



Importance of climate uncertainty for projections of forest ecosystem services

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Abstract

Mountain forests provide a wide range of ecosystem services (ES, e.g., timber production, protection from natural hazards, maintaining biodiversity) and are especially sensitive to climate change. Dynamic vegetation models are commonly used to project climate change impacts on forests, but the sensitivity of process-based forest landscape models (FLMs) to uncertainties in climate input data has received little attention, especially regarding the response of ES. Using a dry inner-Alpine valley in Switzerland as a case study, we tested the sensitivity of a process-based FLM to different baseline climate data, lapse rates, and future climate change derived from different climate model combination chains and downscaling methods. Under the current climate, different sources of baseline climate accounted for the majority of the variation at lower elevations, while differences in lapse rates caused large variability at higher elevations. Under climate change, differences between climate model chains were the greatest source of uncertainty. In general, the largest differences for species were found at their individual regional distribution limits, and the largest differences for ES were found at the highest elevations. Thus, our results suggest that the greatest uncertainty for simulating forest ES is due to differences between climate model chains, and we recommend using as many climate scenarios as possible when projecting future forest response to climate change. In addition, care should be taken when evaluating climate impacts at landscape locations that are known a priori to be sensitive to climate variation, such as high-elevation forests.

Keywords Climate change impact · Downscaling · Dynamic vegetation model · Ensembles · Landscape model · LandClim · Rockfall protection

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Introduction

Climate change is expected to have strong influences on natural and anthropogenic systems (IPCC 2014), although the severity depends on the region and the sensitivity of the indicator (e.g., Dunford et al. 2015). Mountain regions may be especially sensitive to climate change due to enhanced climate warming at higher elevations (Pepin et al. 2015) and the potential for increased risk of natural hazards such as rockfall, landslides, avalanches and floods (e.g., Huggel et al. 2010; Keiler et al. 2010).

Impact models use climate change projections to predict how selected systems may respond to shifts in climatic patterns. In mountain regions, this has included, among others, climate-induced changes to forest growth and gravitational protection services (e.g., Elkin et al. 2013; Maroschek et al. 2015), changing streamflow and habitat provisioning for fish (Papadaki et al. 2016), or drinking water availability (Marques et al. 2013). To quantify uncertainty in model projections, *best practice* encourages climate change impact models to use as many combinations of global and regional climate models (GCMs, RCMs) as possible (e.g., Araújo and New 2007; Christensen et al. 2007), although this is not always done. Uncertainty has also been examined by looking at the variability between emission scenarios (e.g., Brown et al. 2015), between GCM-RCM model chains *within* a single emission scenario (e.g., Buisson et al. 2010), between impact models (e.g., Burke et al. 2017), and between different downscaling methodologies (Bosshard et al. 2013; Camici et al. 2014). While all sources of variability can increase uncertainty in model projections, there is a need to identify and rank the most important (i.e., those that cause the greatest differences in model results). We will focus specifically on uncertainty caused by variability in climate input data, specifically related to uncertainty within known quantified limits. For ecosystem service (ES) provisioning in mountain forests, potentially important sources of climate variability include historical climate, temperature lapse rates, and precipitation gradients, as well as methods for downscaling climate model outputs to the landscape scale.

Using the best available climate input data should be a priority for impact assessments, but there has been almost no research on forest model sensitivity to variability in climate data at the landscape scale. This is the scale at which forest management occurs, and accurate predictions are of key importance especially under a rapidly changing climate. The only previous study that we are aware of quantified uncertainty in a forest biogeochemical model and focused on the sensitivity of hydrology, water quality, and forest growth to various downscaling methods (Pourmokhtarian et al. 2016). Accurately downscaling climate projections is a priority for assessing climate change impacts that may be influenced by both long-term changes (e.g., Nishina et al. 2015) and changes

in day-to-day variability (e.g., Camici et al. 2014). The sensitivity of tree growth and species composition to long-term climatic signals is well established (Babst et al. 2013), and there is increasing evidence that forest properties are also sensitive to short-term climate variability (Elliott et al. 2015).

Interestingly, Pourmokhtarian et al. (2016) found that the choice of downscaling methodology was not as important as the choice of historical observations that was used to train their model. Forests that we observe today reflect past climatic and growing conditions (e.g., Gimmi et al. 2009), and it is these current forests that will respond to future climate change. Baseline climate is typically used to “spin up” impact models to represent current forests, before applying future climate change scenarios. As there are several potential sources for baseline climate (e.g., weather stations, gridded and interpolated datasets such as WorldClim; Hijmans et al. 2005), the bias from the choice of historical climate data may be an important source of variability that has previously been largely ignored.

Impact models that simulate mountain regions have yet another source of climatic variability—temperature lapse rates and precipitation gradients (Zhang et al. 2015). The methods and data used to derive elevational lapse rates are often coarse and not scrutinized further in climate sensitivity analyses, although they could be important for landscape-scale impact models that use these rates to interpolate climate throughout the catchment area.

The objective of the present study is to test the sensitivity of a forest landscape model to the uncertainty induced by different approaches for providing climatic input data in mountain regions. More specifically, we will address the following: (1) How sensitive are simulation results to different sources of baseline climate data, temperature lapse rate, and precipitation gradients? (2) How much of the variability in future climate change impacts in forest ecosystems is due to the choice of baseline climate data, lapse rates, or the choice of GCM-RCM model chain? (3) How important is the methodology for downscaling future large-scale climate change data to the landscape level? Separating and quantifying these uncertainties will improve our understanding of the sensitivity of forest landscape projections and identify ways to reduce them.

Methods

Case study landscape

The Saas valley (46° 11' N and 7° 93' E) is a dry inner-Alpine region located in the southwestern Swiss Alps. It was selected because it covers a large elevation range (from 600 to 2500 m a.s.l.) and has very different environmental conditions at the lowest and highest elevations, thus rendering it a good

template to comprehensively evaluate the sensitivity of ecosystem model projections to climate-related uncertainties. The valley bottom is very dry and precipitation is the most important limiting factor for tree growth and the main determinant of species composition (Bigler et al. 2006), whereas at higher elevations temperature limitations drive species performance (Vitasse et al. 2012). Lower elevations (600–1000 m a.s.l.) are dominated by drought-tolerant *Pinus sylvestris* and *Quercus pubescens*, with increasing abundances of other deciduous species at mid-elevations (1000–1200 m a.s.l.). Higher elevation forests (1200–1800 m a.s.l.) are dominated by *Picea abies*, with *Pinus cembra* and *Larix decidua* occurring further up and near the treeline (up to 2300 m a.s.l.) (Elkin et al. 2015). Future climate change is expected to have a strong impact on forests in this region (Elkin et al. 2013), in particular, low-elevation forests are at risk due to increasing drought frequency and intensity (Elkin et al. 2015).

Dynamic forest landscape model

LandClim is a process-based forest landscape model (Schumacher et al. 2004) designed to simulate forest dynamics and disturbances at large spatial scales (10^3 to 10^6 ha) over long periods of time (decades to thousands of years). We chose LandClim since it has successfully been applied to simulate forest dynamics in Central Europe and the Mediterranean under current (Schumacher et al. 2006), past (Henne et al. 2011) and future climatic conditions (Bouriaud et al. 2015). In addition, LandClim has previously been evaluated and applied in the Saas valley to simulate the provisioning of ecosystem services (ES) under current and future climate (Briner et al. 2012; Elkin et al. 2013).

In LandClim, landscapes are represented as a 25-m \times 25-m grid with specific topographic and climatic input variables for each cell. Within each cell, a simplified forest gap model (Bugmann 2001) simulates tree establishment, growth, competition, and mortality on an annual time step. Trees are simulated using a cohort approach (i.e., a computational simplification where one representative individual is simulated for all trees of the same species and age within a cell), as individuals within a cohort have similar traits and a similar response to environmental conditions (Bugmann 1996). The model simulates the number of trees in a cohort and the mean biomass of an individual tree. Individual tree growth is simulated using a logistic growth equation, where species-specific maximum growth rate and size are reduced by light availability, degree-day sum, and a drought index (Schumacher et al. 2004). Light availability is calculated for each grid cell, based on light extinction calculated with the Lambert-Beer Law (Monsi and Saeki 2005).

Tree establishment and mortality are stochastic processes. Each year, the potential for tree establishment is determined as a function of several environmental filters (i.e., available light

at the forest floor, minimum winter temperature, growing degree-day sum, drought index, and browsing). Even if all the environmental filters are passed, there is an additional stochastic process to capture all the factors not explicitly modeled. This takes the form of a random number drawn from a uniform distribution in the range [0,1] that must exceed a user-defined establishment probability. Mortality is determined as a combination of stress (sequential years of poor growing conditions), density-dependent and intrinsic mortality (increasing probability of mortality as the tree approaches its maximum lifespan). The mortality probability is translated stochastically into mortality events. Further, mortality can be caused by disturbances such as fire, wind, and bark beetles, but these agents were turned off in the current simulations. LandClim version 1.4 was used for this study.

LandClim produces a variety of outputs for each cohort in each grid cell, including stem density and biomass, diameter at breast height (DBH), height, and age. These variables can then be used to calculate a variety of ES metrics. For this study, we calculated three ES including (i) total biomass (sum of all aboveground biomass across all species and cohorts), (ii) biodiversity, and (iii) rockfall protection. These represent the most important ES in this region, as these forests are used for timber production, biodiversity conservation, and protection against gravitational hazards (Briner et al. 2013). Biodiversity was calculated using the Shannon diversity index (typically ranges from 1 to 4) and protection using the Rockfall Protection Index (RFPI, ranges from 0 to 6) as defined by Elkin et al. (2013).

Climate data

LandClim requires monthly mean temperature and precipitation sums, which are usually derived from a reference weather station. The elevation of the weather station is used, along with temperature and precipitation lapse rates, to extrapolate the climate data throughout the landscape using the DAYMET algorithm (Thornton et al. 1997).

Baseline climate and lapse rates

We used 30 years of historical baseline climate data (1981–2010) from two sources (Table 1):

- (I) Monthly values for mean temperature and precipitation sums from the MeteoSwiss weather station Visp (650 m a.s.l.) at the bottom of the valley. A nearby station outside the Saas valley, Montana (1427 m a.s.l.), was used to calculate mean monthly lapse rates. We refer to these climate data as *station climate* and *station lapse rate* (Appendix A, Fig. A1).
- (II) Monthly temperature and precipitation values from an observation-based, 2 km gridded data set (temperature:

Table 1 Simulation design, for quantifying the sensitivity of a forest landscape model (LandClim) to various sources of uncertainty from climate input data. Other sources of variation are also accounted for (i.e., initial forest state, stochastic processes in LandClim, randomization of baseline climate data), as each replicate has a different random number seed and a different randomized climate data. The

downscaling comparison (D) were the only simulations where each replicate was also initialized with a different forested state. Note that the roman numerals refer to future climate products, and letters refer to simulations. Additional details for both climate and simulations are found in the “Methods” section

Uncertainty	Initialized forest	Base climate – Lapse rate	Climate change	Replicate	n
(A) <i>Current climate data source</i>	1 × Station – Station 1 × Station – Grid 1 × Grid – Station 1 × Grid – Grid	→ Station – Station calculated → Station – Grid calculated → Grid – Station calculated → Grid – Grid calculated	none	10	4 · 10 = 40
(B) <i>Future climate change (relative to current conditions)</i>	1 × Station – Station 1 × Station – Grid 1 × Grid – Station 1 × Grid – Grid	→ Station – Station calculated → Station – Grid calculated → Grid – Station calculated → Grid – Grid calculated	10 Local downscaled delta change (ii) ETHZ_HadCM3Q0_CLM HC_HadCM3Q0_HadRM3Q0 SMHI_HadCM3Q3_RCA SMHI_ECHAM5_RCA MPL_ECHAM5_REMO KNMI_ECHAM5_RACMO ICTP_ECHAM5_REGCM DMI_ECHAM5_HIRHAM CNRM_ARPEGE_ALADIN SMHI_BCM_RCA	1 2 3 4 5 6 7 8 9 10	4 · 10 · 10 = 400
(C) <i>Regional versus downscaled projections</i>	1 × Station – Station	→ Station – Station calculated	10 Local downscaled delta change (ii) Probabilistic regional delta change (i)	10	1 · 11 · 10 = 110
(D) <i>Downscaling methodology</i>	10 × Station-Station	→ Station – Station calculated	Local downscaled delta change (ii) for ETHZ_HadCM3Q0_CLM Transient bias-corrected (iii) for ETHZ_HadCM3Q0_CLM	10	1 · 2 · 10 = 20

Frei 2014, MeteoSwiss 2013a; precipitation: MeteoSwiss 2013b) from which a 48-km × 58-km rectangle that encompasses the Saas valley was extracted. As a surrogate for the “base station,” we used the climate data at 700 m a.s.l. and re-calculated mean monthly temperature and precipitation lapse rates using all of the cells in the extracted area. We refer to this climate data as *grid climate* and *grid lapse rate*.

Future climate

We used three climate products for one emission scenario, IPCC’s SRES A1B greenhouse gas emission scenario (Nakicenovic et al. 2010). This emission scenario was selected because it had already been downscaled using three methods (described below), i.e., climate forcing data were readily available.

(i) *Regional delta change* (Appendix A, Fig. A2). We used the median estimate of the probabilistic regional CH2011 scenario product at daily resolution that is provided for three regions in Switzerland (CH2011 2011), for three scenario periods (2021–2050, 2045–2074, and 2070–2099). We took the mean of the northwestern and north-eastern parts of Switzerland (CHW and CHNE) to get values for the central Alps. For obtaining transient

scenarios, a linear interpolation of delta change values was applied between the central year of each scenario period (2035, 2060, 2085), with a start in 1994 to be consistent with the reference period of 1980–2009. This is the same methodology employed by Elkin et al. (2013). The final transient scenario series used as input for LandClim was obtained by modifying the baseline climate with these transient delta change values (additive for temperature and multiplicative for precipitation) and aggregating to monthly resolution (Fig. 1).

(ii) *Local delta change* (Appendix A, Fig. A2). We used the daily local CH2011 product, i.e., daily temperature and precipitation changes, downscaled for the station Visp for ten individual GCM-RCM model chains (Table 1). As for the regional delta change, we applied a linear interpolation between the three scenario periods to obtain transient changes in temperature and precipitation from 1994 to 2100 for each GCM-RCM model chain. The final transient forcing series was obtained in the same way as for (i) above.

(iii) *Downscaled and bias-corrected* (transient product until the year 2099). Quantile mapping was used to bias-correct and downscale the RCM output for daily temperature and precipitation to the Visp station (Rajczak et al. 2016). This was performed only for the ETH_HadCM3Q0_CLM model chain (Appendix A, Fig. A3). The bias-corrected approach yields a slightly lower rise especially of summer temperatures during the

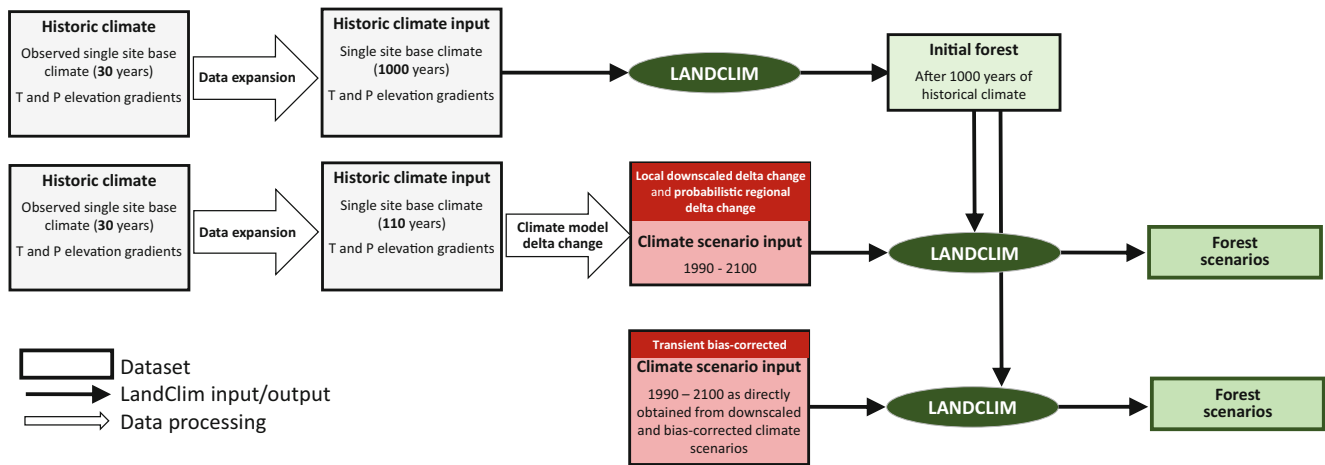


Fig. 1 Schematic of the preparation of climate input for LandClim

twenty-first century. The daily values were aggregated to monthly mean temperatures and precipitation sums, for input to LandClim.

Simulations

Spin up

To expand the 30-year baseline climates (station climate and grid climate) into longer time series, we randomly sampled with replacement (extracting between 1 and 30 years at a time) to create 10 different 1000-year climate series for the station data, and 10 for the gridded data. The baseline climates were paired with lapse rates from both station and grid, creating four combinations of baseline climate–lapse rate. These 1000-year climate data sets were used to grow the forest from bare ground, using the 15 tree species found in this region (Appendix B). The final state of the landscape was saved (Fig. 1), and these forests were used to initialize the matching simulations described below (i.e., *station climate + station lapse rate*, or *station climate + grid lapse rate*, etc.). All simulations had the same forest management regime applied, designed to increase the protection value of forests by increasing regeneration and structural diversity (for details cf. Elkin et al. 2013).

Below, we describe the methodology for deconstructing climate-related uncertainty in the simulation results. For more details about the methods, cf. Appendix B.

Uncertainties from baseline climate and lapse rates (A)

To examine the sensitivity of the simulation results to uncertainties in baseline climate and lapse rates, we created 10 replicates for each of the four combinations of *baseline climate* and *lapse rate* (Table 1).

Uncertainty from baseline climate and lapse rate relative to projection uncertainty (B)

To understand the importance of baseline climate and lapse rate relative to the uncertainty in future climate projections, we ran all combinations of baseline climate data × lapse rates × 10 GCM-RCM model chains that had been down-scaled to produce a local delta change (scenario product (ii); Table 1).

Uncertainty from climate downscaling methodology (C and D)

For examining the influence of the downscaling method, we kept the baseline climate and lapse rate constant and always used the station data and station lapse rates. First, we compared the regional and local delta change values (see section “Future climate” (i) and (ii) above). These relative changes to temperature and precipitation were applied to 10 randomly generated baseline climate series, from 1990 to 2100. This created a total of 110 simulations (10 replicates of the regional climate change, and 10 replicates for each of the 10 GCM-RCMs, Table 1). Second, we compared the local delta change to the bias-corrected climate (see section “Future climate” (ii) and (iii) above).

Analysis

We analyzed several species-specific variables, including mean biomass (t/ha), mean diameter at breast height, and mean age within each grid cell. However, all three species-level variables showed similar responses so only the results for biomass are included in the manuscript. We also analyzed three important ES: total biomass, biodiversity, and rockfall protection.

For each 10-m elevation band (from 640 to 2400 m a.s.l.), we performed an ANOVA and used the total and partial sum

of squares to calculate the effect size (η^2) for each variable, i.e., the proportion of the total variance explained by each factor. Other sources of variability between simulations are captured in the residuals, and could be due to the stochastic processes in LandClim, or the randomization of the 30-year baseline climate into longer time series. This analysis was done for simulations in uncertainty scenarios A and B.

To compare the results from the probabilistic regional scenario to the local delta change values for each GCM-RCM (uncertainty scenarios C), we calculated the total possible range of all simulations that used the local delta change (i.e., for each elevation, the maximum and minimum simulated). We refer to this as the 100% range. We also calculated the 50% range, i.e., the 25th–75th percentile, of all of the local delta change simulations. This was done for mean species biomass as well as the ES described above. We then calculated the proportion of the regional results along the elevation gradient that were contained within the 100 and 50% range.

To compare the results from the local delta change value to the bias-corrected climate (uncertainty scenarios D), we analyzed the three ES metrics through time, at every elevation (although only four representative elevations are shown below). We used a linear mixed effects model that included the effect of climate scenario, time, and the interaction between climate and time. The initial forest state was included in the error term. All analyses were performed in the statistical software R (v3.1.1).

Results

Sensitivity to uncertainties in baseline climate and lapse rates (A)

Variation in simulation results due to the choice of baseline climate and lapse rate had the largest impacts at the edges of a species' elevation distribution (Fig. 2). Generally, the baseline climate accounted for more variability at low elevations, whereas lapse rate became more important with increasing elevation. The species that was least sensitive to differences in baseline climate or lapse rates (i.e., *Pinus mugo*) has the lowest growing degree requirements and the highest drought tolerance (i.e., it is not strongly limited by temperature nor precipitation), whereas those species that were very sensitive to differences in climatic input data (e.g., *Fraxinus excelsior*, *Quercus robur*, or *Picea abies*) have some of the lowest drought tolerances or highest degree-day requirements.

The simulated ES indicators showed a similar pattern, with baseline climate contributing more to variability particularly at lower elevations, and lapse rate having a stronger impact at higher elevations (i.e., > 2100 m a.s.l., Fig. 3). For total biomass, variability in different baseline climates accounted for

approximately 25 to 60% of the variation below 1500 m a.s.l., and lapse rates accounted for a similar percentage > 2100 m a.s.l. (Fig. 2a). For most of the elevation gradient, however, the residuals were the largest component of variability for total biomass. For the biodiversity and rockfall protection indices (Figs. 2b, c), however, baseline climate and lapse rates typically accounted for > 50% of the variability and up to 90% at some elevations.

Sensitivity to uncertainties in baseline climate, lapse rate, and future climate (B)

Variability induced by the GCM-RCM model chain was the largest source of systematic uncertainty for most species (Fig. 4), accounting for up to 33 and 88% of the variability, depending on the species. Some species were less sensitive to the differences between future climate data, such as *Abies alba* and *Larix decidua*, whereas others were much more sensitive to differences between GCM-RCM model chains, in particular *Acer* sp., *Quercus* sp., *Fraxinus excelsior*, and *Tilia platyphyllos*. This is not to say that certain species did or did not respond to climate change, but rather that the magnitude and direction of their response was consistent regardless of the GCM-RCM model chain used.

The ES indicators were also more sensitive to differences between GCM-RCM model chains than to baseline climate or lapse rates, for most of the elevation range (Fig. 5). Across the entire elevation gradient, biodiversity and rockfall protection indices were more sensitive to differences in climate input data compared to total biomass. In the year 2100, variability caused by different baseline climates was still an important factor for all three ES metrics at high elevations (Fig. 5), while the different lapse rates were important for total biomass and rockfall protection.

Impact of climate downscaling methodology

Regional versus local delta climate change (C)

At the end of the twenty-first century, most tree species were projected to shift their biomass distribution to higher elevations (Fig. 6), resulting in decreasing biodiversity at lower and increasing biodiversity at higher elevations (Fig. 7). For most low-elevation species, biomass simulated with the probabilistic regional climate change scenarios matched quite well those under the ensemble projections, usually falling in the range of projections from the ten individual local climate change simulations (Fig. 6, Table C1). However, this was not true at higher elevations, where simulations using the probabilistic regional projections became noticeably different from the local scenarios. Particularly *Picea abies*, *Pinus cembra*, and *Larix decidua* showed quite different patterns above 2100 m a.s.l. (Fig. 6).

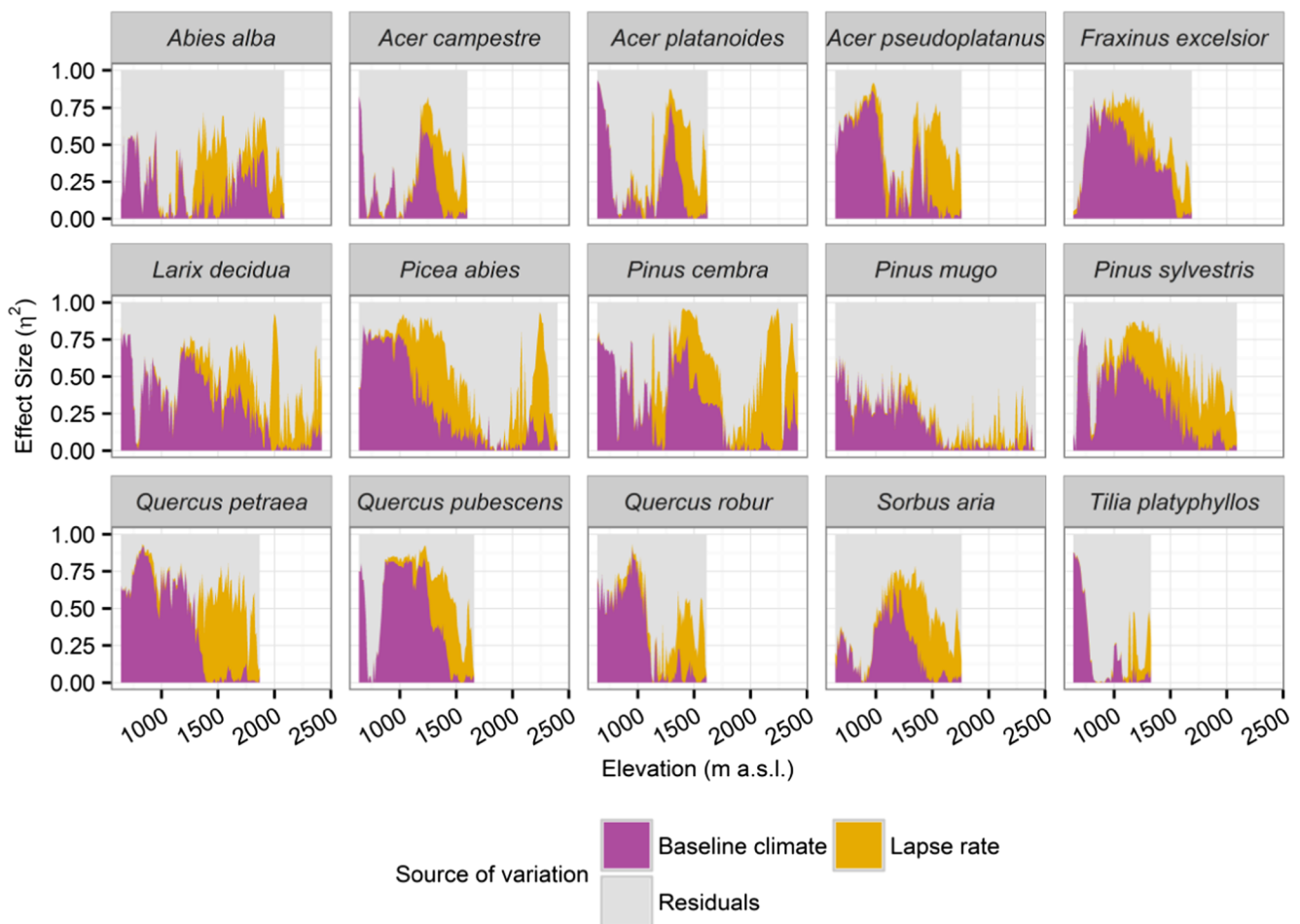


Fig. 2 The proportion of variability caused by the choice of baseline climate and lapse rate on mean biomass for each species, under current climatic conditions along the entire elevation gradient in the Saas valley. An explanation of effect size (η^2) can be found in the “Methods” section

Differences in the downscaling methodology also caused elevation-dependent differences in the simulation of ES metrics. Below 2000 m a.s.l., the probabilistic regional climate change simulations were within the 100% ensemble range for all three indicators (Fig. 7). However, above 2100 m a.s.l., the probabilistic regional climate change simulations were again very different from the simulations that used the individual locally downscaled climate change data. The probabilistic regional climate change simulations featured higher total biomass, lower biodiversity, and increased rockfall protection between 2100 and 2400 m a.s.l (Fig. 7).

Above 2100 m a.s.l., there is a sharp decrease in water holding capacity (“bucket size”; cf. Appendix B), which is pivotal for simulating drought in LandClim. The probabilistic regional climate change projections have a higher frequency and severity of annual droughts (Appendix A, Fig. A4) and are also somewhat colder than most of the locally downscaled GCM-RCM models (Appendix A, Fig. A5). The interaction between increased drought and colder temperatures drove the differences in the simulation

results between the two downscaling approaches > 2100 m a.s.l.

Local delta climate change versus local bias-corrected climate change (*D*)

The simulated ES metrics responded to future climate change in a similar manner when using either the bias-corrected climate change method or the downscaled delta change method (Fig. 8), with time having a significant effect for all indicators at all elevations. However, there were systematic differences between downscaling methods. The higher spring and summer temperatures in the delta change method (Appendix A, Fig. A3) caused more drought limitations for tree growth at low elevations, resulting in lower total biomass (Fig. 8). The difference in the climate produced by the two downscaling methods also resulted in a significant impact on simulated tree diversity. Although both methods showed a decrease in species diversity at lowest elevations, and generally increasing diversity at higher elevations in the second half of the century

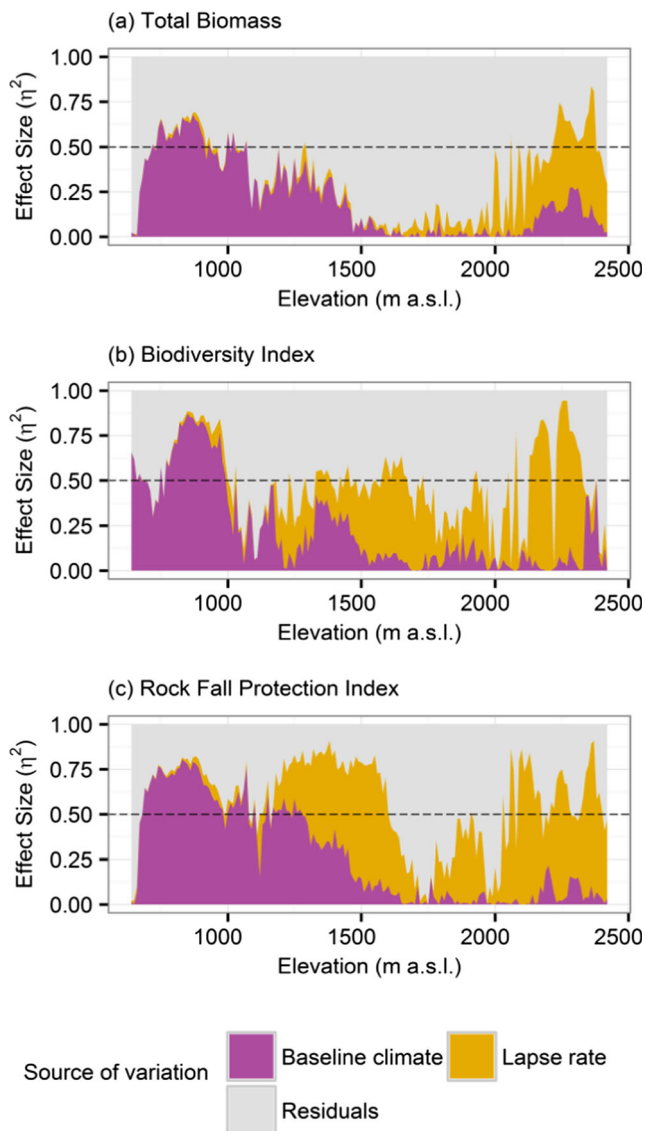


Fig. 3 The proportion of variability caused by the choice of baseline climate and lapse rate on the provisioning of several forest ecosystem services including **a** total above ground biomass, **b** biodiversity, and **c** rock fall protection, under current climatic conditions along the entire elevation gradient in the Saas valley. The dashed line is placed at 50% to aid interpretation

(Fig. 8), the bias-corrected method consistently had lower tree diversity at higher elevations. The delta change method also had higher variability between simulation replicates, specifically at lower elevations for total biomass and biodiversity. This may be due to the fact that bias-corrected approach excludes the sampling of different initializations, and thus there is no variation between the 10 replicates from climate. This is not true for the delta change method, where each of the 10 replicates is slightly different due to the randomized sequence of historical climate that the relative change was then applied to (see the “Methods” section and Appendix B). Rockfall protection was generally insensitive to the downscaling methodology (Fig. 8).

Discussion

Our systematic evaluation of the sensitivity of a forest landscape model to various components of climate input data showed that all sources increase variability in the simulation of forest dynamics and the provisioning of ecosystem services. We found that our simulation results were most sensitive to the choice of historical baseline climate at lower elevations, whereas differences between lapse rates caused the greatest variability at higher elevations. However, under future climate change, the most significant source of variability was from the choice of GCM-RCM model chain (which becomes even more important under longer scenarios beyond 2100, results not shown). In addition, we found that the methodology used for downscaling future climate also influenced the results, but depended on the tree species, ES indicator, and elevation. Below, we discuss in more detail our key questions (i) the choice of baseline climate and lapse rates, (ii) the relative importance of climatic uncertainty compared to random variability, (iii) how downscaling methodology matters for forest projections, and (iv) recommendations for reducing uncertainty.

Choice of baseline climate and lapse rates at low and high elevation

Our inner-Alpine case study valley has very different environmental conditions at the lowest and highest elevations, with precipitation limiting tree growth at low elevations and temperature limiting trees at high elevations. These elevation-dependent drivers of tree growth and forest composition are captured in all baseline climate simulations. The two baseline climates have almost the same temperature, but the station climate data has lower precipitation amounts (Fig. A1). As a result, LandClim results were not as sensitive to differences between the two baseline climate inputs at higher elevations, while the differences between baseline climates were quite important at lower, drought-prone elevations.

Conversely, differences in lapse rate estimates were much more important at higher elevations. This is partly because our simulations were based on a low-elevation climate station, and thus lapse rate-induced differences in temperature and precipitation were small at low elevations and increased with elevation. In addition, this is also the area where temperature is the dominant factor limiting tree growth and establishment (Vitasse et al. 2012). One way to minimize the lapse rate-induced elevation-dependent bias would thus be to use a “virtual” climate station at an intermediate elevation, or to choose the elevation of the base climate station based on a priori assumptions about where the most relevant changes in ecosystem

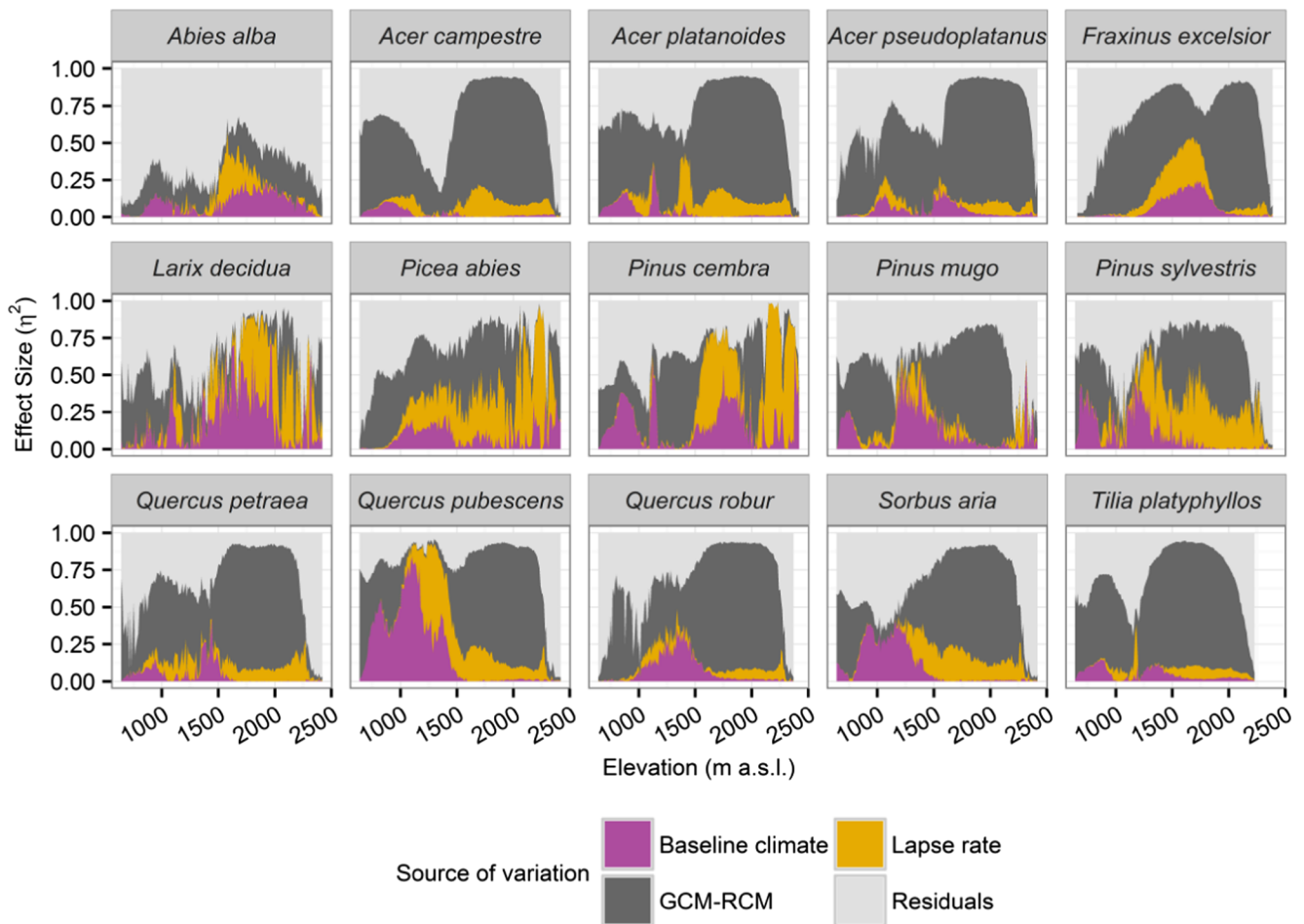


Fig. 4 The proportion of variability caused the choice of baseline climate, lapse rate, and GCM-RCM model chain on mean biomass for each species. The results shown are for the year 2100, along the entire elevation gradient in the Saas valley

properties are expected to occur. Thus, our results support previous modeling studies in alpine regions, such as Zhang et al. (2015) who found that simulating snowmelt would be vastly improved with more accurate temperature lapse rates and precipitation gradients. Despite the fact that lapse rates were found to be important, it is important to note that the climate projections employed in this study do not consider possible future lapse rate changes (Kotlarski et al. 2015).

The relative importance of climatic uncertainty

LandClim is a stochastic process-based model; hence, at least some of the variability in simulation results are due to the outcome of these random processes in the model (i.e., establishment and mortality). Thus, when we refer to the relative importance of climate uncertainty, we are comparing the variability due to climate input data to variability from the amount of stochasticity that is intrinsic to the forest landscape model being used. Within our case study, we aggregated the results by elevation band.

This decision was based on an a priori expectation that the strong elevation gradient that is characteristic of the region is a key determinant for vegetation composition (Bigler et al. 2006), as well conforming to how forest landscape models are commonly applied and analyzed (e.g., Henne et al. 2015; Thrippleton et al. 2014). However, aggregating and interpreting model results at a different spatial grain, or along a different environmental axis, can substantially alter the relative importance of climatic uncertainty. For example, when our results were evaluated at the level of individual raster cells ($25 \times 25 \text{ m}^2$), the dominant source of uncertainty was the intrinsic stochastic processes that underpin LandClim (results not shown) and the relative importance of climatic uncertainty at that spatial resolution is much smaller. This is because differences between establishment and mortality can result in very different successional states (e.g., a young forest compared to a mature forest) when comparing individual cells. Thus, evaluating the relative importance of climate uncertainty should be done with an appreciation of both the ecological grain at which climatic

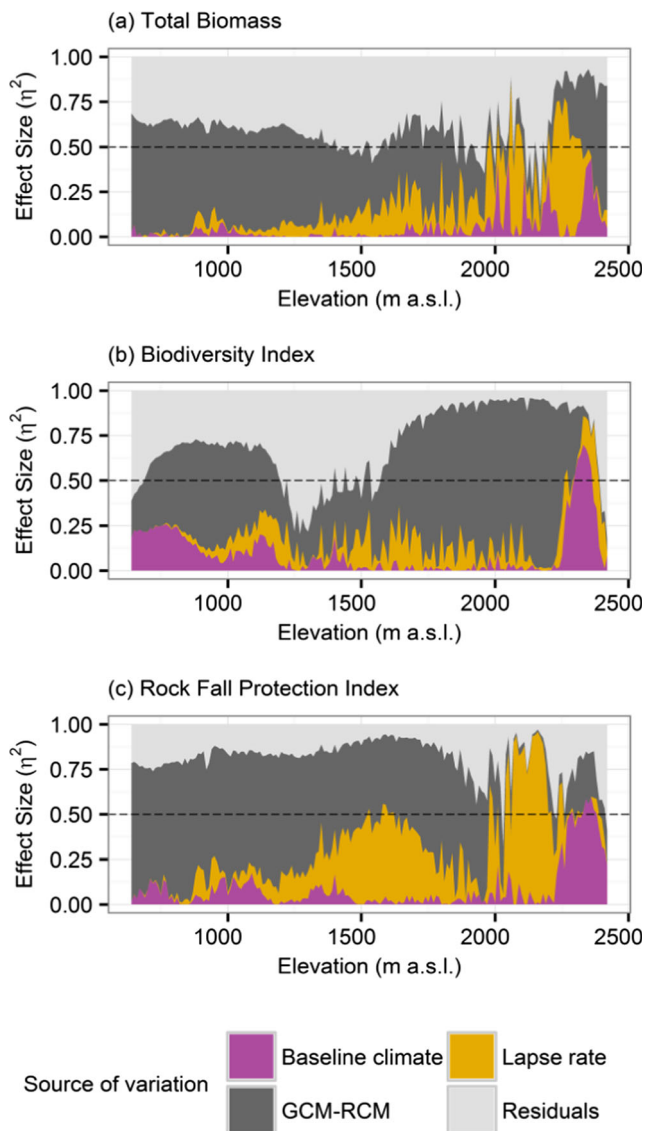


Fig. 5 The proportion of variability caused by the choice of baseline climate, lapse rate, and GCM-RCM model chain on the provisioning of several forest ecosystem services including **a** total above ground biomass, **b** biodiversity, and **c** rock fall protection. The results shown are for the year 2100, along the entire elevation gradient in the Saas valley

input variables are used in the model and the spatial scale at which model output is evaluated.

Downscaling methodology for future climate change

Our results demonstrated how the choice of downscaling methodology, and the realized interaction between temperature and precipitation changes, can have important consequences for simulating the impact of climate change in mountain forests.

In LandClim, species are limited by temperature (growing degree-days), soil moisture (drought index), and light availability (competition). These factors are non-linear, and small

differences in any of them can cause large changes to simulated forest properties (Elkin et al. 2012). Even though the probabilistic regional climate projections appeared to be in the middle of the local scenarios of the ten individual climate model chains (Fig. A2), the joint and non-linear influence of temperature and precipitation on soil moisture resulted in a higher frequency and severity of droughts (Fig. A4) and concomitant impacts on the projected growth of drought-sensitive species. This caused a reduction in *Picea abies*, the most abundant and least drought-tolerant species at 2100 m. a.s.l., and an increase in the more drought-tolerant *Pinus cembra*. Although *Larix decidua* is quite drought tolerant, it is very shade intolerant and thus was not an effective competitor. We suggest that this elevation is the point where soil water holding capacity becomes more limiting than precipitation (Fig. B1). For the locally downscaled models that are wetter compared to the probabilistic regional climate projection, this transition occurred at higher elevations.

The locally downscaled climate projections using either the bias-corrected or the delta change methodology also produced different results in LandClim. The differences in tree diversity at higher elevations and in total biomass at low elevations were caused by the higher summer temperatures resulting from the delta change method (Fig. A3). Higher drought at low elevations reduced total biomass, whereas increased warming at higher elevations induced a considerable turnover of species. The large elevation gradient that characterizes our study area contributed to the detection of differences caused by downscaling methodologies; Pourmokhtarian et al. (2016) applied an ecosystem model in a much smaller study area with only a 200-m elevation gradient and found that different downscaling methods had only a limited impact on their results.

It is difficult to evaluate which downscaling methodology produces “better” results. Rather, a more appropriate question to ask is what are the objectives of the impact study? One clear advantage of the bias correction method is that it allows for the possibility for the frequency and magnitude of future extreme events to emerge from the historic climate forcing data (Fig. A3; Ivanov and Kotlarski 2017). This is important for predicting impacts on indicators that respond to short-term changes. Furthermore, forest structure and dynamics are shaped by a variety of natural disturbances (Seidl et al. 2011), and extreme events are of crucial importance for stand-replacing disturbances such as wildfires (e.g., Hernandez et al. 2015) and bark beetle outbreaks (e.g., Kolb et al. 2016). Thus, simulations that include disturbances may be more sensitive to downscaling methodologies.

Increasing confidence in model results

We found that simulated landscape properties were sensitive to all sources of climate uncertainty that were

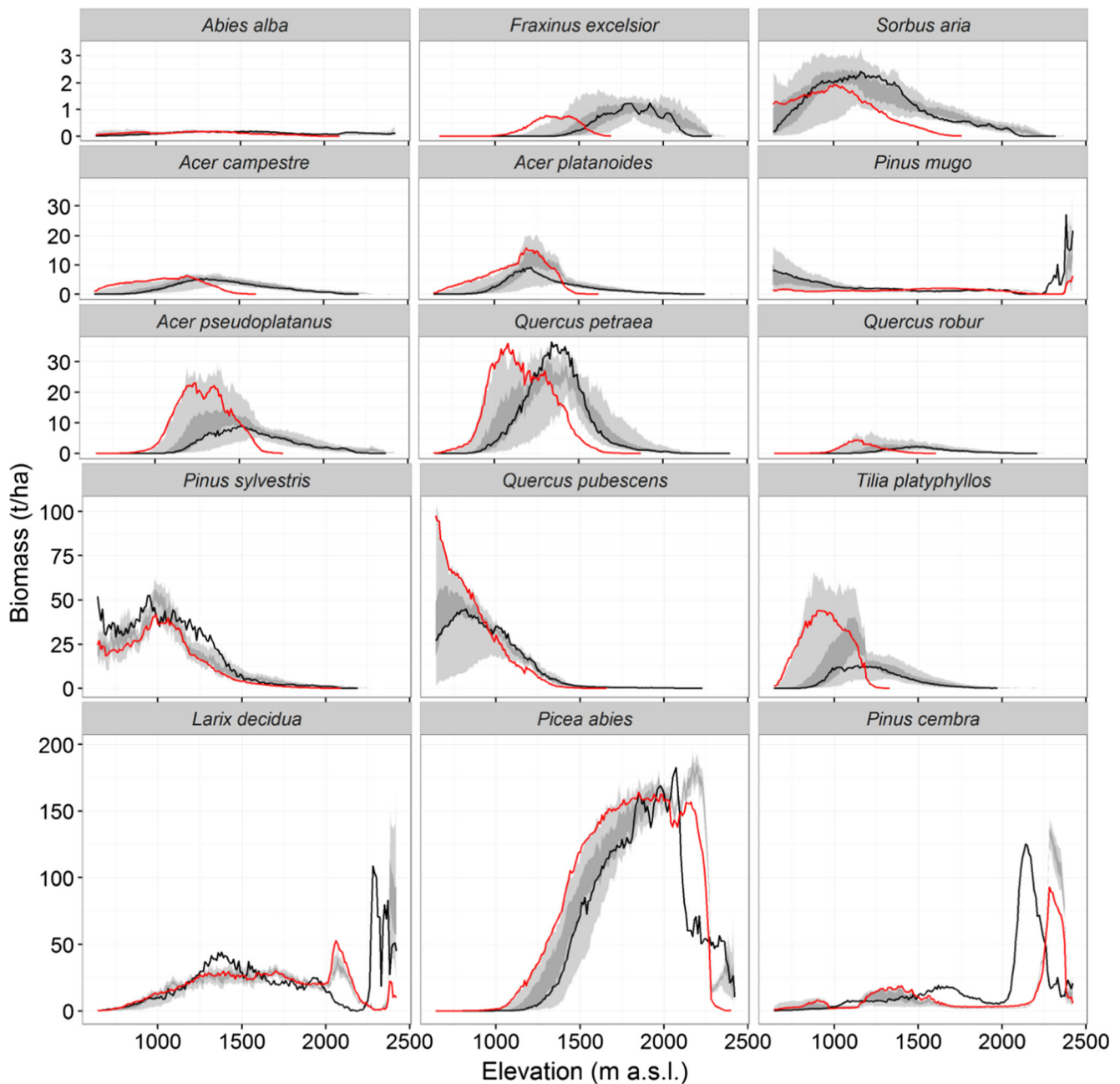


Fig. 6 Simulated biomass of each tree species along an elevation gradient in the Visp valley for the year 2100. The black line shows the mean of 10 replicated simulations that used the regional median delta change product. The light gray areas show the 100% range of all of the simulations that used the delta change products downscaled for Visp (i.e., 10 replicates for

each of the 10 GCM-RCM downscaled model chains), and the dark gray areas show the 50% range. The red line is included for a reference and shows the biomass of each species under current climate. Note the different scales for the y-axis

considered in our study, at some point in space and time. However, there are steps that can be taken to increase confidence in the simulation results, depending on the objective and spatial grain of the study. Projects that aim to evaluate landscape-level responses over longer time frames will likely be better served by using gridded climate data that more accurately reflect regional climate expectations. Climate from weather stations would be more appropriate

for small landscapes (Pourmokhtarian et al. 2016) or that are situated in locations with unusual climatic conditions. Studies focusing on indicators that are less sensitive to local climate details, such as total biomass in our study, can also be interpreted in a broader context if gridded climate data are used.

If long-term, accurate, baseline climate data are not available for a reliable model “spin up,” it may still be

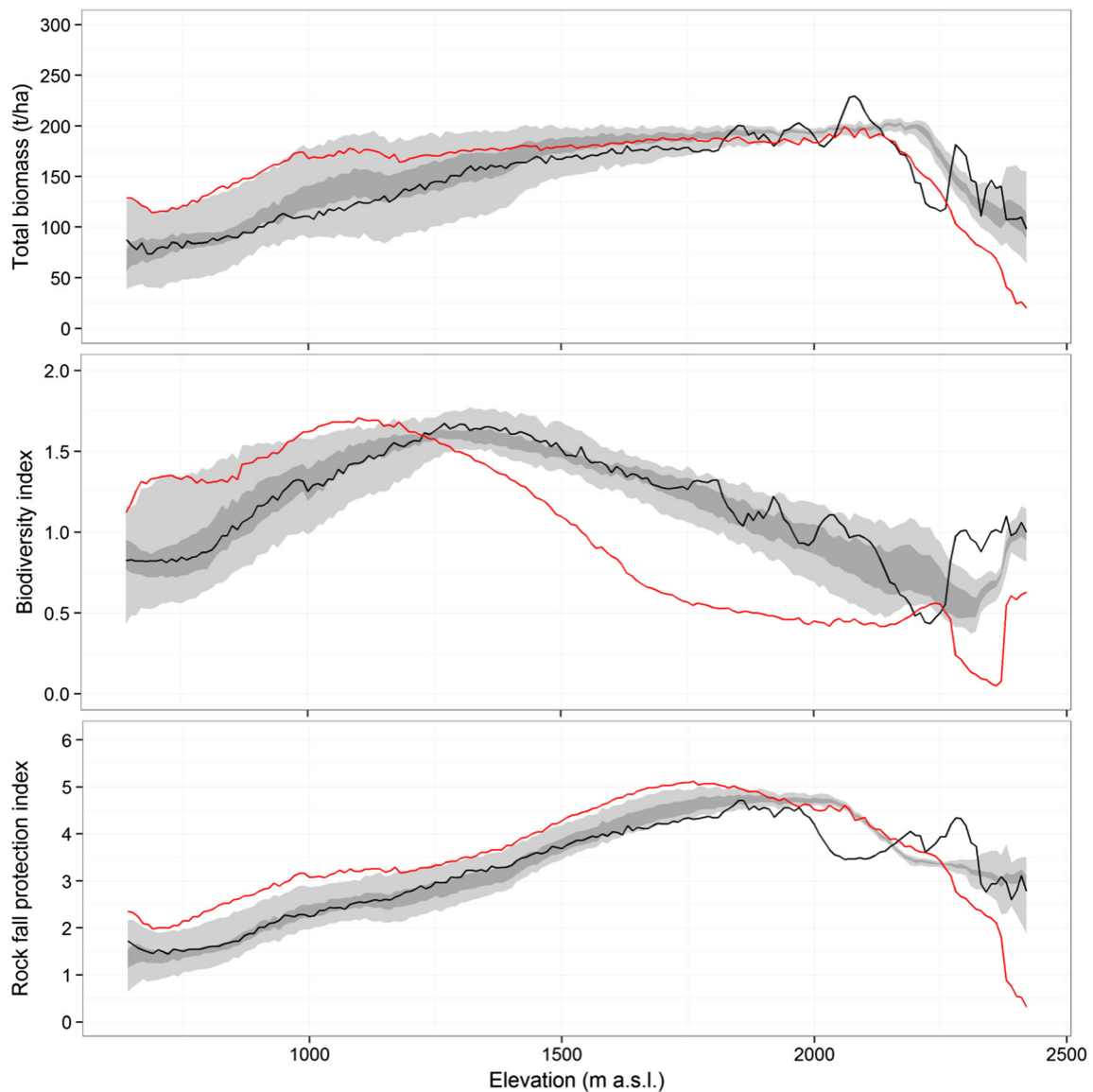


Fig. 7 Simulated ecosystem service provisioning along the elevation gradient in the Saas valley for the year 2100. The black line shows the mean of 10 replicated simulations that used the regional median delta change product. The light gray areas show the 100% range of all of the simulations that used the delta change products downscaled for Saas (i.e.,

10 replicates for each of the 10 GCM-RCM downscaled model chains), and the dark gray areas show the 50% range. The red line is included for a reference, as this shows the ecosystem service provisioning under current climate

possible to minimize this deficiency by initializing forest models with inventory data (cf. Temperli et al. 2013), as this would place less emphasis on the quality of the baseline climate for spinning up the model to a forested state. As found in our study as well as many other studies (e.g., Buisson et al. 2010; Woldemeskel et al. 2016), differences between GCM-RCM model chains cause large uncertainty in impact assessments. Thus, we recommend using as many climate models as possible to capture the uncertainty of these projections, rather than relying on one single trajectory of future climate data.

Conclusions

We systematically addressed the impacts of multiple sources of climatic uncertainty on projections from a forest landscape model. For simulating current conditions, differences in both baseline climate and lapse rate had a considerable impact on simulated forest properties and species abundances. Under future climate change, baseline climate became less important, and differences between GCM-RCM model chains accounted for a large fraction of the variability. In general, the greatest variability was found at the elevational edges of a species' distribution. This has

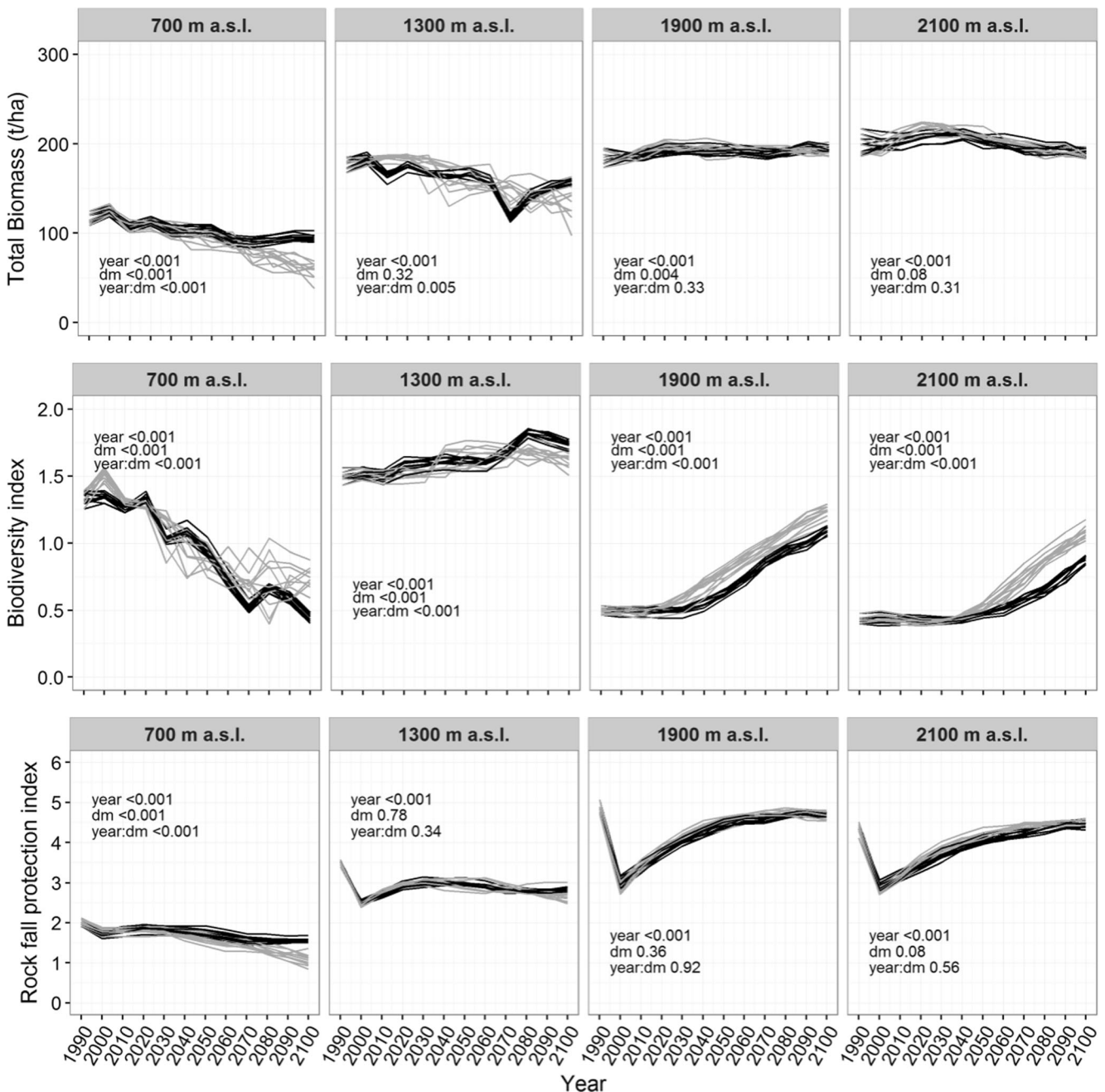


Fig. 8 Response of the provisioning of ecosystem services over time, at selected elevations, in the Saas valley. Both climate simulations use the same GCM-RCM model chain and emission scenario (ETH_HadCM3Q0_CLM, A1B) and differ only in their downscaling methodology (bias-corrected = black line, delta change = gray line). Each of the

10 replicates was initialized with a different forest structure. In each panel, the numbers are the results of the linear mixed effects models, which included year, climate downscaling method (dm), and the interaction between year and downscaling method (year/dm), and indicate the significance value for each variable

important implications for studies that aim to predict shifts in species and community composition along elevation gradients. Ecosystem service (ES) metrics were *relatively* less sensitive to differences in climatic input data and downscaling methodology. Thus, when using these models to project ES changes, greater flexibility is possible in the choice of climatic source data.

In mountain regions, projections for high-elevation forests have the largest degree of uncertainty, and the choice of climate model and downscaling methodology can produce very different results. Efforts to increase the accuracy of climate projections at high elevations would thus make a large difference for impact modeling, especially as these areas are likely to be among the most sensitive to future climate change (Pepin et al. 2015).

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