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ORIGINAL ARTICLE

Assessing uncertainty in bioclimatic modelling: a comparison of two high-resolution climate datasets in northern Patagonia

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Abstract

Climate change is reshaping forest ecosystems, presenting urgent and complex challenges that demand attention. In this context, research that quantifies interactions between climate and forests is substantial. However, modelling at a spatial resolution relevant for ecological processes presents a significant challenge, especially given the diverse geographical contexts in which it is applied. In our study, we aimed to assess the effects of applying CHELSA v.2.1 and WorldClim v2.1 data on bioclimatic analysis within the Río Puelo catchment area in northern Patagonia. To achieve this, we inter-compared and evaluated present and future bioclimates, drawing on data from both climate datasets. Our findings underscore substantial consistency between both datasets for temperature variables, confirming the reliability of both for temperature analysis. However, a strong contrast emerges in precipitation predictions, with significant discrepancies highlighted by minimal overlap in bioclimatic classes, particularly in steep and elevated terrains. Thus, while CHELSA and WorldClim provide valuable temperature data for northern Patagonia, their use for precipitation analysis requires careful consideration of their limitations and potential inaccuracies. Nevertheless, our bioclimatic analyses of both datasets under different scenarios reveal a uniform decline in mountain climates currently occupied by *N. pumilio*, with projections suggesting a sharp decrease in their coverage under future climate scenarios.

Keywords Climate change · Regional climate models · Terrain · WorldClim · CHELSA

Introduction

Climate change poses significant challenges to forest ecosystems, affecting their composition, structure, and function. Rising temperatures, shifting precipitation patterns, extreme

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weather events, and hazards such as droughts and wildfires are altering their ecological dynamics. These changes can lead to shifts in species distribution and disruptions due to transformed ecological processes such as tree establishment and tree mortality (Rodríguez-Catón et al. 2016, Srur et al. 2016, 2018; Tovar et al. 2022) along with changing patterns of invasive species (Iglesias et al. 2022). Additionally, the loss of glacier-fed rivers and decreased snowpack levels impact hydrological regimes, further intensifying stress on ecosystems (Aguayo et al. 2019; Rivera et al. 2023).

Studying the nexus of climate and ecosystems, bioclimatology emerges as a comprehensive framework. It explores in depth the intricate relationship between climate variables and biological processes, with a particular emphasis on their impact on species and ecosystems. This analytical approach integrates climatology, ecology, and biology to understand species distribution and interactions in space and time (Saslis-Lagoudakis et al. 2014). Thus, bioclimatic analysis can be a basis for biodiversity conservation (Ferrier et al. 2020), future-oriented forestry management (MacKenzie and Mahony 2021), and enhancing ecosystem resilience (Piraino et al. 2022). To effectively address these challenges and capture the nuances of small-scale ecological processes, research must be conducted at a relevant spatial scale, ensuring the precision needed for detailed bioclimatic insights.

Nevertheless, modelling at high-resolution presents a significant challenge, especially given the diverse geographical contexts in which it is applied. Peripheral mountainous regions, in particular, face hurdles due to limited coverage of in-situ observations (Condom et al. 2020; Thornton et al. 2022) and their inherent topographic complexity. Access to reliable climate information at high resolution for these regions is often challenging. The scarcity of precise and localised data restricts the ability to capture the intricate interactions and dynamics of the systems under study, thereby introducing significant uncertainties into model outputs. Furthermore, limited availability of data complicates the validation and calibration of models, reducing their reliability in decision-making processes (Otto et al. 2016; Littell et al. 2011).

Climatologies at high resolution for the Earth's land surface areas (CHELSA) (Karger et al. 2017) and WorldClim (Fick and Hijmans 2017) stand out as proven climate datasets for bioclimatic analysis, valued for their high spatial resolution, global coverage, and user-friendly accessibility. Both datasets provide researchers with a range of climatic variables crucial for understanding ecological processes and environmental changes within bioclimatic analysis (Körner et al. 2011; Pesaresi et al. 2017; Pham et al. 2023). Nevertheless, studies in different geographical settings have shown that particularly precipitation-related variables may lack reliability and should be examined carefully (Bobrowski and Schickhoff 2017; Bobrowski et al. 2021; Abdulwahab et al. 2022). Applying and comparing both datasets can thus shed light on the specific needs and challenges in accurately modelling a region's ecological and climatic dynamics.

Within the Andes of northern Patagonia, a pronounced precipitation gradient stretches from west to east over a relatively short distance, leading to a distinct vegetation productivity gradient across the region (Kitzberger et al. 2022). This underscores the importance of precipitation-related bioclimatic variables at high resolution for accurately understanding the region's complex ecosystem dynamics. However, despite the area's unique terrain and the critical role of input data in bioclimatic analysis (Morales-Barbero and Vega-Álvarez 2019), there is a notable research gap in comparing different datasets for bioclimatic analysis within northern Patagonia. The study by Derguy et al. (2022), which compares bioclimatic changes based on two local climate models in southern South America, stands as a rare but vital exception. However, similar studies are needed to uncover the strengths, limitations, and potential biases of various datasets, thereby improving the accuracy and reliability of bioclimatic models (Bobrowski and Schickhoff 2017; Abdulwahab et al. 2022).

In our study, we hypothesised that within the Río Puelo catchment area in northern Patagonia, precipitation-related variables would demonstrate greater uncertainty compared to temperature-related variables, as observed in other geographical settings. Guided by this hypothesis, our primary objective was to assess the impact of using CHELSA and WorldClim data on bioclimatic analysis in this region. To do this, we first compared current and future bioclimates based on these two distinct climate datasets, conducting an inter-comparison to identify any inherent patterns, trends, or discrepancies. Subsequently, we performed a comparison against available reference data to contextualise our findings further. This approach was designed to provide a comprehensive understanding of the potential implications of employing CHELSA and WorldClim data for bioclimatic studies within the Río Puelo catchment.

Data and methods

Study area

The Río Puelo watershed in northern Patagonia, spanning from 41.2° to 42.5° South and 72.2° to 71.5° West, crosses the Río Negro and Chubut provinces in the Andes and features diverse topography and notable climatic gradients. Precipitation decreases from west to east due to the rain shadow of western mountains (Villalba et al. 2003), while an elevation range from 190 to 3157 m affects temperature and precipitation patterns, including snowfall. The area's macroclimate is influenced by the Antarctic Oscillation (AAO) and the El Niño-Southern Oscillation (ENSO). Dominant vegetation includes *Austrocedrus chilensis* and *N. antarctica*, *N. dombeyi*, and *N. pumilio*, with certain *Nothofagus* species at their climatic limit in the east (Amigo and Rodríguez-Guitián 2011; Kitzberger et al. 2022).

Study design

The experimental design of the study (Fig. 2) comprises two principal comparative analyses based on CHELSA and WorldClim. The first phase involves deriving current and future bioclimatic zones for a comparison between both data sources, which aims to identify intrinsic patterns, trends, or discrepancies between both datasets that are then framed as different types of uncertainty. In the initial phase of our study, we leverage climate, species, and elevation data to delineate bioclimatic zones. This process is critical for identifying areas with distinct climate characteristics that influence local vegetation patterns. In the second phase, historical data from CHELSA and WorldClim, alongside meteorological station data, are applied in a validation to contextualise and the findings of the first phase. Collectively, these comparative phases constitute a comparative framework for examining the applied climate datasets.

Elevation data

We used the digital elevation model of the Shuttle Radar Topography Mission (SRTM) at a spatial resolution of 1 arc second which corresponds to approximately 28 m within the study area (Farr et al. 2007).

Historical climate data

For both evaluation processes (Fig. 2), we investigated the climate datasets of WorldClim v2.1 and CHELSA v2.1. These are publicly available, easily accessible, and of high spatial resolution (required to capture altitudinal layers of vegetation). Due to these advantageous properties, both datasets are widely used—highly cited within Clarivate Web of Science—and applied in ecological research (e.g. Fuentes-Castillo et al. 2020), hydrological modelling (e.g. Oliveira-Júnior et al. 2021), and studies related to agriculture and forestry (e.g. Barrueto et al. 2018; Fadrique et al. 2018). This widespread use underscores the significance and the comprehensive nature of the datasets in ecological modelling. Nevertheless, it should be mentioned that other high-resolution datasets and attempts to correct the datasets exist (Beck et al. 2020). However, within the scope of our study, we specifically concentrate on two datasets that have extensively been applied within our area of investigation.

CHELSA V.2.1 is a gridded climate dataset with a 30 arc-second resolution (~0.8 km for the study area), covering monthly temperature and precipitation from 1979 to 2013. It uses ERA-Interim climatic reanalysis, with a temperature algorithm based on statistical downscaling and a precipitation algorithm considering orographic factors, corrected using Global Precipitation Climatology Centre (GPCC) and Global Historical Climatology Network (GHCN) data. Topoclimatic effects are covered through integration of Global Multi-resolution Terrain Elevation Data (GMTED2010) (Karger et al. 2017, 2021). WorldClim 2, similarly at 30 arc-second resolution, provides a 30-year average of temperature and precipitation from 1970 to 2000, based on weather station data interpolated with elevation (SRTM), coastline proximity, and satellite parameters, including land surface temperatures and cloud cover from MODIS (Fick and Hijmans 2017).

Next to gridded climate data, and as an integral part of the validation (Fig. 2), meteorological station data (Fig. 1) for El Bolsón (41.9°S; 71.5°W at 343 m.a.s.l.), Río Villegas (41.6°S; 71.5°W at 526 m.a.s.l.), a location west of El Bolsón (hereafter referred to as Río Azul [41.9°S; 71.6°W at 347 m.a.s.l.]), as well as two locations in the valley of Río Manso (hereafter referred to as Río Manso Inferior [41.6°S; 71.8°W at 439 m.a.s.l.] and Río Manso Confluencia [41.6°S; 71.7°W at 455 m.a.s.l.]) was retrieved from Servicio Meteorológico Nacional (2023) and Sistema Nacional de Información Hídrica (2023). In order to function as a source of validation for high-resolution climate datasets, only station data with available timeseries from 1990 until 2018 was chosen. With the exception of El Bolsón, only data concerning precipitation was accessible for the remaining stations.

Future climate data

Building on the pre-selection by Karger et al. (2017), grounded in the Intersectoral Impact Model Intercomparison Project (ISIMIP) (Lange 2021), and considering the constrained overlap between CHELSA and WorldClim, our analysis was narrowed to a suite of five readily available climate models and two shared socioeconomic pathways (SSP). Specifically, we utilised the pathways SSP1-2.6 and SSP3-7.0 as well as the climate models GFDL-ESM4, MRI-ESM2-0, UKESM1-0-LL, IPSL-CM6A-LR, and MPI-ESM1-2-HR, all of which are based on CMIP6. The scenario SSP1-2.6 with 2.6 Wm^{-2} by the year 2100 is comparable to the optimistic scenario RCP2.6 and was designed with the aim of simulating a development that is comparable to the 2 °C target, according to the Paris Agreement (UNFCCC 2015). This scenario, too, assumes climate protection measures being taken. The scenario SSP3-7.0 with 7 Wm^{-2} by the year 2100 is located in the upper-middle part of the full range of scenarios. It was newly introduced after the RCP scenarios, closing the gap between RCP6.0 and RCP8.5 (O'Neill et al. 2016). CHELSA and WorldClim data

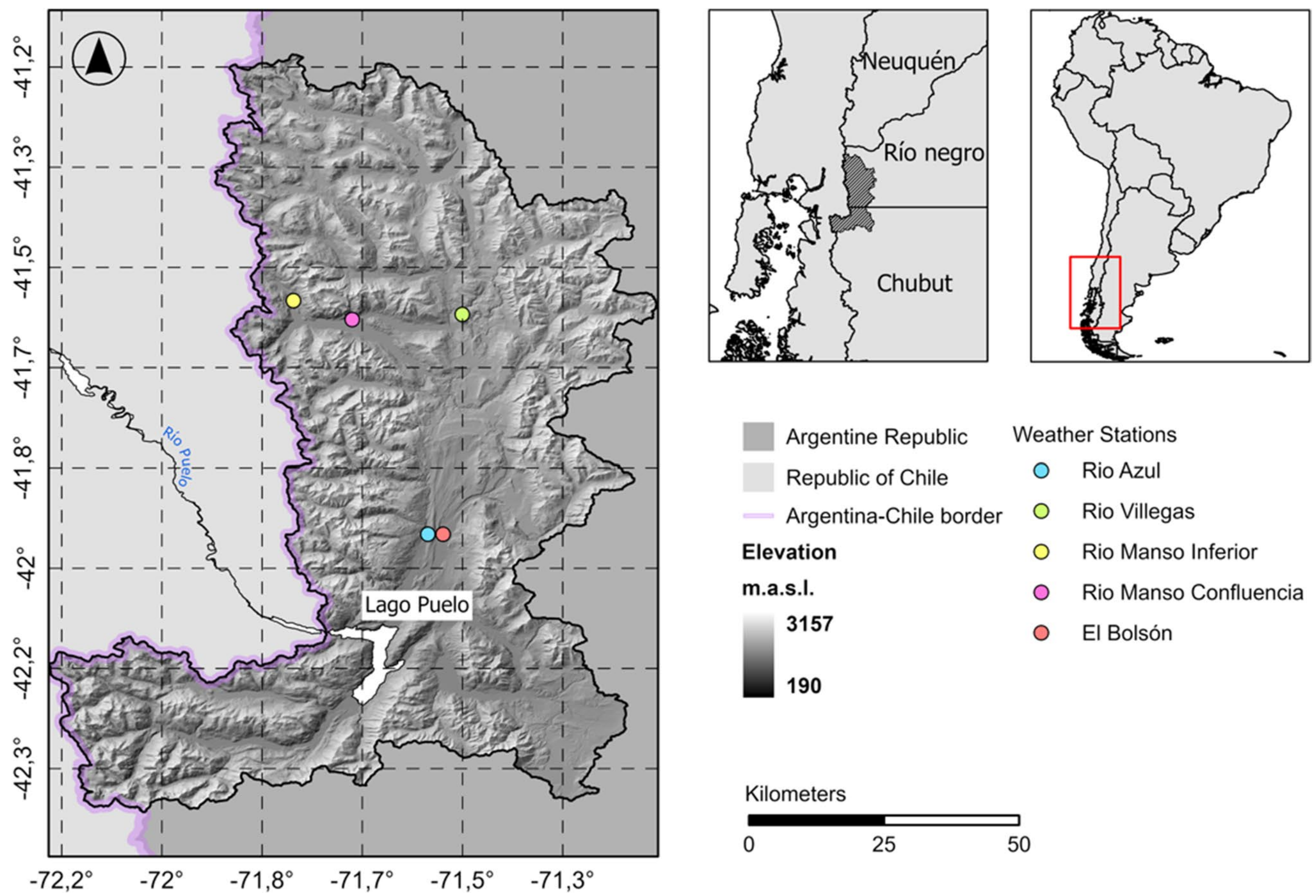

Fig. 1 Map of eastern Río Puelo watershed (showing Río Puelo and Lago Puelo exclusively), located at the Argentina-Chile border in north-west Patagonia. Topography of the study area is illustrated on basis of the digital elevation model SRTM (Farr et al. 2007)

differ in timescales, with CHELSA using 30-year intervals (2011–2040, 2041–2070, 2071–2100) and WorldClim using 20-year intervals (2021–2040, 2041–2060, 2061–2080, and 2081–2100).

Species data

To identify the best data source for establishing vegetation-relevant bioclimatic zones, we extracted occurrence data from the Global Biodiversity Information Facility (GBIF.org 2021) based on the key natural tree species in northern Patagonia: *A. chilensis*, *N. antarctica*, *N. dombeyi*, and *N. pumilio*. Within the process, only species occurrences within the Patagonia region were selected. Thus, anthropogenic distributions (e.g. from botanical gardens) were excluded. Simultaneously, we analysed the updated Forest Type Classification of Andean Patagonia of the year 2016 which is based on field and remote sensing data (CIEFAP-MAyDS 2016). Out of three available classification levels, level two, which classifies the main forest types within the study area, was used within the present study (Supplementary Fig. 1). According to the authors, the second classification level comes with an overall accuracy of 87%.

Bioclimatic analysis

Bioclimates of both high-resolution climate datasets were calculated based on the World Wide Bioclimatic Classification System (WBCS) of Rivas-Martínez et al. (2011). The classification system integrates both moisture levels and temperature conditions to define distinct bioclimatic classes, essential for understanding various ecosystems and climatic impacts (Andrade and Contente 2020, Pesaresi et al. 2017, Torregrosa et al. 2013, Cutini et al. 2021, Del Arco Aguilar and Rodríguez Delgado 2018, Rodríguez-Catón et al. 2016, Szabó et al. 2021). On one side, it categorises climates into ombric types based on the ombrothermic index (Io), indicating moisture availability with classifications such as arid, semiarid, and dry, each specified further into 'lower' and 'upper' horizons based on Io value ranges (Table 1). On the other side, it details thermotypic classifications through the thermotypic index (*Tp*), delineating temperature-based categories like Supramediterranean, Oromediterranean, and

Table 1 Ranges of the annual ombrothermic index (Io) and the annual positive temperature in tenth degrees (Tp) that determine ombric and thermotypic horizons within the study area (in reference to Fig. 2)

Ombric types	ID	Horizon	Io
Arid	1	Lower	0.41–0.70
	2	Upper	0.71–1.00
Semiarid	3	Lower	1.01–1.50
	4	Upper	1.51–2.00
Dry	5	Lower	2.01–2.80
	6	Upper	2.81–3.60
Subhumid	7	Lower	3.61–4.80
	8	Upper	4.81–6.00
Humid	9	Lower	6.01–9.00
	10	Upper	9.01–12.00
Thermotypes	**ID**	**Horizon**	**Tp**
Supramediterranean	1	Lower	1201–1500
	2	Upper	901–1200
Oromediterranean	3	Lower	676–900
	4	Upper	451–675
Crioromediterranean	5	Lower	101–450
	-	-	-

Crioromediterranean, again divided into ‘lower’ and ‘upper’ horizons based on Tp value ranges (Table 1):

where Tp is $\sum Ti_{1-12} > 0°\mathrm{C}$ in tenths of degrees; Pp is the positive annual precipitation of the months with an average monthly temperature (Ti) higher than 0 °C; and Io is $\left(\frac{Pp}{Tp}\right)10$.

This dual approach allows for a comprehensive understanding of climatic conditions, offering insights into the suitability of regions for different types of vegetation, agriculture, and habitat sustainability. All bioclimates were calculated using ‘raster’ in RStudio (Hijmans 2023). Since mountains represent altitudinal thermic variations, classification of macro-bioclimate (submediterranean) was elaborated through temperature and precipitation values of the valley floors considering the macro-climate of the nearest listed station (Esquel; 42.9°S; 71.2°W at 815 m.a.s.l.) according to Rivas-Martínez et al. (2011). As such, the site is located at the border to a temperate macrobioclimate (west) and thus classified as ‘extremely strong submediterranean’ climate (submediterraneity index of El Bolsón = 539) of a balanced oceanic type (simple continentality index of El Bolsón = 14.21) (Rivas-Martínez et al. 2011; Servicio Meteorológico Nacional 2023).

Based on the bioclimatic classification, we derived four bioclimatic zones (A, B, C, and D) in relation to the four primary tree species (*A. chilensis*, *N. antarctica*, *N. dombeyi*, and *N. pumilio*) for both climate datasets (Fig. 3). Each zone encompasses the primary bioclimates (more than 5% of occurrence) associated with a dominant tree species. Hence, in order to determine a bioclimatic zone, occurrence data of a species was layered with our previously created bioclimatic classification and then filtered by all encompassed bioclimatic classes that have a share greater than 5%. Due to the very low amount of available species data within the investigation area (cf. GBIF.org 2021), base data for tree species distribution was adopted from the available forest classification product of CIEFAP-MAyDS (2016).

In order to model bioclimatic projections, different scenarios and timescales were calculated based on the above mentioned SSPs and CMIP6 models. For this purpose, an altitudinal level of 1800 m.a.s.l. was set to restrict potential upshifting of habitat-specific species pools above bare rock terrain without natural soil, where the establishment of natural subalpine *N. pumilio* forest can be excluded. Within this study, relative cover is defined as factor of change and can be explained as the proportion (in percent) of a bioclimatic zone in reference to the total area of the eastern Río Puelo watershed. For each projection, points of origin are the reference periods of CHELSA (1981–2010) and WorldClim (1970–2000). Projections were individually calculated for each GCM and SSP.

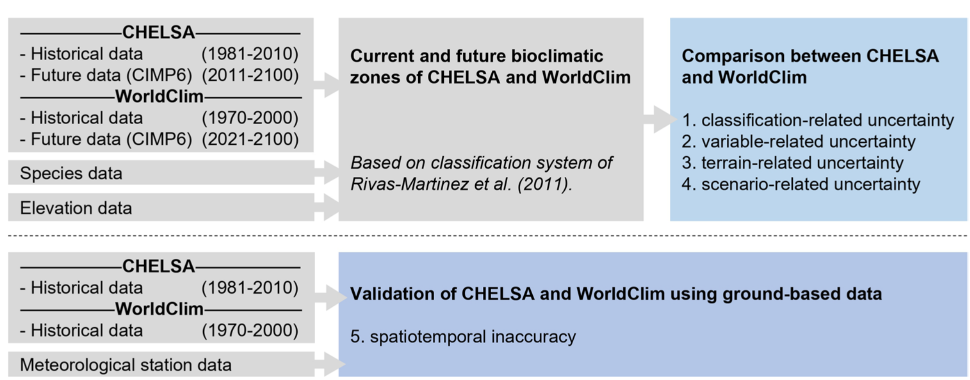

Fig. 2 Comparative framework for assessing bioclimatic modelling uncertainty using historical and future climate data, as well as species, elevation, and meteorological station data. Where grey boxes represent the data input as well as the bioclimatic pre-analysis and coloured boxes represent the two validation phases

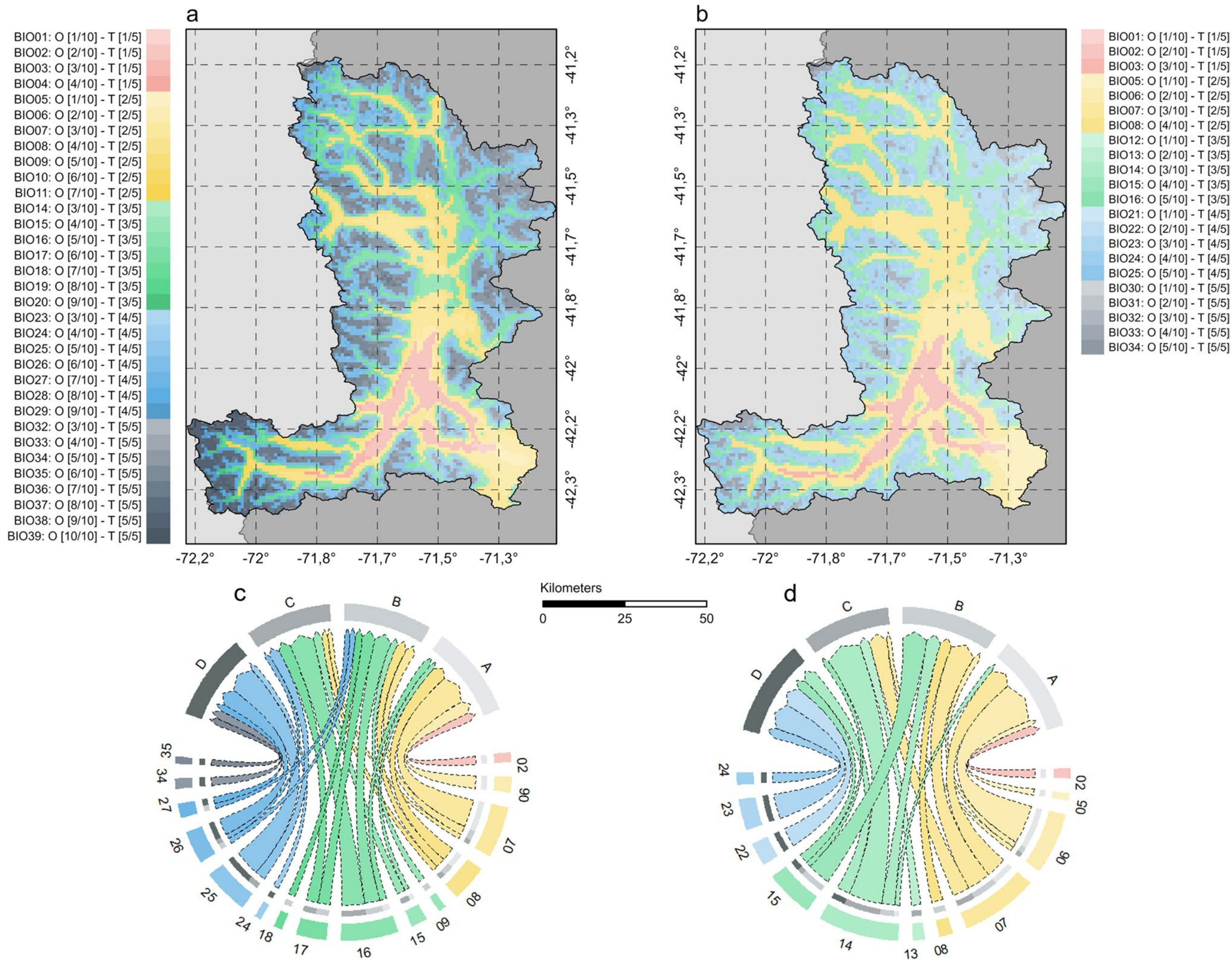

Fig. 3 The bioclimatic zones of the eastern Río Puelo watershed, analysed using two key datasets: CHELSA, with data averaged from 1981 to 2010 (Karger et al. 2021), and WorldClim, with averages from 1970 to 2000 (Fick and Hijmans 2017). Each dataset categorises the region's ombric and thermotypic horizons, ranging from arid to humid and from lower supramediterranean to lower crioromediterranean, respectively. Visual differentiation is achieved through varying colour intensities, indicating moisture variations. Additionally, the figure marks bioclimatic zones A through D, representing species and showing their bioclimates and relative cover percentages across these environmental gradients

Comparison between data sources

In the first step of the comparison between data sources, we used linear regression analysis (Lumley 2020) to explore *uncertainties linked to our bioclimatic classification*, focusing on the impact of various predictor variables, including 19 bioclimatic factors (Supplementary Table 1) from Brun et al. (2022) and Fick and Hijmans (2017), on forest distribution. This aimed to test our zonation's explanatory power to variations arising from different species datasets. The analysis, utilising data from CIEFAP-MAyDS (2016) and GBIF.org (2021), sought to pinpoint the most suitable input data for bioclimatic zonation and evaluate the explanatory power and associated uncertainties of the WBCS in our study area.

In the second step of the comparison between data sources, a descriptive analysis of distribution patterns, using 'ggridges' (Wilke 2022), served as support to identify *variable-related uncertainties* in regard to ombric and thermotypic horizons. This visualisation tool offers good capabilities for visualising changes in distribution over time and space. To better understand variability of means and extremes of both variables, the 0.1, 0.5, and 0.9 quantile were retrieved for each period, SSP, GCM, and high-resolution climate dataset. Since a considerable amount of ground-based data for validation and prioritisation of climate datasets was missing, we considered the disagreement between CHELSA and WorldClim as a way to quantify spatial consistency regarding the precipitation and temperature-related variables (annual ombrothermic index and positive annual temperature).

In the third step, we assessed *terrain-related uncertainty* by measuring the percentage of non-intersecting pixels between CHELSA and WorldClim datasets regarding ombric horizons, thermotypic horizons, and bioclimates. We evaluated each cell for overlaps across these data sets and criteria. Non-intersecting pixels indicated higher uncertainty. To analyse topographical characteristics of cells without intersection, we utilised SRTM-DEM for slope and elevation data. Spatial analyses were conducted in RStudio using 'rgdal' (Bivand et al. 2023), 'raster' (Hijmans 2023), and 'sf' (Pebesma 2018; Pebesma and Bivand 2023) tools, based on EPSG:22181.

In the last step of the comparison between data sources, we compared future scenarios of both climate datasets as they were calculated by the bioclimatic analysis in the first place (section 'Species data'). This step unveiled the *scenario-related uncertainty* due to the application of different GCMs and SSPs. The subject of the comparison is the bioclimatic zones A, B, C, and D, as well as their relative coverage degree.

Validation of data sources

In a second step of our framework (Fig. 2), we identified spatiotemporal inaccuracy in climate data as deviations over time (months) or across locations (from west to east) through a validation of both datasets. This inaccuracy is measured by the relative precipitation or absolute temperature differences between high-resolution climate datasets and meteorological station data. Since station data was limited to a common reference period starting from 1980, a validation period from 1980 to 2010 was used to validate CHELSA and WorldClim datasets, which cover the periods 1981–2010 and 1970–2000, respectively. Spatiotemporal inaccuracy assessments focused on temperature and precipitation for El Bolsón, and precipitation only for Río Azul, Río Villegas, Río Manso Confluencia, and Río Manso Inferior due to data limitations.

Results

Bioclimatic analysis

Our bioclimatic analysis revealed differing categories between CHELSA and WorldClim datasets (Fig. 3a and b). CHELSA spans from lower arid and lower-supramediterranean to upper humid and lower crioromediterranean, whereas WorldClim covers a narrower range, from lower arid and lower-supramediterranean to lower dry and lower crioromediterranean. Variations in thermotypic horizons are represented by different colours, and ombric horizons by colour intensity. WorldClim data, indicated by lower overall colour intensity, shows fewer wet end scale bioclimates (compare Table 1). Despite these differences, there is substantial overlap in the supramediterranean zone, highlighted by red and yellow categories.

Further clarification of these patterns is provided by examining the bioclimatic zones, as illustrated in Fig. 4c (1981–2010 average of CHELSA) and Fig. 4d (1970–2000 average of WorldClim). As previously stated, the bioclimatic classification based on CHELSA data is more diversified compared to that derived from WorldClim data, leading to similarly diverse bioclimatic zones. In either case, all, or most of the upper oromediterranean as well as the lower crioromediterranean bioclimates are dedicated to zone D, where *N. pumilio* is predominant. Due to a low cover of natural forests in the low-lying areas south of El Bolsón, bioclimates of a supramediterranean character are almost non-existent within the present zonation. Finally, yet importantly, a large overlap of bioclimates between zones B and C (CHELSA) and zones A, B, and C (WorldClim) can be noticed.

Classification-related uncertainty

Analysing classification-related uncertainty, we found varying determination coefficients across datasets and bioclimatic indices, underlining how species and climate data choices affect bioclimatic zoning. Coefficients ranged from low (0.10 with GBIF and WorldClim) to moderate (0.50 with CIEFAP-MAyDS and WorldClim) across species datasets (GBIF, CIEFAP-MAyDS), climate datasets (CHELSA, WorldClim), and classification indices (annual ombrothermic index, annual positive temperature). Significant correlations with species distribution were found for both indices using CIEFAP-MAyDS data, but only for the annual ombrothermic index with GBIF data. Linear model fitting indicated improved results with more predictor variables (Supplementary Figs. 2 and 3), highlighting the significant impact of input data on bioclimatic zones.

Future bioclimates and variable-related uncertainty

Analysing variable-related uncertainty reveals distinct patterns in current and future precipitation and temperature distributions (Fig. 4), highlighting pronounced contrasts between CHELSA and WorldClim data (Supplementary Tables 2 and 3). The most conspicuous appearance is the contrast of the precipitation related variable between CHELSA (Fig. 4a, c, e) and WorldClim (Fig. 4g, i, k). Whereas a value of 2.5 (Io) is at the 0.5 quantile of CHELSA data, a value of 2.5 (Io) is beyond the 0.9 quantile of WorldClim data. This explains the substantial differences between

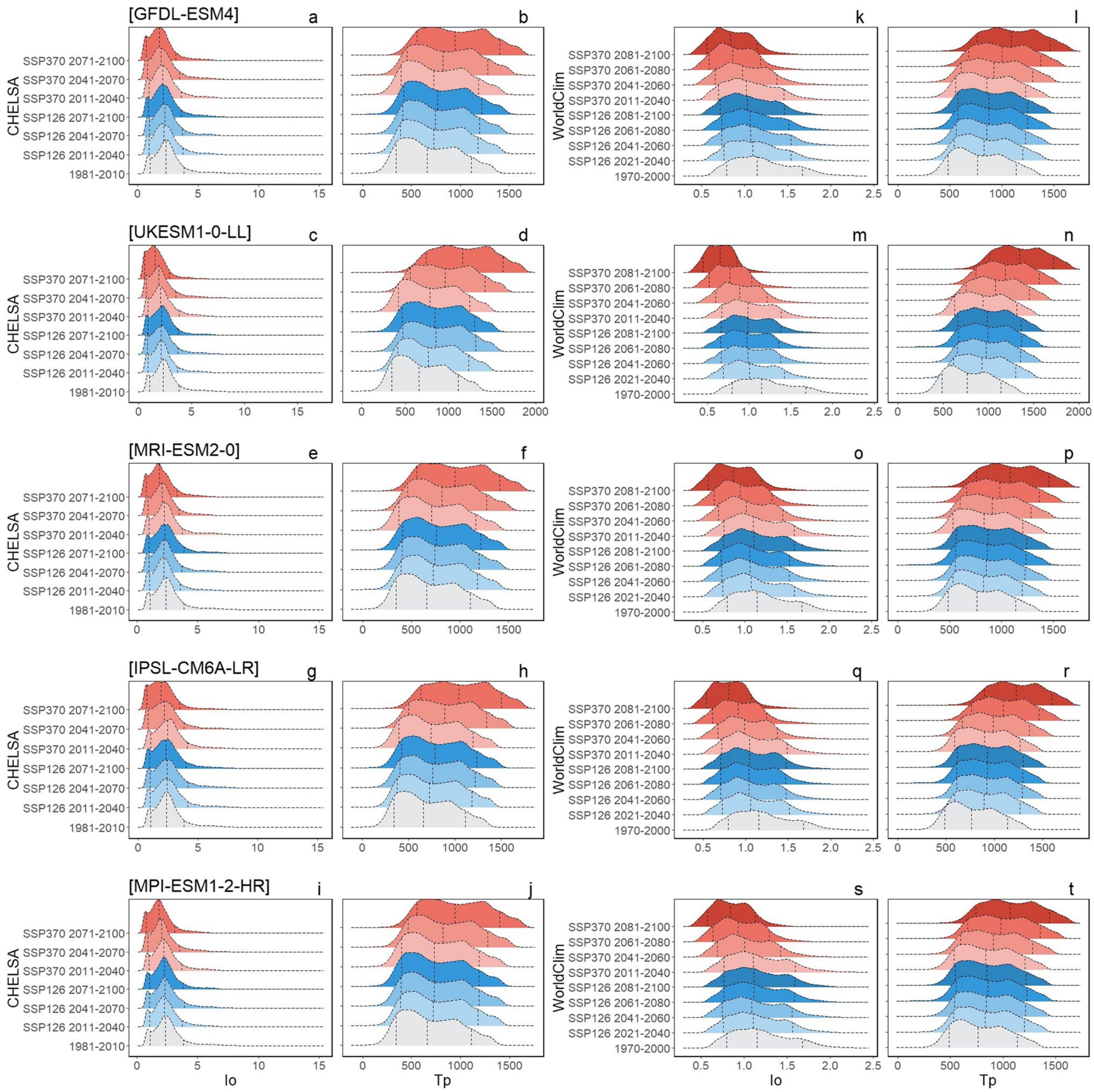

Fig. 4 Current and future densities of the annual ombrothermic index (Io) and the positive annual temperature (Tp) with marked quantiles (0.1, 0.5, and 0.9) for CHELSA (a–j) and WorldClim (k–t) under different shared socioeconomic pathways (blue for SSP1-2.6 and red for SSP3-7.0) and on basis of different global climate models

both datasets regarding the determination of ombric horizons. Instead, distributions of temperature-related variables are more similar to each other. In regard to future conditions, lower (0.1) and upper (0.9) quantiles for all scenarios show a shift to warmer and dryer bioclimates. Within the WorldClim dataset, strong variations regarding the precipitation related variable can be seen between UKESM1-00-LL (Fig. 4i) and the other two GCMs (Fig. 4g and k). Especially for the SSP3-7.0 scenario at the end of the century, range between the 0.1 and the 0.9 quantile is relatively small in case of the UKESM1-00-LL GCM (i, SSP3-7.0 2081–2100).

Terrain-related uncertainty

Terrain-related uncertainty analysis showed varying intersection levels between ombric and thermotypic horizons across datasets for reference periods, influenced by elevation and slope. Ombric horizons had a low 11% intersection, while thermotypic horizons showed a 62% intersection (Fig. 5 and Supplementary Fig. 4). Higher intersections for ombric horizons were generally below 600 m above sea level (m.a.s.l.) with slopes under 10°, despite some outliers. Thermotypic horizon intersections were mainly below 800 m.a.s.l., with exceptions. Regarding the overall bioclimatic classification (Fig. 5c), higher intersections were noted along Río Azul (label 1), Río Foyel (label 2), Río Manso (label 3), and the areas around Lago Puelo and Lago Epuyén (label 4), while lower intersections were found in the Río Turbio catchment area (label 5), in narrow valleys of tributary streams (label 6), and around Lago Marscardi, Lago Giullelmo, and Lago Fonck (label 7).

Future bioclimates and scenario-related uncertainty

In examining the scenario-related uncertainty inherent in the projected impacts on bioclimates, our analysis demonstrates the multifaceted declines and shifts in the near and distant future. Overall, the datasets from both CHELSA and WorldClim demonstrate a notable variability in the reference periods as well as projected future bioclimatic cover, revealing trends where certain bioclimatic zones are expected to experience increases, while others may face declines (Fig. 6). These trends are not uniform but rather vary significantly across different models and scenarios (e.g. SSP3-7.0 for UKESM1-0-LL and all other models), highlighting the nuanced responses of bioclimates to changing climatic conditions. The evident discrepancies between the projections of CHELSA and WorldClim underscore the inherent uncertainties within climate impact models based on input data, thus warranting a careful and cautious interpretation of future bioclimatic trends. However, despite the variability, results from all projections consistently indicate a pronounced decline in the bioclimates of zone D. This zone is associated with the upper orobiome, where *N. pumilio* predominates (see Fig. 3). Zone D inhabits oro- and to some extent crioromediterranean bioclimates and can thus be classified as a bioclimatic segment of a typical mountain biome (Rivas-Martínez et al. 2011). Hence, a strong areal decrease can be attributed to an upward shift of the limit of *Tp* and an expansion limit at the upper orographic or rather edaphic tree line, where rocky habitats and lacking soil prevent the establishment of native subalpine *N. pumilio* ecosystems. This trend is particularly strong for scenarios based on the global climate model UKESM1-0-LL, where zone D shrinks to 28.5% (WorldClim) and 25.1% (CHELSA) under SSP1-2.6 respectively 1.3% (WorldClim) and 0.8% (CHELSA) under SSP3-7.0.

Spatiotemporal inaccuracy

Figure 7 shows the analysis of spatiotemporal inaccuracies showing differences between gridded climate datasets and meteorological station observations, particularly for precipitation. The analysis expands along a west-to-east gradient (Fig. 7a to c) and includes two stations in the central area (Fig. 7d to f). Across this gradient, gridded datasets often overestimate monthly precipitation compared to stations, with varying degrees of accuracy. Specifically, Río Manso Inferior and Río Villegas data consistently show higher precipitation in gridded datasets year-round with a mean absolute error (MAE) of 24.28% for CHELSA and 37.29% for WorldClim at the first and mean MAE of 47.44% for CHELSA and 19.85%

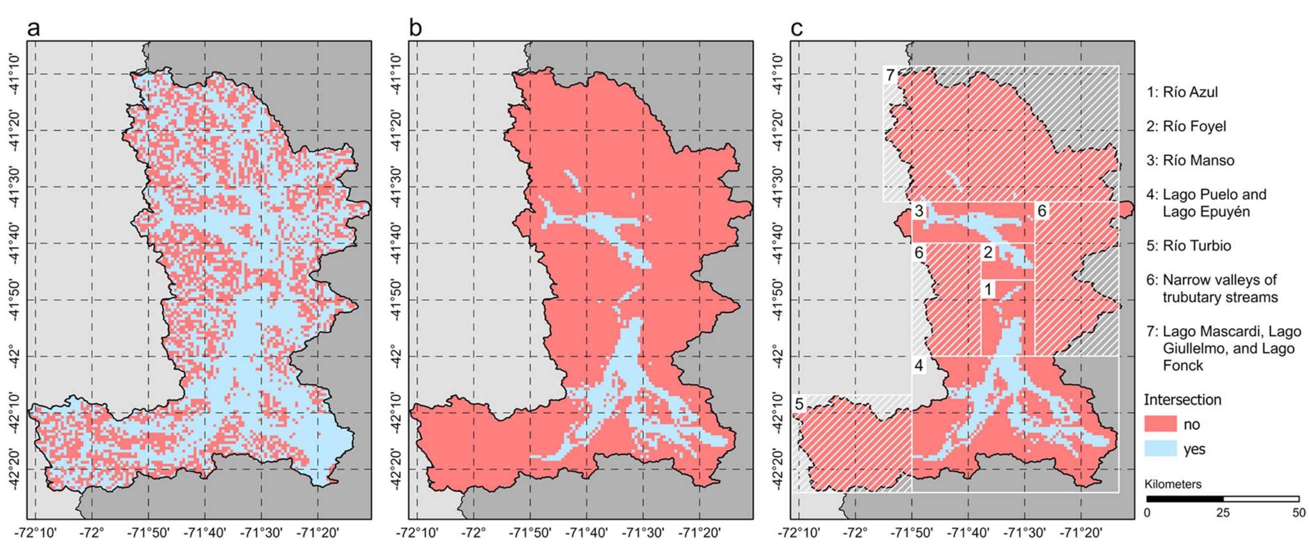

Fig. 5 Spatial intersection between (a) thermotypic horizons, (b) ombric horizons, and (c) bioclimates based on reference periods of CHELSA and WorldClim. Where red pixels are without and blue pixels are with intersection between both datasets. Marks of (c) represent points of reference for specific areas with (transparent) and without (hatched) intersection of the overall bioclimatic classification

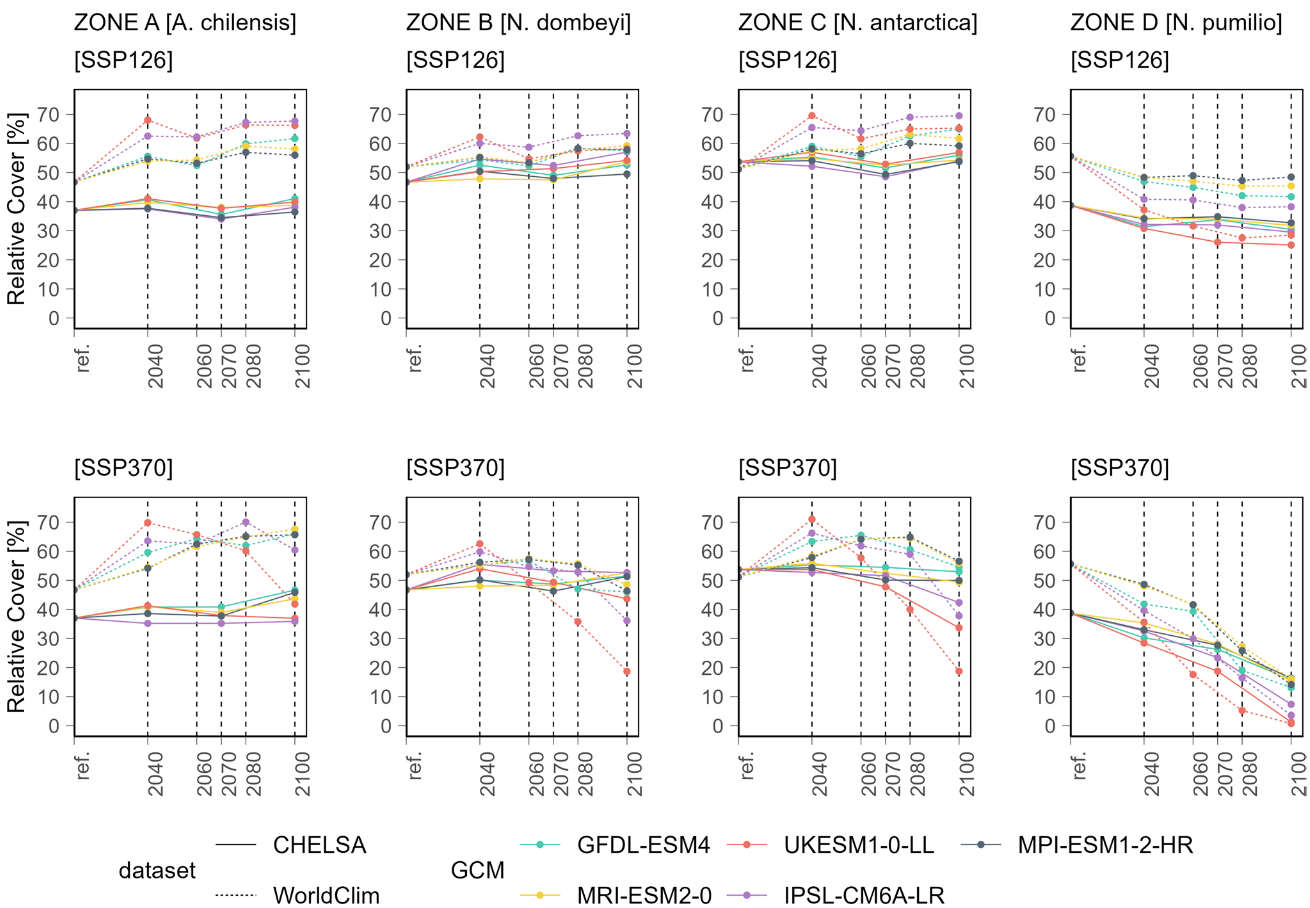

Fig. 6 Potential development of bioclimatic zones under different scenarios with reference to main tree species based on CHELSA and WorldClim climate data. Where CHELSA is marked by solid lines and WorldClim by dashed lines

for WorldClim at the latter. At Río Manso Confluencia, station data typically exceeds gridded estimates except in March, July, and September with a mean MAE of 14.32% for CHELSA and 21.09% for Worldclim. At Río Azul, underestimations are common, except in specific months like March and July. Here, mean MAE is only 6.80% for CHELSA and 17.81% for WorldClim. El Bolsón Airport's data shows no consistent trend, with notable overestimation by WorldClim in July and a mean MAE of only 4.78 for CHELSA and 15.56% for WorldClim. Temperature analysis for El Bolsón reveals closer alignment in late autumn and winter, though gridded datasets tend to underestimate, with some exceptions. Overall, variability and inconsistencies across months and years prevent a definitive judgment on the datasets relative reliability.

Discussion

In this study, we combined bioclimatic modelling with a comparison of two widely used high-resolution climate datasets. Our aim was to study the current and future bioclimatological conditions of an area that is characterised by complex topography, diverse structure of mountain climates, and limited data availability. Due to climatic data limitations, we focused on evaluating several types of uncertainty and inaccuracy that come along with the application of WorldClim and CHELSA.

Comparison of CHELSA and WorldClim

As expected, the comparison between CHELSA and WorldClim, in regard to temperature-related variables, reveals broad consistency. Both bioclimatic classifications show substantial overlaps, especially in the low-lying sections of the investigation area, below 800 m.a.s.l. Current and future temperature densities are similar for the reference periods, as well as for all scenarios. Therefore, our findings are consistent with those of Bobrowski and Schickhoff (2017) that found high consistency between temperature-related variables of CHELSA and WorldClim in the Himalayas. Furthermore, the results of the validation show that discrepancies between both gridded climate datasets and station data are rather marginal. However, there are some qualitative

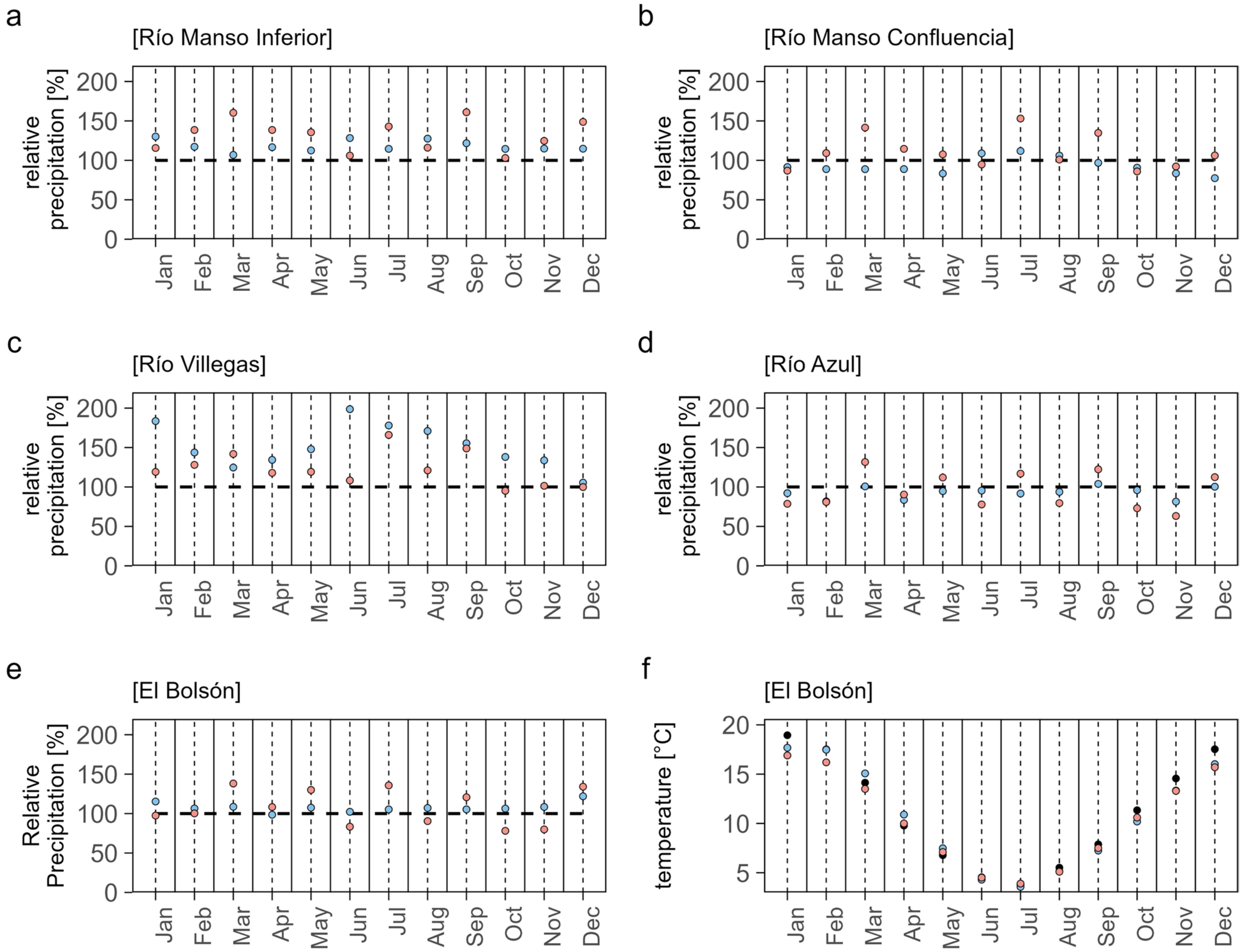

Fig. 7 Comparative analysis of monthly relative precipitation and temperature estimates by gridded climate data across five locations. Panels (a) to (e) show the monthly relative precipitation measured by station data (black line) and estimated by CHELSA (blue) and WorldClim (red), highlighting the variability and patterns of overestimation or underestimation of the datasets across a west-to-east precipitation gradient (a to c) as well as two stations located in the centre of the investigation area (d and e). Panel (f) presents a comparison of monthly temperature records of the station with estimates of the gridded datasets, demonstrating seasonal alignment and deviations

differences between seasons, and accuracy for both datasets is higher from May to September.

The perspective changes markedly with respect to precipitation-related variables. In this case, only 11% of the classes overlap when both climate datasets are compared independently of external reference data. Moreover, this overlap approaches zero in areas characterised by steep slopes (approximately above 10°) and higher elevations (approximately above 600 m.a.s.l.). The densities of current and future precipitation show wide variations for the reference periods and individual scenarios, with CHELSA's estimates in precipitation significantly exceeding those of WorldClim. The selection of a wide range of GCMs is crucial, as demonstrated by the significant differences observed between the models used in this study (e.g. UKESM1-0-LL in comparison with all other models). This discrepancy is further confirmed by validating the estimates against station data, which reveals marked monthly fluctuations in both overestimation and underestimation, along with significant interannual variability. It is crucial, however, to approach these results with caution, as the rain gauges at the stations (mostly tipping buckets) are known to underestimate precipitation during snowfall (Kochendorfer et al. 2020). Despite these limitations, the findings are consistent with those reported in the study by Morales-Barbero and Vega-Álvarez (2019), which identified large discrepancies between climate datasets in mountainous regions on a global scale. Similarly, Bobrowski et al. (2021) highlight the potential drawbacks of using CHELSA and WorldClim data for ecological modelling in remote areas of the Himalayas, primarily due to major differences in precipitation-related variables. As stated previously, within the eastern Río Puelo watershed, the notable inconsistency between the datasets can be attributed to CHELSA data indicating higher precipitation levels, in contrast to WorldClim data, which shows lower levels. This observation is in line with the findings of Bobrowski et al. (2021). The appearance of precipitation related overestimation and underestimation was also perceived by Newell et al. (2022) for complex topography with low density of meteorological stations in northern Peru. In this respect, our study confirms the findings of lower accuracy of precipitation-related variables compared to temperature-related variables derived from high-resolution climate data as stated by Fick and Hijmans (2017), Karger et al. (2017), and Beck et al. (2020). This is warranted by local terrain conditions and wind patterns that significantly influence small-scale atmospheric processes, making them largely independent of latitude or altitude (Bobrowski and Schickhoff 2017). Hence, estimating precipitation in remote and complex terrains, as given by the Río Puelo watershed, remains a significant challenge. Moreover, the underlying CMIP6 models generally struggle with accurately representing the spatial patterns of precipitation in Patagonia, as indicated by Gateño et al. (2024) and Salazar et al. (2024). However, the models preselected by Karger et al. (2017) perform relatively well in northern Patagonia, according to a comparative study by Salazar et al. (2024).

In summary, while CHELSA and WorldClim provide valuable temperature data for northern Patagonia, their use for precipitation analysis requires careful consideration of their limitations and potential inaccuracies. Practitioners and researchers should prioritise dataset validation with local observations and remain cautious of seasonal and topographical factors that may influence data reliability. Furthermore, future studies could benefit from utilising probabilistic meteorological datasets, such as EM-Earth. These datasets typically outperform deterministic ones in regions with complex topography and significant uncertainties due to sparse measurements. They may not only offer a better understanding of uncertainty but also provide a more accurate representation of extremes (Tang et al. 2022).

Bioclimatic analysis

Concerning bioclimatic analysis, we found a strong decline in mountain climates that are currently occupied by *N. pumilio*. This decline is particularly strong for SSP3-7.0 scenarios, where projections show a decrease to 15% and less of relative cover by end of the century. Our study is thus in line with Tovar et al. (2022), indicating a decrease of Temperate deciduous forests in the Andes. A decline in unique bioclimates of mountainous areas can be explained by the interaction of changing climate and an upper altitudinal limit. This has been observed in other geographies (Zomer et al. 2014) and is closely linked to complex topographies. There is robust evidence that global warming will lead to an upward shift of bioclimatic zones, consequently posing a risk of range contraction and extinction for species inhabiting mountainous regions (Adler et al. 2023). Overall, the future climate of northern Patagonia is expected to be warmer and drier (Gateño et al. 2024; Salazar et al. 2024), with critical impacts on water resources (Aguayo et al. 2019; Pessacg et al. 2020) and corresponding impacts on regional ecosystems.

Implications for regional ecosystems

Despite assessed uncertainties, our study reveals consistent bioclimatic trends across both climate data sets and different scenarios. These are especially evident regarding exposures of oro- and crioromediterranean climates and shed light on the future of *N. pumilio* forests (Supplementary Fig. 5) under a changing climate in northern Patagonia.

Northern Patagonian forests with a predominance of evergreen species, such as *N. dombeyi* and *A. chilensis*, change to *N. pumilio*-dominated Subantarctic-Andean deciduous forests (Adenocaulo-Nothofagetalia pumilionis Oberd. 1960 em. Hildebrand-Vogel, Godoy & Vogel 1990 [Nothofagetea pumilionis-antarcticae Oberd. 1960]) above certain altitudes. This vegetation shift indicates a division into different altitudinal zones, each characterised by specific plant communities whose life forms and species composition differ significantly (Aschero et al. 2022; Cagnacci et al. 2020). Biotic exchange by the invasion of non-native species such as *Pinus contorta* (Supplementary Figs. 6 and 7) poses a significant ecological threat to ecosystems of oromediterranean and crioromediterranean climates (cf. Sala et al. 2000), particularly above the treeline of *N. pumilio*, altering fire dynamics and threatening native ecosystems (Raffaele et al. 2016). Since fire is a current and most likely amplified future threat (Kitzberger et al. 2022), 'new forests', 'higher timberline', 'timber production at higher altitudes', etc. cannot be considered strong 'restoration' arguments.

Longitudinally, vegetation types below the subalpine level change less discriminatory and more ecotonal, with deciduous forests (Myrceugenio-Nothofagetum dombeyi Eskuche 1999), mixed forests (Austrocedro-Nothofagetum dombeyi Eskuche 1968), and coniferous forests (Gavileo-Austrocedretum Eskuche 1968) showing overlapping species compositions. This is in line with our study indicating a large overlap between bioclimates of zone B (*N. dombeyi*) and C (*N. antarctica*) but a relative distinction between zone A (*A. chilensis*) and B (*N. dombeyi*) as well as D (*N. pumilio*) from zone A (*A. chilensis*), B (*N. dombeyi*), and C (*N. antarctica*). However, even though our classification results show a minimal overlap between zone A (*A. chilensis*) and C (*N. antarctica*), a combination of both species can usually be observed in the succession process of the lower slopes or valley bottoms. This continuum suggests a complex interaction amongst forest types, potentially offering resilience against disturbances like wildfires. However, future climate change may challenge this balance, with *N. dombeyi* and *A. chilensis* showing differing moisture preferences (Veblen 2007) and the potential for range contractions under changing climatic conditions.

Limitations and further research

While our study did not focus on future species coverage projections, it signals potential risks to species like *N. pumilio*. In this respect, future studies should explore how species respond to climate change, including the impact of climate extremes on ecosystem disturbances. Understanding the bioclimatology of Wintero-Nothofagetea species and climate change effects on their viability is crucial for informed forest management. We advocate for maintaining and expanding meteorological monitoring to enhance climatology data accuracy, and the improvement of gridded climate datasets, as seen in Beck et al. (2020). Our findings also suggest that bioclimatic projections could lead to divergent adaptation strategies. Following Gregor et al. (2022), it is important to tailor climate-smart forestry to specific scenarios. For these reasons, we recommend using our data to foster local dialogue and workshops, improving regional decision-making with expert insights into adaptation strategies and embracing a transdisciplinary approach to unite various knowledge systems for better climate understanding and decision-making, as discussed by Bremer et al. (2019) and Moure et al. (2023).

Conclusion

Our study investigates the bioclimatological conditions of northern Patagonia, facing complex topography and sparse data, through a comparative analysis of high-resolution climate datasets CHELSA v2.1 and WorldClim v.2.1. Our findings underscore substantial consistency between these datasets for temperature variables, confirming the reliability of both for temperature analysis. However, a strong contrast emerges in precipitation estimates, with significant discrepancies highlighted by minimal overlap in bioclimatic classes, particularly in steep and elevated terrains. Such variations underscore the challenges of accurately modelling precipitation in mountainous regions, where local topography and wind patterns play crucial roles. Thus, the study highlights the importance of a comparison between different data sources and validations against ground-based data and the careful consideration of precipitation-related variables in bioclimatic modelling within the Río Puelo watershed.

However, despite the differences of the applied climate datasets, our bioclimatic analysis reveals a concerning decline in mountain climates suitable for *N. pumilio*, with projections suggesting a sharp decrease in their coverage under future climate scenarios. This demonstrates that, despite the detected uncertainties, it is possible to identify vulnerable bioclimatic zones within the Río Puelo watershed based on CHELSA and WorldClim data.

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Data availability Derived data supporting the findings of this study are available upon request from the corresponding author.

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