



Comparison of simulations from a state-of-the-art dynamic global vegetation model (LPJ-GUESS) driven by low- and high-resolution climate data

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Abstract. Simulations of dynamic global vegetation models (DGVMs) are typically conducted at a spatial resolution of 0.5°, while higher-resolution simulations remain uncommon. This coarse resolution eliminates detailed orographic features and hence, associated climate variability, which are especially pronounced in mountainous regions. The impact of disregarding such variability on vegetation dynamics has not been thoroughly examined. In this study, we explore the differences in vegetation outcomes between the DGVM LPJ-GUESS simulations conducted at high and low spatial resolutions. Using the CHELSA algorithm, we create an elevation-informed high-resolution climate dataset for a domain encompassing the European Union and use it to perform simulations. Comparative analysis reveals significant systematic discrepancies between the two resolutions. Furthermore, we quantify the extent to which the underrepresentation of orographic climate variation affects regional predictions across the European Union.

1 Introduction

The rapidly progressing climate change reinforces the urgency with which political and societal measures need to be implemented to reduce greenhouse gas emissions and to mitigate further climate change as much as possible, while also considering appropriate adaptation measures. Due to the complexity of general circulation models, global climate change projections are still available only at very coarse spatial resolutions (> 0.5 degrees; e.g., Masson-Delmotte et al., 2021). These allow to assess very well the basic response of the earth system to climate change. But impacts of climate change on ecosystems and societies are felt locally; weather extremes in particular can happen at scales of few km, rather than tenths or hundreds of km. Many mitigation and adaptation measures that are being discussed rely on the ecosystem services provided by natural and managed ecosystems (Shin et al., 2022; Smith et al., 2022). Their design and permanence require climate change projections of a spatial resolution much closer to the spatial extents of the ecosystems under study. For instance, using the dynamic global vegetation model LPJ-GUESS, Lagergren et al. (2024) explored how climate change and CO₂ impacts of different vegetation types in Fennoscandia would affect habitats of rare and threatened species and also how reindeer grazing (an important source of income for the local population) would be affected. High-resolution climate for these analyses provided important information on, e.g., seasonal and altitudinal distribution of snowfall. Similarly, in the Spanish region of Catalonia 1km downscaled climate



projections supported simulations of future productivity of a number of species of wild edible mushrooms, which provide both large economic and recreational value (Morera et al., 2024). In this study, too, the capability to resolve climate gradients in mountain areas underpins confidence in the projected patterns.

Several downscaling methods exist that can be applied to overcome the mismatch between coarse global climate projections, and the fine-resolution needs of impact models (Karger et al., 2023). The potential advantage of applying a downscaling that can be adopted flexibly for any region of the world is obvious as it allows to explore and compare climate change impacts using consistent climate driving data (Karger et al., 2023). Still, producing and applying high-resolution climate data faces various computational challenges, such as memory, run-time, and storage limitations. This, together with the large energy consumption of high-performance computer clusters, requires careful consideration as to when simulations at high spatial resolution obtain necessary information– and for which questions coarse scale simulations suffices.

Here we present a downscaled climate product for the European region at 0.05° for use in climate change impact studies (Sect. 3). The downscaling adopts the approach presented in Karger (2022) and Karger et al. (2023), and uses ISIMIP3b 0.5° climate data (Lange and Büchner, 2021) to obtain their high-resolution counterpart. We used the downscaled data to force LPJ-GUESS simulations and, applying an ensemble approach, tested whether systematic differences in simulated output emerged between fine and coarse resolutions (Sect. 4). Lastly, we evaluated the impact of this bias on the scale of European Union (Sect. 5). The work is part of an ongoing effort to incorporate a simplified downscaling method into LPJ-GUESS, which eventually should allow users to downscale flexibly different climate projections for different regions.

2 Methods

2.1 CHELSA

CHELSA (Karger et al., 2017, 2021, 2023) is a family of semi-mechanistic algorithms designed to perform spatial downscaling of near-surface climate data. The original implementation (Karger, 2022), scales ISIMIP3b temperature, precipitation, and downwelling shortwave radiation from an input resolution of 0.5° down to $0.0083(3)^\circ$. The code additionally requires 3D data from the CMIP6 ensemble (Jungclaus et al., 2019), as well as static data such as high-resolution surface elevation.

2.1.1 Temperature

For every low-resolution grid cell, the temperature is projected to the sea level via Eq. (1);

$$T_{lr}^{sea} - T_{lr}^c = \gamma(H^{sea} - H_{lr}^c), \quad (1)$$

where γ is the lapse rate, T_{lr}^{sea} is the temperature to compute, H^{sea} is the sea-level elevation, and T_{lr}^c and H_{lr}^c are, correspondingly, the temperature and elevation of the cell. The lapse rate γ is obtained by applying linear regression to CMIP6 pressure-level data. The projected values T_{lr}^{sea} are interpolated using B-splines to obtain high-resolution sea-level temperatures (T_{hr}^{sea}). For every high-resolution grid point, the surface temperature is computed using the interpolated values, the surface



elevation, the lapse rates and Eq. (2):

$$55 \quad T_{hr}^c - T_{hr}^{sea} = \gamma(H_{hr}^c - H^{sea}). \quad (2)$$

Elevation values are from the Global Multi-resolution Terrain Elevation Data 2010 (Danielson and Gesch, 2011), with the spatial resolution of 30 arcsec. This method is used to downscale mean, maximum, and minimum daily temperatures.

2.1.2 Precipitation

In the most general case, CHELSA downscales precipitation based on two factors: the orography and cloud cover of the area (Karger et al., 2021). The latter is based on satellite images of the Earth, and thus, can only be used in processing of precipitation within the period 1981–2010 when the images are available. Outside that period, CHELSA considers only orographic precipitation. The downscaling accounting for orographic precipitation is done by computing the wind effect index H for each high-resolution cell. This index reflects how much moisture gets pushed up towards the top of a mountain as well as rain shadow in its leeward direction. The H index is corrected according to the atmospheric boundary layer height to account for the contribution of the surface pressure level to the wind effect. Lastly, the low-resolution precipitation p_{lr} is multiplied by the corresponding H indices and normalized to obtain high-resolution precipitations p_{hr} , so that within each low-resolution grid cell the sum of the values p_{hr} remains equal to p_{lr} .

2.1.3 Surface downwelling shortwave radiation (RSDS)

The total shortwave radiation, measured in W/m^2 is represented as (Karger et al., 2023):

$$70 \quad S_n = (S_s + S_h + S_t)(1 - r). \quad (3)$$

Here, S_s is direct solar radiation reaching the surface, computed according to the position of the Sun with respect to the high-resolution grid cell. Diffuse solar radiation S_h , which is the energy re-emitted by the atmosphere, takes into account the percentage of the sky observable from a grid cell. S_t is the sum of the incoming radiation reflected off high-resolution grid cells in close proximity. r here is surface albedo. S_s , S_h and S_t components are adjusted according to the surrounding topography to take into account shadowing and obstruction of light. In the end, S_n is reduced in accordance with the cloud cover produced by orography, which is calculated in a similar way to 2.1.2.

2.2 Bootstrap hypothesis test

In order to test whether two random samples come from distributions having equal means, we employ the so-called bootstrap two-sample heterogenic location test (see Dikta and Scheer, 2021, Sect. 4.3) and its implementation in R package boot (Angelo Canty and B. D. Ripley, 2024; Davison and Hinkley, 1997). Assume that there are two samples: $\mathbf{X}_n = \{X_1, \dots, X_n\}$ and $\mathbf{Y}_m = \{Y_1, \dots, Y_m\}$. $\mathbf{X}_n$ is drawn from distribution F , and $\mathbf{Y}_m$ is drawn from G , where both distributions are univariate and have finite (but not necessarily equal) variances σ_x and σ_y as well as mean values μ_x and μ_y . The goal is to test null-hypothesis



H_o against the alternative H_a :

$$H_o : \mu_x = \mu_y \quad \text{vs} \quad H_a : \mu_x \neq \mu_y \quad (4)$$

85 Following the standard bootstrap approach,

$$X_{li}^*, \quad i \in [1, \dots, n], \quad \text{and} \quad Y_{lj}^*, \quad j \in [1, \dots, m], \quad l \in [1, \dots, L], \quad (5)$$

are obtained via sampling with replacement from sets $\{X_1, \dots, X_n\}$ and $\{Y_1, \dots, Y_m\}$ respectively, and bootstrap counterparts of the sample means and variances are computed:

$$\begin{aligned} \bar{X}_{l;n}^* &= \frac{1}{n} \sum_{i=1}^n X_{li}^*, \quad s_{l;x}^{*2} = \frac{1}{n-1} \sum_{i=1}^n (X_{li}^* - \bar{X}_{l;n}^*)^2, \\ \bar{Y}_{l;m}^* &= \frac{1}{m} \sum_{j=1}^m Y_{lj}^*, \quad s_{l;y}^{*2} = \frac{1}{m-1} \sum_{j=1}^m (Y_{lj}^* - \bar{Y}_{l;m}^*)^2 \end{aligned} \quad (6)$$

90 Under H_o , the following limiting result holds, which is used by the test:

$$\begin{aligned} T^* &:= \frac{(\bar{X}_{l;n}^* - \bar{X}_n) - (\bar{Y}_{l;m}^* - \bar{Y}_m)}{\sqrt{s_{l;x}^{*2}/n + s_{l;y}^{*2}/m}} \xrightarrow{d} \frac{\bar{X}_n - \bar{Y}_m}{\sqrt{s_x^2/n + s_y^2/m}} =: T, \\ \text{when } n &\rightarrow \infty, \quad n/m \rightarrow \lambda, \quad 0 < \lambda < \infty \quad L > n + m. \end{aligned} \quad (7)$$

T is used as a test statistic with the distribution of T^* , providing a p-value for the difference of the two populations. Here, the classical two-sided test is used: if T lies beyond 95% of the generated sample of T^* (no matter to which side), then the null-hypothesis is rejected, otherwise— accepted.

95 We chose this test for two reasons. First, its only restriction on data is possessing a finite variance, which is justified by conservation laws of physics. On the contrary, parametric tests, such as Z-test, require assuming at least a certain distribution family, which is too constraining, as we apply the testing procedure to a number of different quantities. Also, a standard t-test cannot be used due to differences in variations of samples we obtain— the low resolution data have smaller variation than the high-resolution ones (see Sect. 4.2). Second, our data is too small to make use of the central limit theorem (see Sect. 100 4.1). LPJ-GUESS simulations are computationally demanding especially on the high resolution, thus generating samples that contain more than 50–100 observations is already a challenging task. When the number of observations is larger, for example in regional studies, the central limit theorem ensures convergence in law of the means of the two samples to normal distributions, and it becomes possible to use Welch's t-test (Welch, 1947) as a good alternative to the bootstrap test.

2.3 LPJ-GUESS

105 2.3.1 Model description

LPJ-GUESS is a process-based Dynamic Global Vegetation Model (DGVM) that incorporates ecosystem biogeochemistry, water cycling, and tree demography (Smith et al., 2001, 2014). The model is able to simulate several types of land cover and



land use change (Lindeskog et al., 2013; Olin et al., 2015; Lindeskog et al., 2021). At any given geographical location (*grid-cell*), the different land cover types constitute separate *stands*, which share the same climate forcings. We restrict our test here
110 to a model configuration that only includes potential natural vegetation. In natural forest stands, vegetation is represented as a mixture of woody Plant Functional Types (PFTs), divided into age classes or *cohorts*, and a grassy understory. Yearly establishment of new cohorts is subject to prescribed bioclimatic limits, which are specific to each PFT. Trees and grasses coexist in the same *patch*, which roughly represents the area of influence of one large, mature tree. Competition for available water, light and nutrients determines the daily rate at which each cohort absorbs atmospheric CO₂. At the end of every simulation year, the
115 assimilated carbon is allocated to leaves, sapwood, or roots according to a set of PFT-specific allometric constraints. Within the stand, horizontal heterogeneity is represented by simulating a number of replicate patches. Establishment of new cohorts, death of individuals, and vegetation-destroying disturbances are modeled as stochastic processes, giving rise to different successional histories for each patch. Wildfires are modelled explicitly (Rabin et al., 2017). Ecosystem pools and fluxes are estimated by averaging over patches.

120 In this paper we used the ‘European Applications’ branch of LPJ-GUESS. This version differs from the standard (global) version in that the PFTs are parametrized based on observed characteristics of common European species (Hickler et al., 2012; Gregor et al., 2022, 2024).

2.3.2 Model modification

Stochastic events in LPJ-GUESS are triggered by the outcomes of a Random Number Generator (RNG). In the unmodified
125 version of the model code, each stand keeps its own random number sequence, which is initialized (seeded) with a hard-coded value when the stand is created at the beginning of the simulation. This implies that all stands in the simulation derive their stochasticity from the same random number sequence. However, ensemble experiments require that observations within the ensemble are statistically independent. In order to emulate statistical independence of stands and gridcells between ensemble realizations, we modified the model code to initialize each stand’s seed as follows:

$$130 \text{ Seed}_{igs} = (1000000 + N_{gc} \cdot i + g) \cdot 1000 + s, \quad (8)$$

where $i = 0, \dots, N - 1$ identifies the simulation within the ensemble, N_{gc} is the total number of gridcells in the simulation domain, $g = 0, \dots, N_{gc} - 1$ runs over gridcells, and $s = 0, \dots, 999$ is a unique stand identifier. This method ensures that each stand in every realization of the ensemble draws random numbers from a different sequence, up to 1000 stands per gridcell. We emphasize, however, that each gridcell contains only one natural vegetation stand in the present study.



135 3 Climate data downscaling

3.1 Data processing

The CHELSA algorithm was used to downscale ISIMIP3b mean, maximum and minimum daily temperatures, precipitation rate, and downwelling solar radiation in the domain defined by $\lambda \in [26.75^\circ\text{W}, 35.25^\circ\text{E}]$; $\phi \in [34.75^\circ\text{N}, 71.75^\circ\text{N}]$, where λ and ϕ are geographical longitude and latitude, respectively. This domain encompasses the continental European Union plus
140 Norway, Iceland, Switzerland, the United Kingdom, the non-EU Balkan states, Moldova, Belarus, and parts of Ukraine, Russia, Morocco, Algeria, and Tunisia. CHELSA generates one TIFF file per day for each of the input variables at an output resolution of $0.0083(3)^\circ$ (approximately 1 km near the Equator). LPJ-GUESS simulations covering the target domain at this resolution are computationally impractical. We thus first upscaled the files to 0.05° by taking the mean of every 6×6 block of adjacent $0.0083(3)^\circ \times 0.0083(3)^\circ$ gridcells. This upscaled version was stored in NetCDF format. Gaps produced by missing days in
145 CHELSA's output ($\sim 0.34\%$ in the historical period, and fewer than 0.14% in the scenarios) were filled with previous day values. The daily NetCDF files were stacked along the time dimension, and we added CF-compliant metadata (Hassell et al., 2017). LPJ-GUESS simulates the whole target period in one gridcell before proceeding to the next location. To optimize data retrieval by the model code, the stacked NetCDF files were *rechunked* along the time dimension. This operation rearranges the internal structure of the file in a way that greatly enhances performance when reading the full time series at a single
150 spatial location. The resulting files underwent quality control, which included checking that there were no missing days, ensuring that all values were non-negative, and manually assessing that annual mean values were reasonable. In addition to the variables downscaled with CHELSA, we remapped ISIMIP3b near-surface wind speed and air relative humidity data to high resolution by applying bilinear interpolation to the original files. These variables are required when running LPJ-GUESS with the SIMFIRE/BLAZE fire model (Knorr et al., 2014, 2016; Rabin et al., 2017) (see Sect. 5). The pipeline scripts were
155 implemented in Bash Script and Python, and use the NetCDF Operators (Zender, 2008) and the Climate Data Operators (Schulzweida, 2023).

The data is freely accessible through KIT/IMK-IFU's *thredds* storage server Otryakhin and Belda (2024), and is made available under the CC BY-SA 4.0 license. Table 1 summarizes the properties of the dataset.

4 Ensemble experiment

160 4.1 Setup

This experiment aims to find systematic differences in regional predictions between low- and high-resolution LPJ-GUESS simulations, arising from underrepresentation of orography-induced climate variability in the low-resolution forcings. To this end, we ran two sets of ensembles of LPJ-GUESS simulations (high- and low-resolution) in selected *study* and *control* regions. The simulations spanned the historical period 1850–2014. The low-resolution simulations were forced with ISIMIP3b climate,
165 while the high-resolution simulations were forced with the downscaled dataset. We chose the Alps as our study region for



Table 1. Characteristics of the final downscaled dataset. Variable names follow the ISIMIP3b nomenclature: daily average temperature, minimum, and maximum ('tas', 'tasmin', 'tasmax'), precipitation ('prec'), downwelling shortwave radiation ('rsds'), wind speed ('sfcwind'), and relative humidity ('hurs').

Spatial resolution	0.05°
Temporal resolution	Daily
Format	NetCDF4
Variables (CHELSA)	tas, tasmin, tasmax, pr, rsds
Variables (interp)	sfcwind, hurs
Spatial extent	$\lambda \in [26.75^\circ\text{W}, 35.25^\circ\text{E}]$ $\phi \in [34.75^\circ\text{N}, 71.75^\circ\text{N}]$
Temporal extent	1850 – 2100
GCM	MPI-ESM1-2-HR
SSP/RCP scenarios	Historical, SSP1-2.6, SSP3-7.0, SSP5-8.5
Total size	1.3TB

Table 2. Characteristics of elevations in the study and the control regions computed using values from GMTED2010 (Danielson and Gesch, 2011). All values are in meters.

Region	Min.	1st Qu.	Median	Mean	SD	3rd Qu.	Max.
Study	0	748	1310	1369	761	1941	4505
Control	69	81	88.0	100.4	44.5	105.0	860.0

its high variability in surface elevation. The control region, located between the Dinaric Alps and the Carpathian Mountains, was chosen to contain comparatively little mountainous terrain (Table 2), while being in close proximity to the Alpine region. The latter condition was intended to prevent significant global differences in climate between the two areas. Figure 1 shows the study and control regions overlayed on an elevation map. The gridcell centers were chosen such that any low-resolution gridcell contains a block of 10×10 high-resolution gridcells, with no high-resolution gridcells outside these blocks (i.e., a perfect overlap of the high- and low-resolution grids). Prominent water bodies were avoided.

The experimental design is outlined in Fig. 2. We considered the regional averages of each modeled variable (Table 3), evaluated in the last year of the simulation (2014), as random variables. We run 50 simulations per region and resolution, giving rise to 44 ensembles of random variables ($11 \text{ modeled variables/simulation} \times 2 \text{ resolutions} \times 2 \text{ regions}$), each containing 50 observations of its random variable. For a given region and resolution, the simulations were identically set up, but used a different seed for the random number generator (see Sect. 2.3.2). Model runs were assumed to be independent and identically distributed. We note that such an assumption is not imposed on pairs of ecosystem variables within the same model run. The patch number was set to 20 in all simulations.

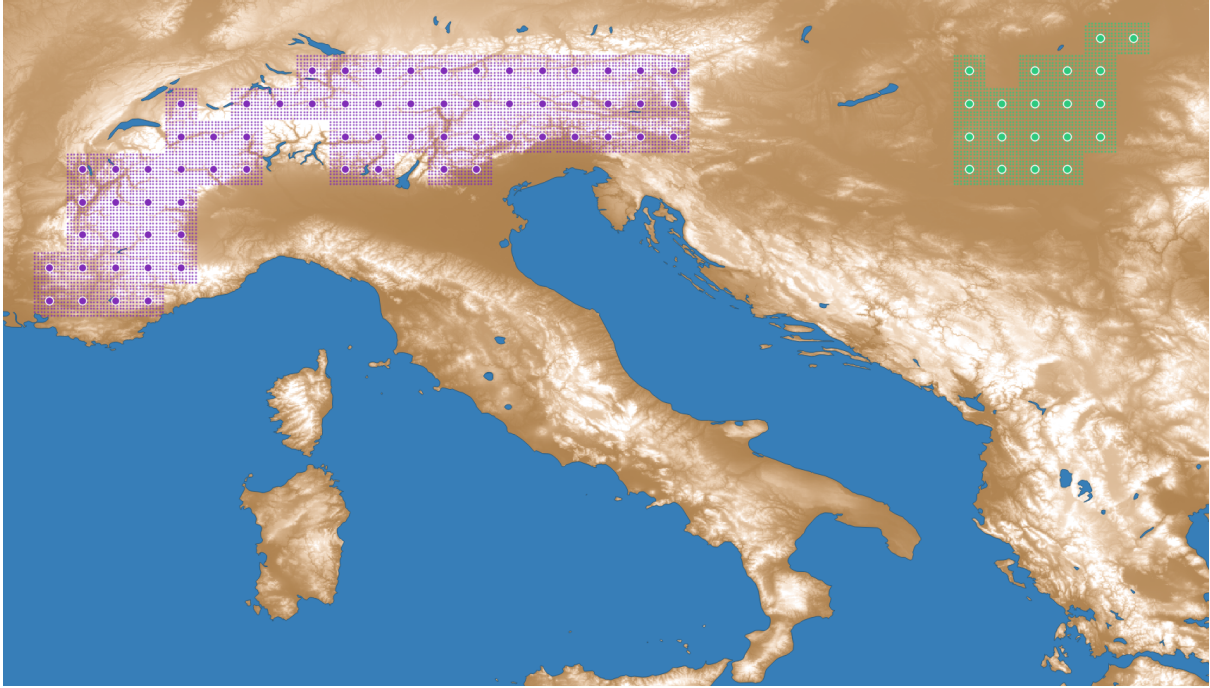


Figure 1. Study (violet) and control (green) regions for the ensemble experiment, overlaid on an elevation map based on values of GMTED2010 (Danielson and Gesch, 2011). The centers of low-resolution gridcells are indicated by solid circles. The smaller dots mark the location of the high-resolution gridcells. Elevation is encoded as a color gradient ranging from dark brown (low elevation) to white (high elevation).

Let μ_{hr}^S , μ_{lr}^S , μ_{hr}^C , and μ_{lr}^C denote the ensemble means of any of the modeled variables, with superscripts ‘S’ and ‘C’ identifying the study and control regions, and subscripts ‘hr’ and ‘lr’ denoting high- and low- resolution. The question of whether there are systematic differences between low- and high-resolution regional predictions in areas with high orographical variability can be cast in terms of two formal hypothesis tests:

$$H_o^S : \mu_{hr}^S = \mu_{lr}^S \quad (\text{There are no differences in the study region})$$

vs

$$H_a^S : \mu_{hr}^S \neq \mu_{lr}^S, \quad (\text{There are differences in the study region}), \quad (9)$$

and

$$H_o^C : \mu_{hr}^C = \mu_{lr}^C \quad (\text{There are no differences in the control region})$$

vs

$$H_a^C : \mu_{hr}^C \neq \mu_{lr}^C, \quad (\text{There are differences in the control region}). \quad (10)$$

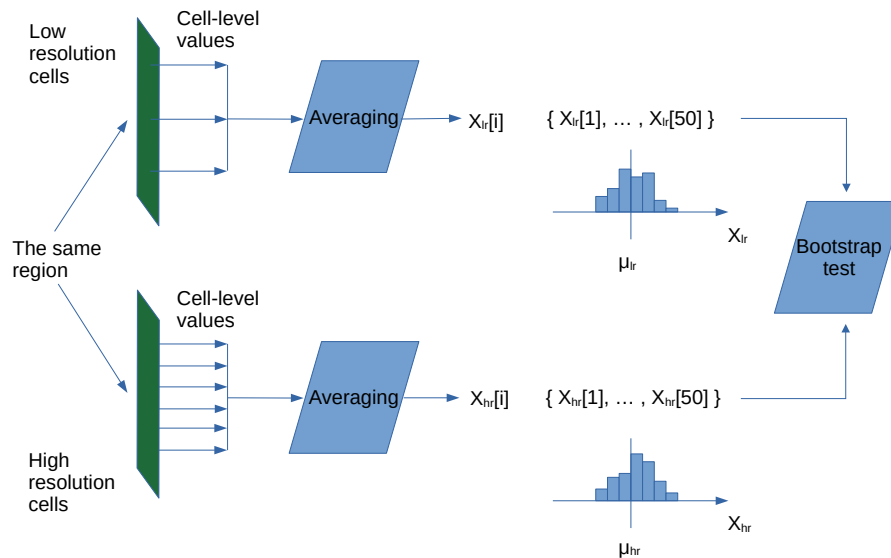


Figure 2. Scheme of computations in the ensemble experiment.

Table 3. List of ecosystem variables modeled by LPJ-GUESS that were included in the experiment. These include carbon fluxes (GPP, NPP, and NEP), carbon pools (C_{lit} , C_{soil} , C_{veg} , and C_{tot}), water cycle variables ($Tr.$ and R_{off}), and vegetation structural variables (FPC and LAI).

Variable	Description	Units
GPP	Gross Primary Productivity	$\text{kgC} \cdot \text{yr}^{-1}$
NPP	Net Primary Productivity	$\text{kgC} \cdot \text{yr}^{-1}$
NEP	Net ecosystem productivity	$\text{kgC} \cdot \text{yr}^{-1}$
C_{lit}	Amount of carbon stored in litter	kgC
C_{soil}	Amount of carbon stored in the soil	kgC
C_{veg}	Amount of carbon stored in above-ground vegetation	kgC
C_{tot}	Total amount of stored carbon	kgC
$Tr.$	Ecosystem transpiration	$\text{mm} \cdot \text{yr}^{-1}$
R_{off}	Runoff	$\text{mm} \cdot \text{yr}^{-1}$
FPC	Foliar Projective Cover	$\text{m}^2 \cdot \text{m}^{-2}$
LAI	Leaf Area Index	$\text{m}^2 \cdot \text{m}^{-2}$

where the subscript ‘o’ denotes the null hypotheses and ‘a’ identifies the alternatives. We tested these hypotheses for every variable by applying the bootstrap test method described in Sect. 2.2.



Table 4. Ensemble experiments carried out in Sect. 4. The experiments differ in the climate data used to force the low-resolution simulations and on whether wildfires are allowed.

Experiment	LR forcing	Fire
I3b/Fire	ISIMIP3b	On
uCH/Fire	Upscaled CHELSA	On
uCH/NoFire	Upscaled CHELSA	Off

CHELSA conserves the amount of precipitation in the upscaled output by construction (Sect. 2.1.2), but does not impose such constraint on mean temperature and radiation. In order to investigate the possible biases associated with this non-conservative
 190 downscaling we repeated the above experiment, this time forcing the low-resolution simulations with CHELSA climate, up-
 scaled back to 0.5° by spatially averaging the high-resolution data. This ensures that mean temperature, radiation and precip-
 itation are the same on both resolutions. In addition, we wished to investigate the impact of fire disturbance on the results of
 the above experiments. This was motivated by the fact that, in LPJ-GUESS, fire disturbance depends on the climate forcings
 through the fire model (Rabin et al., 2017). To explore this effect we rerun the last experiment with fire switched off. The
 195 characteristics of the three ensemble experiments are summarized in Table 4.

4.2 Results and analysis

The results of the first experiment (I3b/Fire) are shown in Table 5. We found statistically significant differences between the
 means of the high- and low-resolution samples ($\delta^S := \mu_{lr}^S - \mu_{hr}^S$) over the study region. The bootstrap test returned a p-value of
 0 for all the variables, leading us to reject H_0^S in favor of the alternative H_a^S .
 200 In the control region all differences between ensemble means, $\delta^C := \mu_{lr}^C - \mu_{hr}^C$, are substantially smaller than their study
 region counterparts, ranging from $|\delta^S/\delta^C| \sim 7$ in the case of NEP and Transpiration to ~ 116 in the case of C_{soil} . For the
 majority of the variables, the p-values indicate a statistically significant difference between ensemble means δ^C . For NEP and
 C_{lit} , however, we found no evidence in the data to reject the null hypothesis H_0^C . This indicates that, for these two variables,
 either there are no significant differences between μ_{lr}^C and μ_{hr}^C , or the ensemble size is too small to detect them with a sufficient
 205 confidence level. Figure 3 shows δ^S and δ^C , as a fraction of μ_{hr} , for all variables. The ensemble mean differences in the study
 region have opposite sign to those in the control region, with the exception of R_{off} .

An additional bootstrap test was run to check whether random variability in the control region could give rise to differences
 between ensemble means as large as those seen in the study region. With low- and high-resolution values in place of X_i and Y_i ,
 we generated the distribution of T^* from the left side of (7), and found the two-sided p-values using $-|\delta^S|$ and $+|\delta^S|$. These
 210 tests returned a p-value $p^X = 0$ for all variables, which strongly suggests that control-region differences as large as those found
 in the study region could not be explained by mere random variability of the ensemble means.

Table 6 shows the results of the second experiment (uCH/Fire). All bootstrap tests returned a p-value of 0 in the study region,
 again indicating very strong evidence of a mean difference between high- and low-resolution outputs. In the control region, 5 of



Table 5. Results of the I3b/Fire experiment. The ensemble means and standard deviations are denoted μ and σ , respectively. The superscripts S and C identify the study and the control regions, respectively. The subscripts hr and lr denote high- and low-resolution. The δ is used for the difference between the low- and high-resolution ensemble means for the given region. The p^S and p^C denote the p-values for the statistical tests defined by Eq. 9 and Eq. 10. The p^X are the p-values for the test defined in Sect. 4.2. A bold font face is used to identify tests with a p-value below the significance threshold. The ratios δ^S/μ_{hr}^S , δ^S/δ^C , and δ^S/δ^C are expressed as percentages.

	GPP	NPP	NEP	C_{lit}	C_{soil}	C_{veg}	C_{tot}	Tr.	R_{off}	FPC	LAI
μ_{hr}^S	0.96	0.52	-0.05	10.7	13.7	15.8	40.2	328	827	0.70	2.64
σ_{hr}^S	0.0005	0.0003	0.0005	0.014	0.004	0.027	0.02	0.20	0.14	0.0006	0.002
μ_{lr}^S	1.19	0.66	-0.06	15.6	19.2	21.2	56.0	374	789	0.80	3.12
σ_{lr}^S	0.006	0.003	0.005	0.154	0.058	0.257	0.17	2.11	1.60	0.006	0.03
δ^S	-0.22	-0.13	0.01	-4.92	-5.44	-5.41	-15.8	-45.7	38.1	-0.10	-0.48
p^S	0	0	0	0	0	0	0	0	0	0	0
δ^S/μ_{hr}^S	-23.4	-25.5	-15.3	-46.0	-39.6	-34.2	-39.2	-13.9	4.6	-14.8	-18.3
μ_{hr}^C	1.08	0.50	0.08	7.27	8.93	17.4	33.6	402	44.5	0.82	3.14
σ_{hr}^C	0.0007	0.0004	0.0013	0.026	0.005	0.04	0.03	0.35	0.22	0.001	0.005
μ_{lr}^C	1.07	0.49	0.08	7.22	8.88	17.2	33.2	395	42.5	0.81	3.13
σ_{lr}^C	0.0073	0.0037	0.0114	0.216	0.041	0.45	0.33	3.14	1.96	0.013	0.036
δ^C	0.012	0.0055	-0.0014	0.050	0.047	0.23	0.33	6.79	2.00	0.004	0.014
p^C	0	0	0.41	0.10	0	0	0	0	0	0.022	0.003
δ^C/μ_{hr}^C	1.2	1.1	-1.7	0.7	0.5	1.3	1.0	2.0	4.0	0.5	0.5
δ^S/δ^C	-18	-24	-7	-98	-116	-24	-48	-7	19	-25	-34
p^X	0	0	0	0	0	0	0	0	0	0	0

11 tests failed to reject the null hypothesis: NEP, C_{veg} , Tr., FPC, and LAI. Interestingly, the C_{lit} test switched to returning a significant p-value. The differences between ensemble means in the study and control regions, δ^S and δ^C , are now both negative (Fig. 3). This sign switch of δ^C with respect to I3b/Fire suggests that CHELSA's non-conservative properties introduce a bias of sign opposite to the response of the model to the altitude-driven climate differences. The relative importance of this effect is much larger over the control region, where it determines the sign of the overall difference δ^C . The change in magnitude of δ^C with respect to I3b/Fire, $|\Delta\delta^C|$, was between $\sim 110\%$ and $\sim 310\%$, except for NEP ($\sim 57\%$). By contrast, $|\Delta\delta^S|$ is much smaller, ranging between $\sim 0.04\%$ and $\sim 14\%$. This may explain the significance switch in the C_{lit} test over the control region; the non-conservative bias present in the I3b/Fire experiment nearly compensates the altitude-induced differences for this variable. This brings the high- and low-resolution means closer together, which makes it more difficult to discern them. When this bias is removed in uCH/Fire, the difference between ensemble means increases, and the bootstrap test is able to detect it.



Table 6. Results of the uCH/Fire experiment. Repeated symbols are as in Table 5. $|\Delta\delta^S|$ and $|\Delta\delta^C|$ are the changes in magnitude of δ^S and δ^C with respect to I3b/Fire, expressed as a percentage.

	GPP	NPP	NEP	C_{lit}	C_{soil}	C_{veg}	C_{tot}	Tr.	R_{off}	FPC	LAI
μ_{hr}^S	0.96	0.52	-0.05	11	14	16	40	328	827	0.70	2.64
σ_{hr}^S	0.0005	0.0003	0.0005	0.014	0.004	0.027	0.019	0.20	0.14	0.0006	0.002
μ_{lr}^S	1.18	0.65	-0.06	15.5	18.5	21	55	367	791	0.81	3.12
σ_{lr}^S	0.0055	0.003	0.004	0.15	0.04	0.22	0.15	2.14	1.5	0.006	0.025
δ^S	-0.22	-0.13	0.01	-4.8	-4.8	-5.5	-15	-39	36	-0.11	-0.48
p^S	0	0	0	0	0	0	0	0	0	0	0
δ^S/μ_{hr}^S	-22.8	-24.4	-14.1	-45.2	-35.1	-34.8	-37.7	-12.0	4.4	-15.9	-18.2
μ_{hr}^C	1.08	0.50	0.08	7.3	8.9	17.4	33.6	401	44	0.82	3.14
σ_{hr}^C	0.0007	0.0004	0.0013	0.026	0.005	0.04	0.03	0.35	0.22	0.002	0.005
μ_{lr}^C	1.08	0.50	0.08	7.37	9	17.47	33.8	402	48	0.82	3.15
σ_{lr}^C	0.007	0.003	0.01	0.24	0.04	0.4	0.3	3.7	2	0.01	0.04
δ^C	-0.004	-0.003	-0.0006	-0.1	-0.08	-0.09	-0.26	-0.7	-4.2	-0.002	-0.009
p^C	0	0	0.75	0.0025	0	0.16	0	0.21	0	0.26	0.10
δ^C/μ_{hr}^C	-0.4	-0.6	-0.7	-1.4	-0.9	-0.5	-0.8	-0.2	-9.4	-0.3	-0.3
δ^S/δ^C	56	41	-12	49	63	63	58	56	-9	53	52
p^X	0	0	0	0	0	0	0	0	0	0	0
$ \Delta\delta^S $	0.73	1.3	27	1.8	11	1.8	4	14	5	11	0.04
$ \Delta\delta^C $	133	156	57	299	263	138	180	110	310	154	166

225 The outcome of the uCH/NoFire experiment is shown in Table 7. Like before, the impact on the control region is comparatively larger than in the study region, as shown by the values of $|\Delta\delta^S|$ and $|\Delta\delta^C|$, and by the fact that some of the tests in the control region returned switched p-values again.

We summarize the analysis described in this section as follows. It was demonstrated that high- and low-resolution simulations produce significantly different average predictions over a study region with high elevation variability. Differences in the control region were also detected, but they are much smaller than in the study region. Climate data downscaled with CHELSA introduces a bias related to its non-conservative treatment of temperature and radiation. This bias is comparable in magnitude to the altitude-related differences in the control region, but small in relation to the magnitude of the variables, and largely inconsequential in the study region. When this bias was removed, average NEP, C_{veg} , Tr., and FPC were indistinguishable in the high- and low-resolution simulations. Fire was found to be a significant contributor to the ensemble mean differences in the control region.

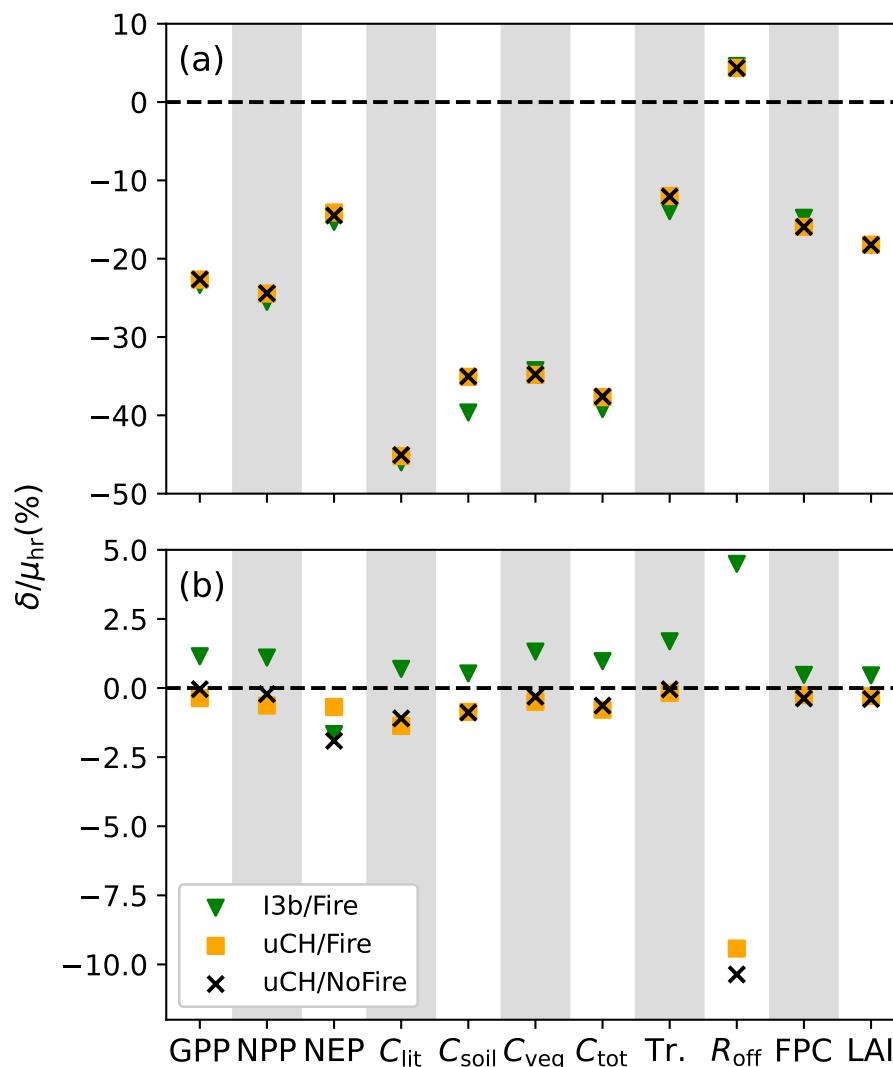


Figure 3. Mean difference between high- and low- resolution ensemble means, as a percentage of the high-resolution ensemble mean, over the study region (a) and the control region (b). The different symbols represent the three experiments; I3b/Fire: low-resolution simulations are forced with ISIMIP3b climate; uCH/Fire: low-resolution simulations are forced with upscaled CHELSA climate; uCH/NoFire: low-resolution simulations are forced with upscaled CHELSA climate and fire is switched off.

CHELSA-downscaled climate data is closer to observations than the original, coarse resolution data (Karger et al., 2021, 2023). This motivates us to consider the difference between high- and low-resolution simulations as a systematic bias incurred when running LPJ-GUESS at low resolution, arising from the underrepresentation of orographical climate variability.



Table 7. Results of the uCH/NoFire experiment. Repeated symbols are as in Table 5. $|\Delta\delta^S|$ and $|\Delta\delta^C|$ are the changes in magnitude of δ^S and δ^C with respect to uCH/Fire, expressed as a percentage.

	GPP	NPP	NEP	C_{lit}	C_{soil}	C_{veg}	C_{tot}	Tr.	R_{off}	FPC	LAI
μ_{hr}^S	0.96	0.53	-0.05	11	14	16	40	328	827	0.7	2.64
σ_{hr}^S	0.0005	0.0003	0.0004	0.013	0.005	0.02	0.01	0.2	0.16	0.0005	0.002
μ_{lr}^S	1.18	0.65	-0.06	16	19	21	55	368	791	0.81	3.12
σ_{lr}^S	0.005	0.003	0.005	0.18	0.041	0.28	0.18	2	1.48	0.006	0.022
δ^S	-0.22	-0.13	0.007	-4.8	-4.8	-5.5	-15	-40	36	-0.11	-0.48
p^S	0	0	0	0	0	0	0	0	0	0	0
δ^S/μ_{hr}^S	-22.6	-24.4	-14.5	-45.1	-35.0	-34.8	-37.6	-12.1	4.3	-15.9	-18.2
μ_{hr}^C	1.08	0.5	0.08	7.28	8.93	17	34	402	45	0.82	3.14
σ_{hr}^C	0.0008	0.0004	0.0011	0.02	0.004	0.042	0.03	0.3	0.22	0.0014	0.004
μ_{lr}^C	1.08	0.5	0.08	7.36	9.01	17	34	402	49	0.82	3.15
σ_{lr}^C	0.007	0.004	0.01	0.215	0.036	0.381	0.3	3.5	1.99	0.013	0.043
δ^C	-0.0004	-0.0011	-0.0016	-0.08	-0.079	-0.055	-0.21	-0.2	-4.6	-0.003	-0.013
p^C	0.63	0.09	0.26	0.0025	0	0.37	0	0.69	0	0.09	0.04
δ^C/μ_{hr}^C	-0.04	-0.22	-1.9	-1.1	-0.9	-0.3	-0.6	-0.05	-10.4	-0.4	-0.4
δ^S/δ^C	545	117	-5	60	61	100	71	215	-8	36	39
p^X	0	0	0	0	0	0	0	0	0	0	0
$ \Delta\delta^S $	0.14	0.08	2.7	0.09	0.04	0.18	0.08	0.53	0.28	0.09	0.23
$ \Delta\delta^C $	90	65	167	20	2.9	37	19	74	10	48	36

5 Comparison of Europe-wide simulations

240 5.1 Setup

In order to assess the impact of systematic biases in low-resolution LPJ-GUESS outputs on a European-regional level, we ran two simulations, at high and low resolutions, in the domain specified in Sect. 3.1. To capture coastline features and inland water bodies as accurately as possible for each resolution, we drop the restriction of one-to-one correspondence between blocks of 10×10 high-resolution gridcells and the low-resolution ones (see Sect. 4.1). The number of patches was set to 100 for both runs, and wildfires were enabled.

5.2 Analysis and results

Forcing LPJ-GUESS with low-resolution climate data introduces a bias in average predictions, related to the underrepresentation of climate spatial variability (Sect. 4). Figure 4 shows this climate-response bias for GPP, averaged over the 2010-2014

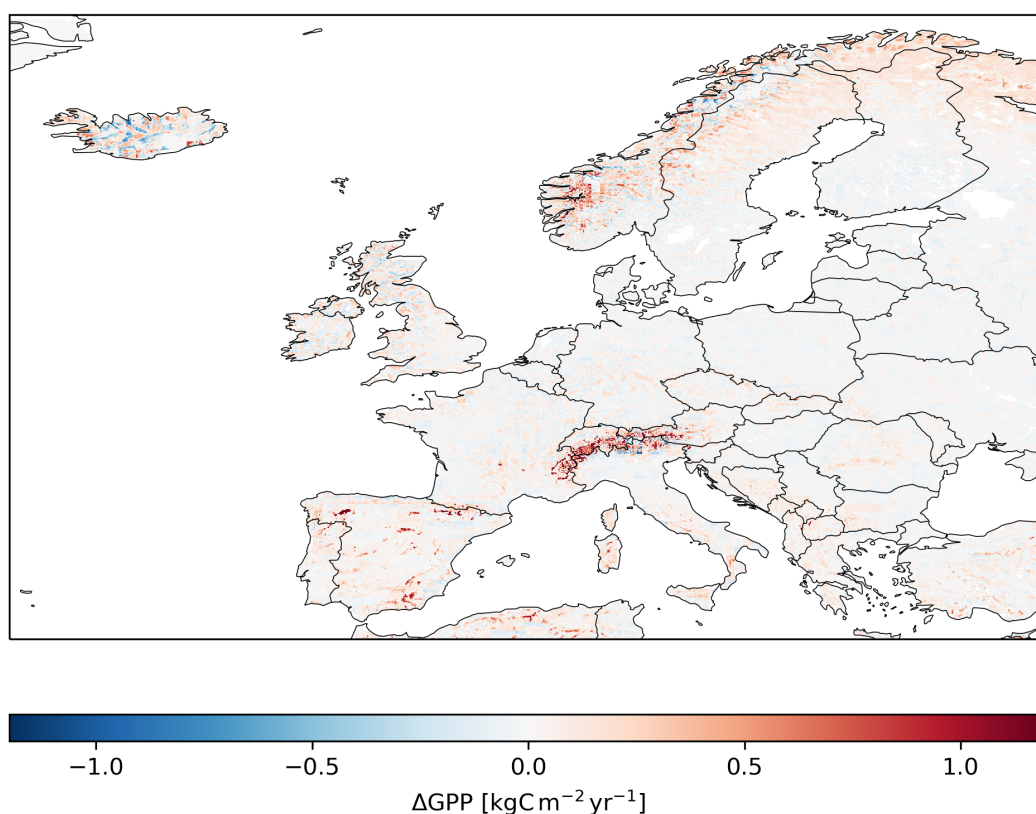


Figure 4. Climate-response bias in low-resolution modeled GPP, calculated as the difference between the low- and high-resolution predictions, averaged over the period 2010-2014. The value from every high-resolution gridcell was subtracted from the value in the corresponding 10×10 low-resolution block. Only fully overlapping low- and high- resolution gridcells are represented. Red indicates a higher GPP value in the low-resolution run than in the high-resolution run.

period. Similar maps for the rest of the variables can be found in the supplementary materials, Sect. 1 Supplement of Comparison of Europe-wide simulations. The most prominent discrepancies concentrate over highly mountainous regions, such as the Alps, the Spanish mountains and the Scandinavian Mountains. Large differences are also seen in Iceland, where the rapidly changing elevation leads to high spatial variability above and below the low-resolution predictions.

Additional bias results from the limitations of the low-resolution grid in representing areas around coastlines and inland water bodies (Fig. 5). In a low resolution simulation, some gridcells protrude outside the coastline, thus covering some sea-surface area (marked A), which is simulated as land. Similarly, the low-resolution grid cannot resolve small lakes, which adds to the overestimation of land-surface area. By contrast, some land-surface areas close to the seashore (marked B) are

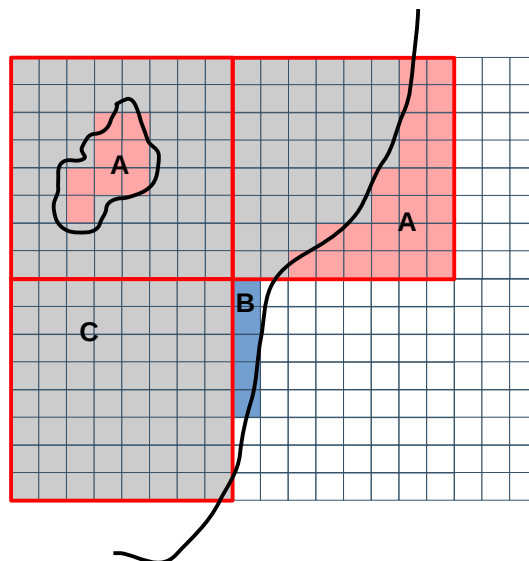


Figure 5. Three low-resolution gridcells (outlined in red) projected onto a high-resolution grid. A small lake and the coastline are represented with black, thick lines. The sea is to the right of the coastline. Red-shaded regions (marked A) indicate areas that are considered land in low-resolution simulations and water in high-resolution simulations. The blue-shaded area (marked B) is accounted for in a high-resolution run, but not in a low-resolution run. Gray areas (marked C) are represented in both high- and low-resolution simulations. White areas are considered water points in both simulations.

correctly accounted for in high-resolution simulations, but cannot be captured in low-resolution. In the European domain under consideration, these two counteracting effects amount to a $\sim 3.5\%$ increase in simulated surface area in the low resolution runs. This leads to a *geographical* bias in regional estimates.

260 Aggregating GPP across the domain yields an average of 7.01 PgCyr^{-1} over the period 2010-2014 for the high-resolution simulation, and 7.40 PgCyr^{-1} for the low-resolution simulation (a 5.5% increase). The climate-response and geographical contributions to this increase are $\delta_{\text{cli}} = 2.1\%$ and $\delta_{\text{geo}} = 3.4\%$, respectively. Table 8 shows aggregate high- and low-resolution values for the rest of the selected variables. The geographical bias is larger in magnitude than the climate-response bias for all variables except the carbon pools (C_{lit} , C_{soil} , C_{veg} , and C_{tot}). The largest relative discrepancy is seen in C_{lit} ; a 10.3% increase respect to the high-resolution value, with contributions $\delta_{\text{cli}} = 6.3\%$ and $\delta_{\text{geo}} = 4.0\%$. In the case of aggregate runoff, the geographical bias ($\delta_{\text{geo}} = 4.1\%$) and the climate-response bias ($\delta_{\text{cli}} = -1.3\%$) act in opposite directions, adding up to a net total of $\delta_{\text{tot}} = 2.8\%$. LAI and FPC values are spatially averaged, as opposed to aggregated, and cannot be separated into geographical and climate-response contributions in the same manner as the rest of the variables.

265



Table 8. Comparison of domain-wide aggregates of selected ecosystem variables for the high- and low- resolution European simulations (HR and LR, respectively). δ_{tot} is the total bias, δ_{geo} is the geographical bias, and δ_{cli} is the bias arising from the difference in climate forcings. Percentages are calculated with respect to the high-resolution values.

	HR	LR	δ_{tot}	δ_{geo}	δ_{cli}
GPP	7.01	7.40	0.39 (5.5%)	0.24 (3.4%)	0.15 (2.1%)
NPP	3.69	3.92	0.24 (6.4%)	0.12 (3.4%)	0.11 (3.0%)
NEP	-0.405	-0.420	-0.015 (-3.8%)	-0.014 (-3.4%)	-0.002 (-0.4%)
C_{lit}	64.1	70.7	6.6 (10.3%)	2.6 (4.0%)	4.0 (6.3%)
C_{soil}	72.0	78.6	6.6 (9.2%)	2.7 (3.7%)	3.9 (5.4%)
C_{veg}	99.1	105.6	6.5 (6.6%)	3.1 (3.2%)	3.4 (3.4%)
C_{tot}	235.1	254.8	19.7 (8.4%)	8.4 (3.6%)	11.3 (4.8%)
Tr.	2.32	2.41	0.09 (3.7%)	0.08 (3.3%)	0.01 (0.5%)
R_{off}	2.54	2.62	0.07 (2.8%)	0.10 (4.1%)	-0.03 (-1.3%)
FPC	0.30	0.32	0.02 (5.3%)	-	-
LAI	1.14	1.20	0.06 (5.4%)	-	-

6 Discussion

We found systematic differences between high- and low-resolution regional predictions in LPJ-GUESS simulations. The high-resolution simulations are performed on a grid that captures coastlines and water bodies more precisely, and are driven by climate that is generally closer to the observed regional climate (see validation sections in Karger et al., 2021, 2023). This motivates us to interpret these differences as systematic biases incurred when running LPJ-GUESS on a coarse grid. As these effects are not related to intrinsic properties of LPJ-GUESS, we infer that predictions by other DGVMs are likely to be affected in a similar manner. We note, however, that gridcells in LPJ-GUESS are independent from each other (there is no lateral information flow) and completely unaware of gridcell size. Hence, resolution only affects LPJ-GUESS simulations through the resolution of the input data, which is not necessarily the case for other models.

One possible mechanism underpinning the difference in modeled GPP between high- and low-resolution simulations in areas with high elevation variability is the non-linear relationship between the mean gridcell temperature and the duration of the growth season, which is dynamically calculated by LPJ-GUESS. The linear relationship between temperature and elevation (Eqs. 1 and 2) implies that air temperatures in higher parts of resolved mountainous areas are lower than the average value in the corresponding low-resolution gridcell, causing a shorter growth season. The lower parts will, in turn, experience a longer growth season. The shorter growth season in high areas leads to reduced productivity and vegetation cover. Because of the non-linear response of the model to climate forcings, this is not fully compensated by the additional productivity in the lower,



285 warmer parts. A similar argument can be made for the photosynthetic rate, which is temperature-dependent. On the other
hand, rainfall redistribution in the high-resolution grid may provide a counteracting effect. CHELSA tends to concentrate the
total amount of rainfall towards high-elevation areas to account for the influence of orography on precipitation, which may
reduce water availability for plant growth in the lower areas. Another counteracting factor is the excess land simulated in a grid
too coarse to resolve small inland water bodies. The interplay between these factors will depend on the specific region being
290 simulated, which emphasizes the complexity of the model's response to orographical and climate drivers.

In areas of low variability in surface elevation, and in the absence of inland water bodies or coastlines, the difference between
LPJ-GUESS outputs at different resolutions is much smaller, and may be safely ignored in calculations involving regional
averages of ecosystem variables. For this type of studies, one could optimize the resource requirements of the simulations by
using a coarser resolution in areas with lower elevation variability and no lakes or coastlines.

295 Systematic biases in model outputs may arise as a consequence of differences in forcings other than resolution. For instance,
high-resolution simulations might be sensitive to the algorithm used to downscale the forcings. In the context of climate miti-
gation, correlations between different climate variables might influence relevant modeled variables (Zscheischler et al., 2019).
Such correlations are not built into univariate methods like CHELSA, but can be captured by dynamical or multivariate down-
scaling. These methods are, however, generally more complex, and might require intensive use of computational resources.
300 Therefore, it might be of interest to find systematic differences between simulations forced by the different methods. This can
be written as the following hypothesis testing problem:

$$\begin{aligned} H_o : \mu_X^{\text{dyn}} &= \mu_X^{\text{CH}}, \\ vs \\ H_a : \mu_X^{\text{dyn}} &\neq \mu_X^{\text{CH}}, \end{aligned} \quad (11)$$

where 'dyn' stands for dynamical downscaling, 'CH' for CHELSA downscaling, and X is the random variable of interest,
which is defined in terms of LPJ-GUESS outputs (for example, the regional average of C_{soil} over the historical period). The
305 following protocol can then be used to test these hypotheses:

1. A *control* set of n LPJ-GUESS simulations, forced by the dynamically-downscaled climate, is produced. Each simulation
uses a different random number sequence, as described in 2.3.2.
2. A *study* set of simulations is produced in the same manner, but forcing LPJ-GUESS with CHELSA-downscaled climate.
3. The simulation outputs are used to sample the random variable X in the study and control groups ($X_1^S, X_2^S, \dots, X_n^S$ and
310 $X_1^C, X_2^C, \dots, X_n^C$).
4. The bootstrap test is run on these samples as described in Sect. 2.2.

A similar setup could also be employed to investigate systematic differences originating from alternative model configu-
rations. For example, one could assess whether the modeled impacts of two different forest managing strategies on regional



carbon sinks are significantly different from each other. In the language of hypothesis testing:

$$H_o : \mu_{NEP}^{rw} = \mu_{NEP}^{st};$$

vs

$$315 \quad H_a : \mu_{NEP}^{rw} \neq \mu_{NEP}^{st}, \quad (12)$$

where ‘rw’ stands for *rewilding*, and ‘st’ denotes *selective thinning*.

7 Summary

In this paper we presented a high-resolution climate dataset for ecosystem modeling applications in Europe. We applied the CHELSA semi-mechanistic algorithm to scale four ISIMIP3b scenarios (historical, SSP1-2.6, SSP3-7.0, and SSP5-8.5) from
320 an original resolution of 0.5° down to 0.05° . Further processing involved quality checks, rechunking to optimize time-series retrieval at a single location, and the addition of CF-compliant metadata. The new dataset is provided in NetCDF format (one file per variable), and is publicly accessible under a CC BY-SA 4.0 license.

We studied systematic differences between high-resolution LPJ-GUESS simulations, forced with the new dataset, and low-resolution simulations. We found that low-resolution simulations are systematically biased. Two main sources of bias were
325 identified: (a) bias associated to the non-linear response of the model to orographical climate variability, and (b) bias associated to the poor representation of coastlines and inland water bodies on a coarse grid. These sources of bias are independent of the downscaling algorithm, and apply to other DGVMs, insofar as their response to climate forcings is non-linear. Climate-response bias can be very large in mountainous areas; low-resolution simulations overestimated average predictions between $\sim 4\%$ and $\sim 45\%$ in an alpine region, as opposed to a mean bias of $\sim 1.4\%$ in a nearly-flat control region. Biases as large as in the
330 alpine region were shown to be vanishingly unlikely in the control region. On a European scale, both sources of bias led to an overestimation of regional averages between $\sim 2\%$ and $\sim 10\%$. This suggests that, when such differences are relevant, a finer resolution over mountainous areas, coastlines and inland water bodies should be considered.

Code availability. The code base used in this work along with intermediate and final results are available in 10.5281/zenodo.14941305 (Otryakhin and Belda, 2025)

335 *Data availability.* The high-resolution climate data described in Sect. 3 is available in IMK-IFU storage
https://thredds.imk-ifu.kit.edu/thredds/catalog/catalogues/luc_and_climate_catalog_ext.html (Otryakhin and Belda, 2024).



Author contributions. DO: conceptualization, data processing and quality control in Sect. 3 and 4, formal analysis, software in Sect. 3 and 4. DMB: conceptualization, data processing in Sect. 3, 4 and 5, formal analysis, software in Sect. 3, 4 and 5. AA: original idea of using CHELSA with LPJG, conceptualization. All authors helped shape the final form of the manuscript

340 *Competing interests.* The Authors declare no competing interest.



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