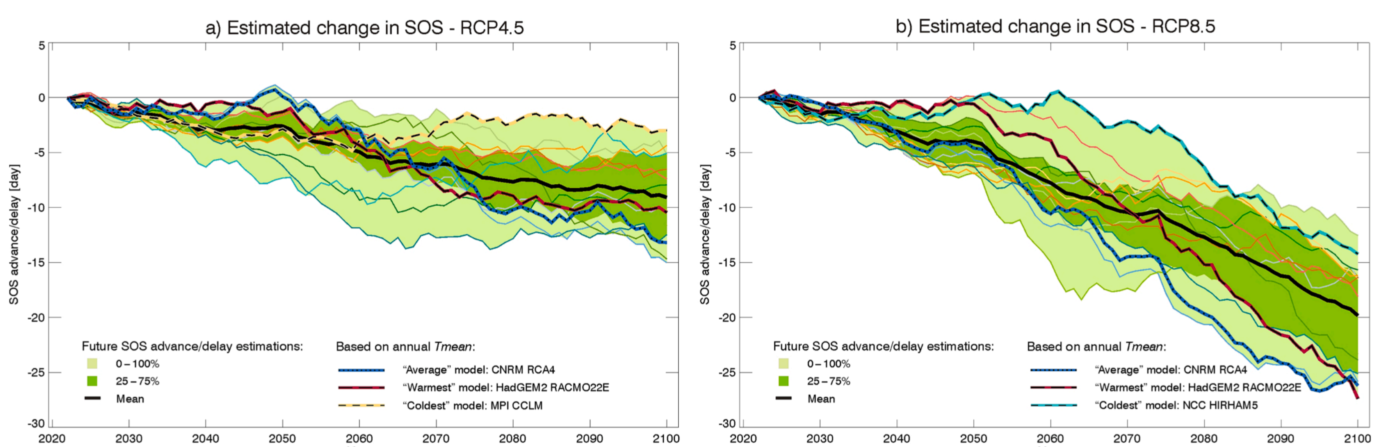

Fig. 10. Estimations of the changes in SOS until 2100 relative to the baseline period (1991–2020) based on RCP4.5 and RCP8.5 scenarios. Solid lines indicate 30-year moving averages of the past 30 years. The coloured lines show the individual models, where the colours are in accordance with Figs. 7–8.

those data. To address this issue we used the MT-CLIM model for the estimation of incoming shortwave radiative flux and VPD. The MT-CLIM is a useful model, but due to the used parametrization, its proper usage might need further elaboration and improvements. Re-evaluation of the aridity correction in MT-CLIM 4.3 would be useful for the areas with increased seasonal aridity. Beyond the issue related to the aridity correction, we also noted possible problems with the global radiation underestimation in coastal areas. The comparison of historic solar radiation in the coastal area of Croatia (Zaninović et al., 2008) with the MT-CLIM estimates reveals underestimation in MT-CLIM. This is in line with the known negative bias in MT-CLIM in coastal regions (Bohn et al., 2013).

The projected climate for Hungary based on different datasets

Several previous studies estimated the projected changes in T_{mean} and *Prec* for Hungary for the end of the 21st century at annual and/or seasonal level, based on the A1B, A2 and B2 scenarios (e.g., Bartholy et al., 2010, 2011; Torma, 2011), and also based on the RCP4.5 and RCP8.5 scenarios. Bartholy and Pongrácz (2017) reported 2.5 °C (RCP4.5) and 5.3 °C (RCP8.5) increases in T_{mean} for 2081–2100, relative to 1981–2000. Bán et al. (2021) reported 2.9 °C (RCP4.5) and 4.0 °C (RCP8.5) increase in annual T_{mean} for 2071–2100, as the mean of 26 models, while Megyeri-Korotaj et al. (2022) got 1.5 °C and 2.9 °C (RCP4.5) and 3.5 °C and 4.0 °C (RCP8.5) increase, based on two models. These studies used 1971–2000 as the reference period. Taking into account the 0.8 °C (FORESEE v4.0) and 0.7 °C (FORESEE-HUN v1.0) differences between 1971 and 2000 and 1991–2020 reference periods as ΔT_{Ref}, and 0.9 °C (FORESEE v4.0) and 0.8 °C (FORESEE-HUN v1.0) differences between 1981 and 2000 and 1991–2020 (see Table S1–S2 and S6–S7), our results of (multi-model mean) 1.6 °C + ΔT_{Ref} (RCP4.5) and 3.2 °C + ΔT_{Ref} (RCP8.5) (Table S4 and S8) increases are in accordance with the previously published RCP-based results.

The projected changes of annual *Prec* for 2071–2100 are between −5% and 16% (RCP4.5) and 0–24% (RCP8.5) based on the above-mentioned three RCP-based studies. Our results indicate an overall increase of 4.2% (RCP4.5) and 6.0% (RCP8.5) based on FORESEE v4.0 (Table S4), and 4.7% (RCP4.5) and 7.1% (RCP8.5) based on FORESEE-HUN v1.0 (Table S8), where the increase between the reference periods ($\Delta Prec_{Ref}$, see Table S1–S2 and S6–S7) contributes to an additional 4.3% and 5.8% increase, respectively, for the two FORESEE datasets.

Considering the seasonal changes, most of the previous studies reported a higher increase in T_{mean} for the summer than for the winter (Christensen, 2005; Bartholy et al., 2010, 2011; Torma, 2011; Bartholy and Pongrácz, 2017). On the contrary, the latest studies based on RCP scenarios (Bán et al., 2021; Megyeri-Korotaj et al., 2022) indicate a higher mean increase for Hungary during winter, which is in agreement with our results (Table S4 and S8). In the case of *Prec* the seasonal distribution of the projected precipitation (Table S4 and S8) corresponds to the results of the previous RCP-based studies. Note that, more comprehensive assessment of EURO-CORDEX projections reported significant differences in precipitation signals at a seasonal scale (Coppola et al., 2021).

Presented applications with emphasis on model selection

In the present study we demonstrated the application of the FORESEE database by coupling the dataset with two simple impact models. We need to stress here that FORESEE is a ready-to-use dataset for impact studies, which means that the end-users only need to download the data and pre-process it for application, with no additional steps.

Annual crop yields strongly depend on the ongoing meteorological conditions and there is an indication that some of the crop types grown in a given region will be negatively affected by future climate change (Asseng et al., 2013; Bassu et al., 2014; Liu et al., 2016). Considering the estimations of weather-induced variability of future winter wheat yield our results of the ensemble simulations based on the ensemble of 14 RCM simulations were negative. We need to emphasize that *this does not necessarily mean a real decrease in the overall winter wheat yield*. Improving agrotechnology (introduction of new cultivars, use of mineral fertilizers, pesticides/herbicides and improving machinery), and also increasing level of atmospheric CO_2 concentration is expected to increase the overall winter wheat yield. Therefore, it is important to recall that the presented results shown in Fig. 9 reflect only the impacts of the meteorological variables. Nevertheless, the consistency of the ensemble results gives confidence that the impact of climate change on the winter wheat yield in Hungary will be negative and considerable. This is an important message as the predicted decline in crop yield caused by the changing weather has to be compensated with the same magnitude by the positive effects (improved agrotechnology, introduction of new cultivars and CO_2 fertiliziation effect).

Without the high number of RCMs included in FORESEE it would be hard to estimate this trend with confidence which emphasizes the need for a large ensemble of climate projections. Note that some stress effects (e.g., heat stress during anthesis or soil water content deficit related stress) are not captured by the model due to the simplicity of the used model. This kind of simplification is inevitable but should be considered in future studies.

Our SOS-related results are in accordance with previous studies both based on observations and future predictions. Xia et al. (2015) gave an estimated 11.3 and 21.6 days advance in SOS for the Northern Hemisphere for 2080–2099 relative to 1985–2004 based on RCP4.5 and RCP8.5 scenarios, respectively (corresponding to a mean trend of −1.21 and 2.27 days decade^{-1}, respectively). However, studies about the observed phenological shifts revealed a strong dependency on the studied period and geographical location (e.g., Stöckli and Vidale, 2004; Jeong et al., 2011; Wang et al., 2015). For the broad-leaved forests of the Northern Hemisphere Zhao et al. (2015) reported a mean trend of −2 days decade^{-1} over 1982–2013.

Model selection is an issue that is inevitable when the resources of a user do not allow for the full exploitation of FORESEE. Our results demonstrated that the selection of climate models (as representative models) to estimate the multimodel mean and the most optimistic/pessimistic scenarios based on the traditional climate variables (annual T_{mean} and/or *Prec*) might not be suitable in impact studies and, as it can be misleading, it should be avoided (see e.g., Hlásny et al., 2016). It means that the full uncertainty of the simulations cannot be captured by naive model selection. This finding might be associated with the projected diverse intra-annual T_{mean} and *Prec* changes of the models (Fig. 8). Clearly, the results of the impact models depend on the intra-annual variability of the meteorological conditions, and also in some cases on multiple variables, which explains this finding. This suggests that other metrics might be proposed to support representative model selection for climate change related impact studies. Nevertheless, at present full exploitation of all ensemble members from the climatic databases is the suggested method to avoid improper representation of the uncertainty.

Given the high number of RCM models in FORESEE (14 for RCP4.5 and RCP8.5) the ensemble-based, probabilistic approach is the recommended method both for the estimation of the climate change signal and the impact models (Stephens et al., 2012). Uncertainty quantification is an essential step together with consistency check of the results in terms of the direction of change per impact model (e.g., overall increase or decrease). The ensemble of the results enables the calculation of probability density functions (PDF; Tebaldi and Knutti, 2007) for impact assessment and decision-making. Further involvement of risk assessment information can improve and extend the applicability of the impact models (Conway et al., 2019).

Conclusion

The updated FORESEE database has two major components, namely FORESEE v4.0 and FORESEE-HUN v1.0, which can serve studies at different scales in diverse disciplines in Central Europe. Interests in FORESEE during the past years indicated the added value of the construction of this public database. The differences between the two new datasets emphasize the importance of the national datasets and the dissemination of observations from dense meteorological networks. The major improvements of the FORESEE database included the 14 new projections based on RCP4.5 and RCP8.5, the construction of the FORESEE-HUN 1.0 dataset, the change in the spatial resolution of FORESEE, the update of the reference observation-based dataset and the introduction of the discontinuity correction.

The presented applications of the extended and upgraded FORESEE database for the possible consequences of climate change demonstrated that the naive model selection logic (which means selecting the "coldest"/"warmest" model from the ensemble to represent the full uncertainty range of the simulations) might be misleading. This suggests that the model selection should be supported by more sophisticated methods e.g., via constructing targeted compound variables that are related to the specific scientific field.

FORESEE is entirely free, ready to use, and can be downloaded from the website of the database. Additional developments will further improve this essential climate service in Central Europe.

Data formats and availability

The climate variables (T_{min}, T_{max}, *Prec*) are disseminated in the form of NetCDF files (created separately by meteorological variables and by models) for the observational period and for the projections. User-friendly MT–CLIM output files containing T_{mean_DL}, RAD_{DL}, VPD_{DL} and LD_{DL} were also created for every grid point both for the observation-based dataset and also for the bias- and discontinuity-corrected datasets. The NetCDF files containing the MT-CLIM variables are also available to the public. The created FORESEE datasets are available on the website of the database with up-to-date and user-supportive information (https://nimbus.elte.hu/FORESEE/).

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CRediT authorship contribution statement

Anikó Kern: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Laura Dobor:** Data curation, Methodology, Writing – original draft, Writing – review & editing. **Roland Hollós:** Data curation, Writing – review & editing. **Hrvoje Marjanović:** Conceptualization, Writing – original draft, Writing – review & editing. **Csaba Zsolt Torma:** Writing – review & editing. **Anna Kis:** Data curation, Writing – review & editing. **Nándor Fodor:** Writing – review & editing. **Zoltán Barcza:** Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The availability (link) to ur data is written in the Manuscript

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Appendix A. Supplementary data

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