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ECOLOGICAL MODELLING

High spatial resolution bioclimatic variables to support ecological modelling in a Mediterranean biodiversity hotspot

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Highlights

- Fine-grain bioclimatic variables are useful to make reliable ecological modelling.
- We propose a high-resolution dataset based on WorldClim 2 bioclimatic variables in Sardinia.
- Fine-grain vs WorldClim 2 differences are not evenly distributed in the territory.
- Greater discrepancies correspond to areas with a complex orographic system.
- We recommend caution using coarse-grain in physiographically complex landscapes.

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Abstract

Understanding the effects of climate on biodiversity and its different levels of response to climatic variation is important for addressing conservation-based questions: the use of bioclimatic variables and species modelling tools is common in environmental, agricultural and biological sciences. Unfortunately, most of the ecological local studies are limited to the use of global data with coarse spatial resolutions, while fine-grain climate data are necessary to capture environmental variability and perform reliable modelling. We propose a high-resolution dataset (40 m grid) of the suite of original coarse-grain bioclimatic variables proposed by WorldClim 2 for the island of Sardinia (Italy); variations among our dataset and WorldClim 2 were calculated and mapped to show the spatial distribution of differences between all pairs of variables.

We observed relevant differences for the bioclimatic variables related to rainfall (mean RMSE = 39.79; mean nRMSE = 0.21) compared to the temperature ones (mean RMSE = 4.81; mean nRMSE = 0.11). Moreover, discrepancies are not evenly distributed in the territory: the greater differences correspond to the areas characterized by complex orographic systems.

Results recommend caution in making ecological assessments based on bioclimatic variables derived from global data with coarse spatial resolutions in physiographically complex landscapes, especially in the Mediterranean regions, characterized by seasonal climatic variations and high levels of biodiversity and biogeographical complexity.

These new data will support a new generation of research studies in a broad array of ecological applications at a much finer scale than previously possible.

Keywords Sardinia, WorldClim, Species Distribution Model, seasonal climatic variations, data reliability

1 Introduction

Climate varies across space and species can shift their distribution in order to find appropriate climatic conditions where they can live suitably (Bellard et al., 2012). In the same way, climate fluctuations drive the ecological changes in species, populations, ecological networks and ecosystems functions and processes (Parmesan, 2006). Climate variation over time, including year-to-year variability, has been linked to a shift in phenology and physiology of plants and animals (Bellard et al., 2012; Parmesan, 2006); moreover, also latitudinal and altitudinal range shifts are well documented for a wide number of species (Lenoir and Svenning et al., 2015), especially for those with high dispersal capacities like marine invertebrates, birds, and insects (Parmesan, 2006).

Bioclimatic variables, unlike climate data, are developed focusing on relevant combination of variables, considering biotic thresholds; hence they better describe, and predict, the response of living organisms (Jennings and Harris, 2017; Rivas-Martínez et al., 2011).

In the middle 1980s, the earliest computer-based methods were developed for estimating mean climate conditions of a given site on Earth's surface, by using point location data sets (Sutherst and Maywald, 1985) or spatially local gridded climate data (e.g. Booth et al., 1987). Following the development of more sophisticated and complex spatial interpolation methods (Hutchinson et al., 1994), modellers have rapidly built spatially gridded climatologies, appropriately scaled on land elevation (Hutchinson, 1995). Subsequently, spatially interpolated gridded climate data have become available for researchers, improving environmental information in sites where there was a lack of local data (Hijmans et al., 2005).

Open data on gridded bioclimate datasets, which differ in their quality over time, space and resolution (from 30 seconds ~1 km2 to 10 minutes ~340 km2 at the equator), are for example WorldClim (Fick and Hijmans, 2017), MerraClim (C. Vega et al., 2017), CHELSA (Karger et al., 2017), CliMond (Kriticos et al., 2012), EuMedClim (Fréjaville and Benito Garzón, 2018) and ENVIREM (Title and Bemmels, 2018). Most of these global datasets consist of monthly average temperature (minimum, maximum and medium), monthly precipitation and solar radiation assessed across a large temporal range, as well as bioclimatic variables. Bioclimatic variables, originally devised by Nix (1986) and deriving from the monthly temperature and rainfall values, describe annual trends (e.g., mean annual temperature and precipitation), seasonal trends (e.g., annual range in temperature and precipitation) and extreme or limiting environmental factors (e.g., temperature of the coldest and warmest month, and precipitation of the wet and dry quarters).

Considering their peculiar characteristics, bioclimatic variables were considered suitable for studying species distributions, under current or possible future conditions, using species distribution modelling (SDM) tools (Kriticos et al., 2012). The use of bioclimatic variables and species modelling tools have thus found a widespread use in environmental, agricultural and biological sciences (Booth et al., 2014; Di Febbraro et al., 2018; Guisan and Thuiller, 2005; Pecchi et al., 2019): assessing the environmental niche of species or their invasion and proliferation; quantifying the impact of climate and other environmental changes on species distributions; modelling species assemblages from individual species predictions; testing biogeographical, ecological and evolutionary hypotheses; identifying sites of high potential of occurrence for rare species; developing strategies and action plans to ensure a long-term conservation of species.

For many applications, fine spatial grain climate data is considered necessary to capture environmental variability, especially in physiographically complex landscapes (Hijmans et al., 2005); for example, they are preferable to study distribution of species with low-dispersal ability (Chust et al., 2004; Franklin et al., 2013; Guisan et al., 2007), species corridors and effects of barriers, or for others detailed ecological or conservation studies (Elith and Leathwick, 2009; Hess et al., 2006; Nezer et al., 2017). Fine-grain climate grids are able to detect potential microrefugia (Hannah et al., 2014; Meineri and Hylander, 2017), i.e. sites with peculiar microclimates that support populations of species outside their main distribution area. Microrefugia are thus particularly relevant to understand the spatial distribution of species in response to climate change (Dobrowski, 2011) and the demographic and genetic performance of populations at the periphery of their range (Papuga et al., 2018; Pironon et al., 2017).

Unfortunately, fine-grain climate grids are only available for limited parts of the world (Hijmans et al., 2005) and most of the ecological local studies are limited to and by the use of global data with coarse spatial resolutions.

The development of high spatial resolution bioclimatic data is particularly important in the Mediterranean basin, one of the 35 terrestrial biodiversity hot spots of the world (Medail, 2017), where climate-driven habitat loss was recognized as a major threat to biodiversity (Barredo et al., 2016). Nevertheless, as for Sardinia, the second-largest island of the Mediterranean basin, several studies to assess the distribution of plants (e.g. Casazza et al., 2014; Fois et al., 2018a; Fois et al., 2018b; Ongaro et al., 2018) or animals (e.g. Iannella et al., 2019; Russo et al., 2014; Sýkora et al., 2017) relied on coarse-grain bioclimatic open data such as Worldclim. To fill this gap in Sardinia, we propose a novel high-resolution dataset (40 m grid, equal to ~ 1.69 arcsec) of the suite of bioclimatic variables proposed by WorldClim 2 (Fick and Hijmans, 2017), one of the most used dataset in ecological modelling (Marchi et al., 2019).

We calculated the suite of 19 bioclimatic variables using a high-resolution monthly climatologies of temperature and precipitation of Sardinia, based on long-term climate time series and local topography.

To assess the differences among our fine-grain dataset and the original coarse-grain bioclimatic variables of WorldClim 2, we performed a quantitative comparison and spatial distribution of errors between all pairs of variables of these datasets.

The high-resolution data produced can be particularly suited for studying species distributions under current conditions, improving ecological studies at finer spatial scales.

2 Study area

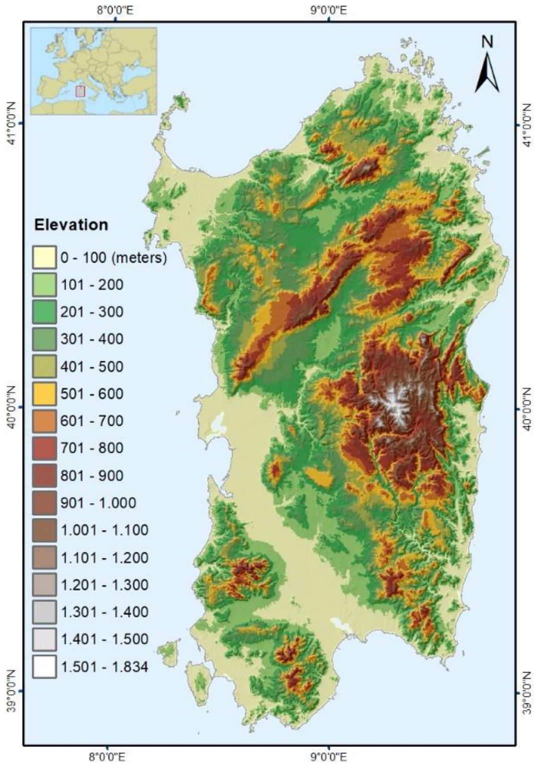
The island of Sardinia, one of the two largest Mediterranean islands, is located in the middle of the western Mediterranean Basin and covers a surface area of around 24,000 km^2 with a coastline of about 1900 km, marked by a variety of landforms (cliffs, sandy dunes, long or pocket beaches). Due to its large extension, the territory is characterized by a complex orographic pattern with hilly lands, plateaus, mountain and plains (Fig.1), placed on heterogeneous geological substrata for age and typology.

More than 600 formations and more second-rank lithostratigraphic units have been recognized (Carmignani et al., 2016): Palaeozoic magmatic intrusive units and metamorphic complexes related to Hercynian Orogenesis; sedimentary successions linked to Mesozoic and Tertiary marine transgression; volcano-sedimentary successions related to the opening of the Tyrrhenian Sea; Quaternary deposits of various origin (alluvial, aeolian, lacustrine, littoral and slope movement-related) covering the previous geological formations.

The climate is typically Mediterranean, with mild and poorly rainy winters, warm and dry summers. Recent detailed bioclimate mapping, using the bioclimatic classification of Rivas-Martínez et al. (2011), identified that the island is characterized by two macrobioclimates (Mediterranean pluviseasonal oceanic and Temperate oceanic), four classes of continentality (from weak semihyperoceanic to weak subcontinental), eight thermotypic horizons (from lower thermomediterranean to upper supratemperate) and seven ombrothermic horizons (from lower dry to lower hyperhumid), whose combination resulted in 43 different isobioclimates (Canu et al., 2015).

The heterogeneous climate, morphology and geological substrata of the island determine a high rate of endemism (Fois et al., 2017) and a wide variety of Potential Natural Vegetation *sensu* Farris et al. (2010), described in detail by Bacchetta et al. (2009).

Fig. 1 Sardinia is the second main island in the Mediterranean and it is characterised by a complex orographic pattern.



3 Methods

Monthly average temperatures (minimum, maximum and mean) and precipitations were originally interpolated to produce the bioclimatic map of Sardinia (Canu et al., 2015). The data at 40 m resolution were created using high quality meteorological data from 203 rain gauges and 68 temperature gauges of the regional climatic database of the Weather and Climate Department (ARPA Sardegna) for the time period 1971-2000. Monthly average temperature and precipitation were interpolated by Regression Kriging, combining a Multiple Linear Regression with an Ordinary Kriging of the regression residuals. Factors such as latitude, longitude, altitude, sea distance and local topography were considered as independent geographic variables to account for topographic effects (Canu et al., 2015).

Starting from this baseline data, we calculated bioclimatic variables at 40 m resolution using the C++ code included in the System for Automated Geoscientific Analysis (SAGA) version 7.5.0 (Conrad et al., 2015). The free and open-source Geographical Information System SAGA under the GNU public license was specifically developed for regional climate and environmental modelling applications (Conrad et al., 2015).

In order to evaluate the extreme or limiting environmental factors, we defined the quarterly parameters by following the definitions provided by WorldClim (Hijmans et al., 2005) and ANUCLIM (Xu and Hutchinson, 2013).

Three types of bioclimatic variables were evaluated (Table 1): variables related to temperature (BIO01-BIO07 and BIO10-BIO11); variables related to rainfall (BIO12-BIO17); variables related to both temperature and rainfall (BIO08-BIO09 and BIO18-BIO19).

The calculation of bioclimatic variables related to temperature was performed using average monthly maximum, minimum and mean temperatures. Cell-by-cell calculations of bioclimatic variables related to rainfall were conducted using monthly average precipitation.

Some descriptive statistics such as mean, minimum and maximum were used to describe the results. To assess the rate of dispersion of data, for each bioclimatic variable we calculated the coefficient of variation (in percentage).

Table 1. Bioclimatic variables, types, descriptions and units of the new high-resolution bioclimatic variables of Sardinia (Italy).

Filename	Type of variable	Description	Unit
BIO01.tif	Temperature-related variable	Annual Mean Temperature	°C
BIO02.tif	Temperature-related variable	Mean Diurnal Range (Mean of monthly (max temp - min temp))	°C
BIO03.tif	Temperature-related variable	Isothermality (BIO02/BIO07) (x 100)	Index
BIO04.tif	Temperature-related variable	Temperature Seasonality (standard deviation x 100)	Index
BIO05.tif	Temperature-related variable	Maximum Temperature of Warmest Month	°C
BIO06.tif	Temperature-related variable	Minimum Temperature of Coldest Month	°C
BIO07.tif	Temperature-related variable	Temperature Annual Range (BIO05-BIO06)	°C
BIO08.tif	Temperature-related and rainfall-related variable	Mean Temperature of Wettest Quarter	°C
BIO09.tif	Temperature-related and rainfall-related variable	Mean Temperature of Driest Quarter	°C
BIO10.tif	Temperature-related variable	Mean Temperature of Warmest Quarter	°C
BIO11.tif	Temperature-related variable	Mean Temperature of Coldest Quarter	°C
BIO12.tif	Rainfall-related variable	Annual Precipitation	mm
BIO13.tif	Rainfall-related variable	Precipitation of Wettest Month	mm
BIO14.tif	Rainfall-related variable	Precipitation of Driest Month	mm
BIO15.tif	Rainfall-related variable	Precipitation Seasonality (Coefficient of Variation)	Index
BIO16.tif	Rainfall-related variable	Precipitation of Wettest Quarter	mm
BIO17.tif	Rainfall-related variable	Precipitation of Driest Quarter	mm
BIO18.tif	Temperature-related and rainfall-related variable	Precipitation of Warmest Quarter	mm
BIO19.tif	Temperature-related and rainfall-related variable	Precipitation of Coldest Quarter	mm

3.1 Comparisons with the WorldClim 2 bioclimatic variables

Comparison among WorldClim 2 and the new high-resolution bioclimatic variables of Sardinia was possible because they were based on the same temporal range: 1970–2000 for WorldClim 2 (Fick and Hijmans, 2017) and 1971-2000 for Sardinia (Canu et al., 2015).

Variables were compared following three main steps: (i) at first, we resampled WorldClim 2 data to the resolution of our variables (40 m) using the nearest neighbour method; (ii) then we checked errors in raster alignment and adjusted alignment using the nearest neighbour method and one of our raster as snap raster, to ensure all cells were properly aligned; (ii) finally we performed the quantitative comparison analyses.

To assess if and where the two datasets are different, we calculated Spearman's correlation coefficient (ρ), the root mean square error (RMSE) and the normalized root mean square error by the mean (nRMSE) between all pairs of variables.

For each variable we mapped the spatial distribution of errors, by means of the difference between the two datasets, namely the new high spatial resolution dataset minus WorldClim 2.

All data manipulation and geographic analyses were performed with R (R Core Team, 2020), using raster (Hijmans, 2020) and gdalUtils (Greenberg and Mattiuzzi, 2020) packages. Metadata of rasters were added using ArcGIS software by Esri.

4 Results

We generated a high-resolution suite of 19 bioclimatic variables of Sardinia: all rasters are provided at roughly 1.69 arcsec (40 m cell size) resolution and in the WGS84 geographic coordinate system (EPSG code of 4326). GeoTIFF rasters of all 19 bioclimatic variables of Sardinia (Italy) are included in Annex I. Metadata files include file name, thumbnail, tags and description for all rasters.

The coefficient of variation (in %) of bioclimatic variables was lower in the temperature-related variables (mean CV = 11.39), higher for the precipitation-related ones (mean CV = 23.79) and intermediate in the variables related to both temperature and precipitation (mean CV = 21.33). In particular, the maximum coefficient of variation of the temperature ones amounts to 33.78 for the Minimum Temperature of Coldest Month (BIO06), with BIO10 having the minimum value (CV = 4.02, Table 2). Within rainfall-related bioclimatic variables, the Precipitation of Driest Month (BIO14) had a higher variation (CV =44.88) than other variables, representing the highest level of variability in all the dataset. Regarding variables related to both temperature and precipitation the Precipitation of Warmest Quarter (BIO18) showed the highest level of variation (CV = 33.77), while the Mean Temperature of Driest Quarter (BIO09) showed the lowest one (CV = 5.27).

Table 2. Mean, minimum, maximum and coefficient of variation (CV) values for each of the new high spatial resolution bioclimatic variables of Sardinia (Italy).

Variable	Name of variable	Mean	Minimum	Maximum	CV (%)
BIO01	Annual Mean Temperature	15.44	8.61	18.12	8.51
BIO02	Mean Diurnal Range (Mean of monthly (max temp - min temp))	9.69	4.06	13.46	13.64
BIO03	Isothermality (BIO02/BIO07) (x 100)	37.08	22.71	43.69	7.99
BIO04	Temperature Seasonality (standard deviation x 100)	571.91	461.06	655.64	4.98
BIO05	Maximum Temperature of Warmest Month	30.59	24.16	33.96	4.40
BIO06	Minimum Temperature of Coldest Month	4.57	-2.13	9.79	33.78
BIO07	Temperature Annual Range (BIO05-BIO06)	26.02	17.45	31.16	7.25
BIO08	Mean Temperature of Wettest Quarter	11.85	3.22	17.36	22.54
BIO09	Mean Temperature of Driest Quarter	23.54	17.43	26.16	5.27
BIO10	Mean Temperature of Warmest Quarter	24.30	18.90	26.16	4.02
BIO11	Mean Temperature of Coldest Quarter	8.60	0.98	12.29	17.98
BIO12	Annual Precipitation	690.58	418.54	1376.38	19.22
BIO13	Precipitation of Wettest Month	100.73	57.82	209.09	19.23
BIO14	Precipitation of Driest Month	8.21	0.46	22.32	44.88
BIO15	Precipitation Seasonality (Coefficient of Variation)	50.23	39.75	60.48	7.28
BIO16	Precipitation of Wettest Quarter	288.68	164.44	582.96	19.26
BIO17	Precipitation of Driest Quarter	36.71	11.24	82.44	32.89
BIO18	Precipitation of Warmest Quarter	39.97	11.24	90.93	33.77
BIO19	Precipitation of Coldest Quarter	222.29	113.18	495.01	23.73

The spatial distribution of the calculated bioclimatic variables is shown according to the three groups temperature (Fig.2), rainfall (Fig.3), temperature and rainfall related variables (Figure 4).

Fig. 2. Temperature-related bioclimatic variables (BIO01-BIO07 and BIO10-BIO11) of Sardinia (Italy).

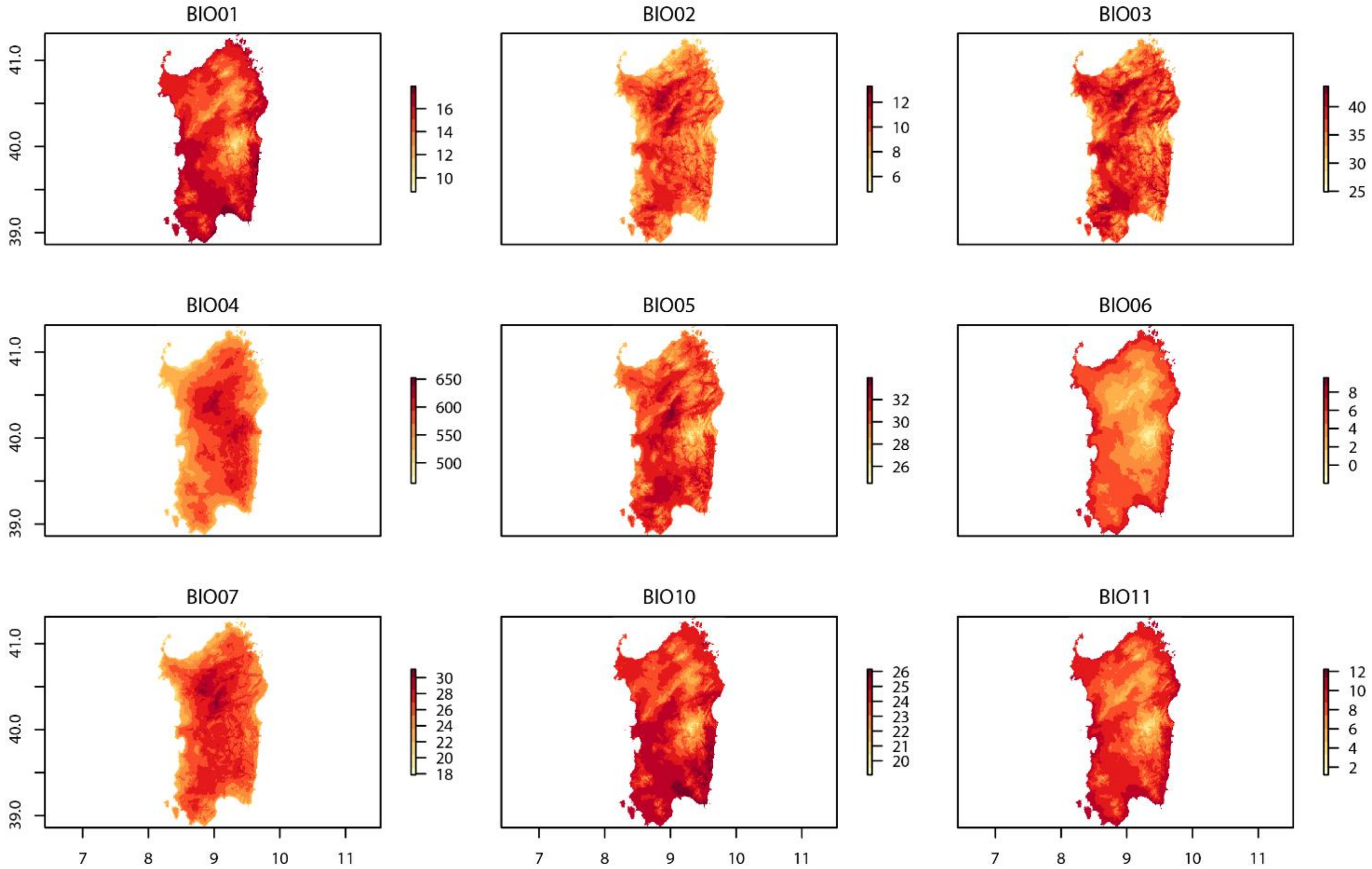


Fig. 3. Rainfall-related bioclimatic variables (BIO12-BIO17) of Sardinia (Italy).

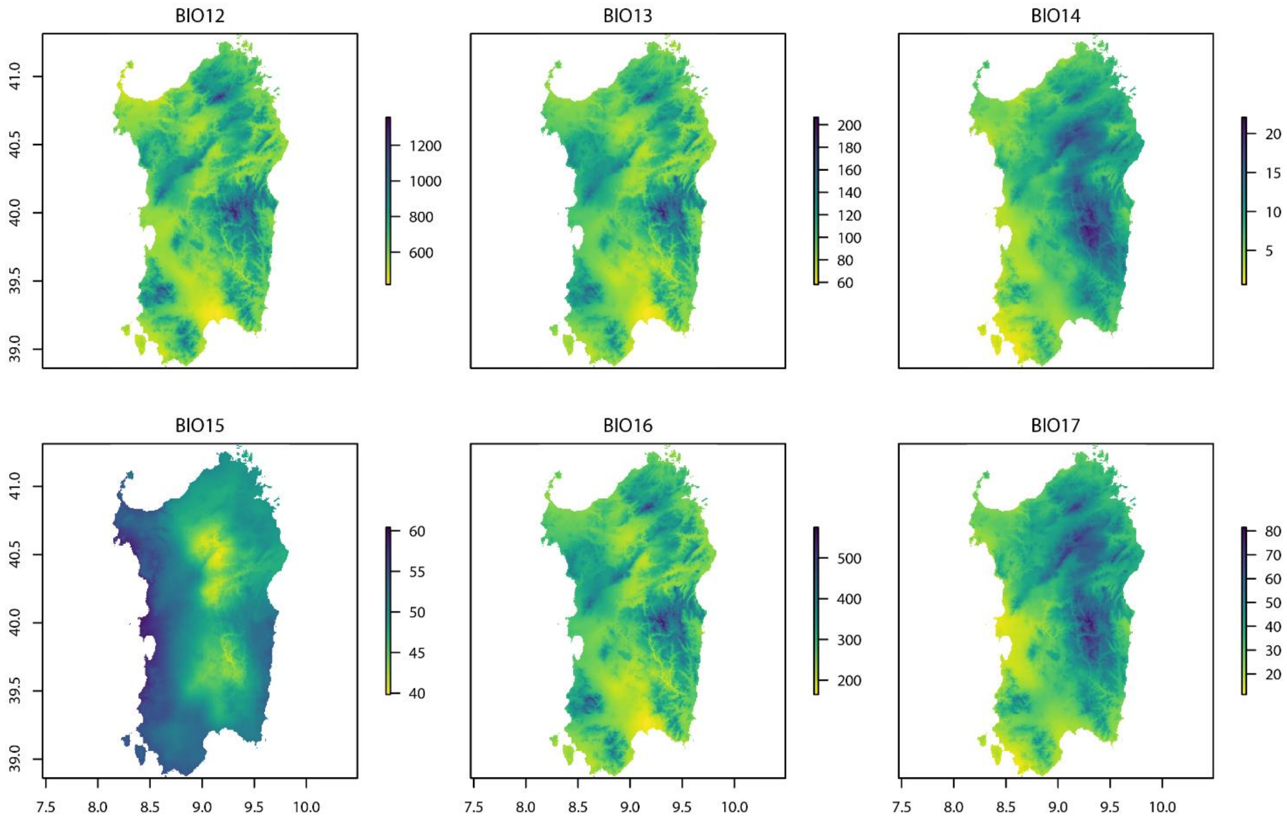
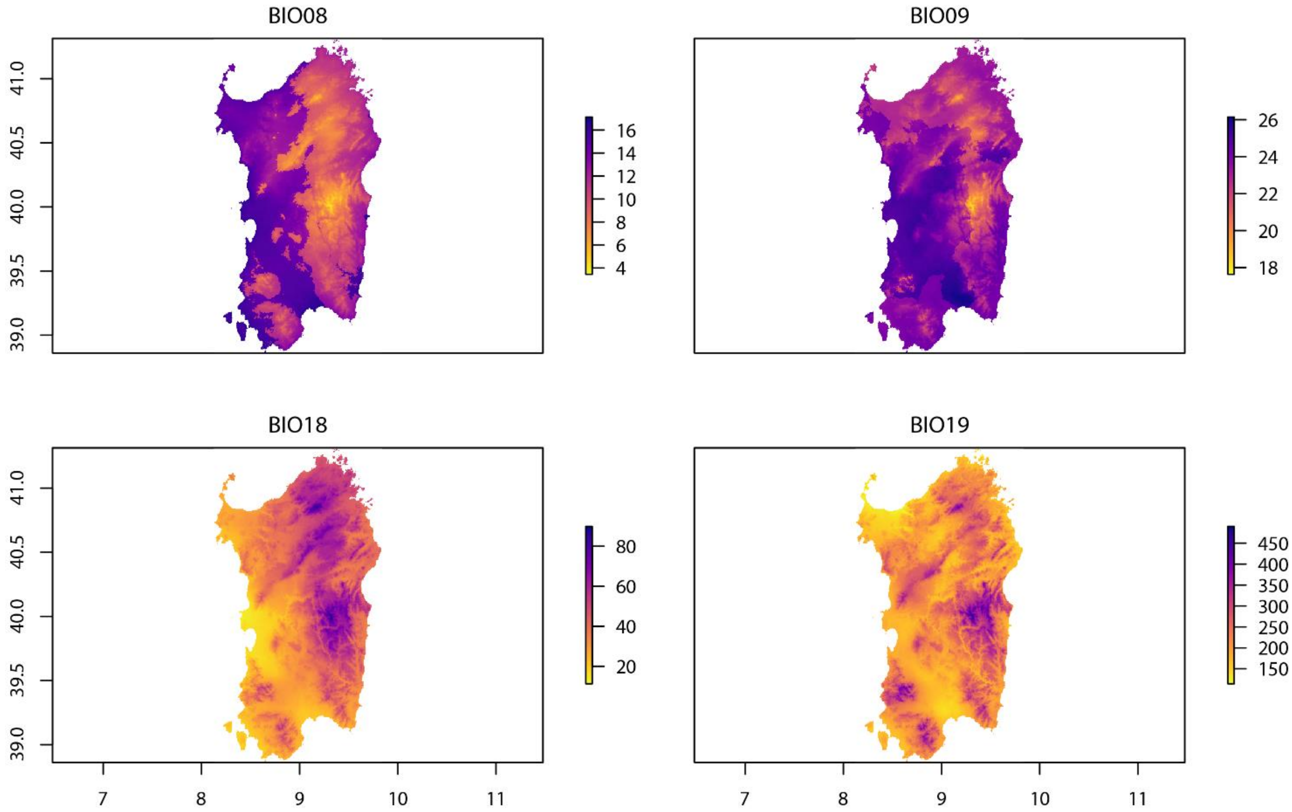


Fig. 4. Bioclimatic variables of Sardinia (Italy) related to both temperature and precipitation (BIO08-BIO09 and BIO18-BIO19).



4.1 Comparisons with the WorldClim 2 bioclimatic variables

The comparison of our high-resolution dataset vs. WorldClim2 in terms of Spearman's correlation coefficient (ρ) showed significant linear correlations (all p-values < 0.001) for all the 19 bioclimatic variables (Table 3) with the highest correlation among BIO11 values and the lowest for BIO15.

The normalized root mean square error (nRMSE) revealed relevant differences (Table 3), in particular for the bioclimatic variables related to rainfall showing a higher discrepancy (mean RMSE = 39.79; mean nRMSE = 0.21) compared to the temperature ones (mean RMSE = 4.81; mean nRMSE = 0.11).

Table 3: Pairwise comparison of the new high-resolution bioclimatic variables and WorldClim 2 bioclimatic variables in terms of Spearman's correlation coefficient (ρ) and normalized root mean square error (nRMSE).

Variable	Name of variable	Spearman's rho	RMSE	nRMSE
BIO01	Annual Mean Temperature	0.94	0.49	0.03
BIO02	Mean Diurnal Range (Mean of monthly (max temp - min temp)	0.76	1.00	0.10
BIO03	Isothermality (BIO02/BIO07) (x 100)	0.72	2.22	0.06
BIO04	Temperature Seasonality (standard deviation x 100)	0.76	31.10	0.05
BIO05	Maximum Temperature of Warmest Month	0.77	3.00	0.10
BIO06	Minimum Temperature of Coldest Month	0.93	2.04	0.45
BIO07	Temperature Annual Range (BIO05-BIO06)	0.79	1.47	0.06
BIO08	Mean Temperature of Wettest Quarter	0.77	1.90	0.16
BIO09	Mean Temperature of Driest Quarter	0.68	1.20	0.05
BIO10	Mean Temperature of Warmest Quarter	0.87	1.53	0.06
BIO11	Mean Temperature of Coldest Quarter	0.96	0.41	0.05
BIO12	Annual Precipitation	0.60	137.00	0.20
BIO13	Precipitation of Wettest Month	0.61	19.57	0.19
BIO14	Precipitation of Driest Month	0.75	2.41	0.29

BIO15	Precipitation Seasonality (Coefficient of Variation)	0.42	4.90	0.10
BIO16	Precipitation of Wettest Quarter	0.56	64.76	0.22
BIO17	Precipitation of Driest Quarter	0.81	10.09	0.27
BIO18	Precipitation of Warmest Quarter	0.55	21.75	0.54
BIO19	Precipitation of Coldest Quarter	0.54	52.59	0.24

All bioclimatic variables related to temperature showed a high correlation ($\rho > 0.70$) with WorldClim 2 (Table 3).

Rainfall-related bioclimatic variables were less strongly correlated with WorldClim 2 than temperature-related ones; Seasonality trend of precipitation (BIO15) was poorly correlated ($\rho = 0.42$).

With regard to bioclimatic variables related to both temperature and precipitation, mean Temperature of Wettest and Driest quarters showed good correlations with corresponded WorldClim 2 bioclimatic variables ($\rho > 0.60$). On the contrary, the precipitation of the driest and warmest quarters highlighted a low correlation ($\rho < 0.60$).

The spatial distribution of errors, calculated as the difference between the two datasets i.e. new high-resolution dataset minus WorldClim2, showed the heterogeneous distribution of the spatial discrepancies of the variables (Figs. 5-7) and a specific pattern according to the different bioclimatic variable analysed. In these figures red colours indicate areas where a given variable was overestimated by Worldclim2, blue colours the underestimated ones.

For example, the spatial distributions of the differences for the Annual Mean Temperature (BIO01) highlighted lower values modelled by WorldClim 2 compared to our dataset in the mountain areas, with differences of more than 2 °C (Fig. 5). Maximum/minimum temperatures (BIO05/06/10) are generally underestimated by WorldClim 2, with peaks up to 7 °C for the maximum temperature of the warmest month (BIO05). Accordingly, the annual range of extreme temperature conditions (BIO07) was underestimated by WorldClim 2 in the internal and mountain areas of the island, being overestimated in coastal areas in the north, south and eastern coast (Fig. 5).

Regarding rainfall-related bioclimatic variables, a markedly different spatial distribution was observed for the Annual precipitation (BIO12), showing a gradient moving from north-west to south-east: in the NW areas WorldClim 2 overestimated, while the SE areas are underestimated, with strong differences (higher than 500 mm) (Fig. 6). Precipitation Seasonality (Coefficient of Variation, BIO15) is strongly overestimated by WorldClim 2 in the internal and mountain areas and slightly underestimated along the S-E coast. The Precipitation of Driest Quarter (BIO17) is generally overestimated, in particular in the NW zones. An asymmetry similar to the one observed for BIO12 was detected for the Mean Temperature of Wettest Quarter (BIO08), with underestimated values in the western part of the island and overestimated ones in the eastern ones (Fig. 7). Furthermore, a general overestimation was observed for the Precipitation of Warmest Quarter (BIO18) in all western areas of the island, from north to south, up to 40 mm (Fig. 7).

Fig. 5. Spatial distribution of the differences between all pairs of the new high spatial resolution dataset and WorldClim 2 temperature-related bioclimatic variables (BIO01-BIO07 and BIO10-BIO11). Red colours indicate overestimated areas by Worldclim2, blue colours the underestimated ones.

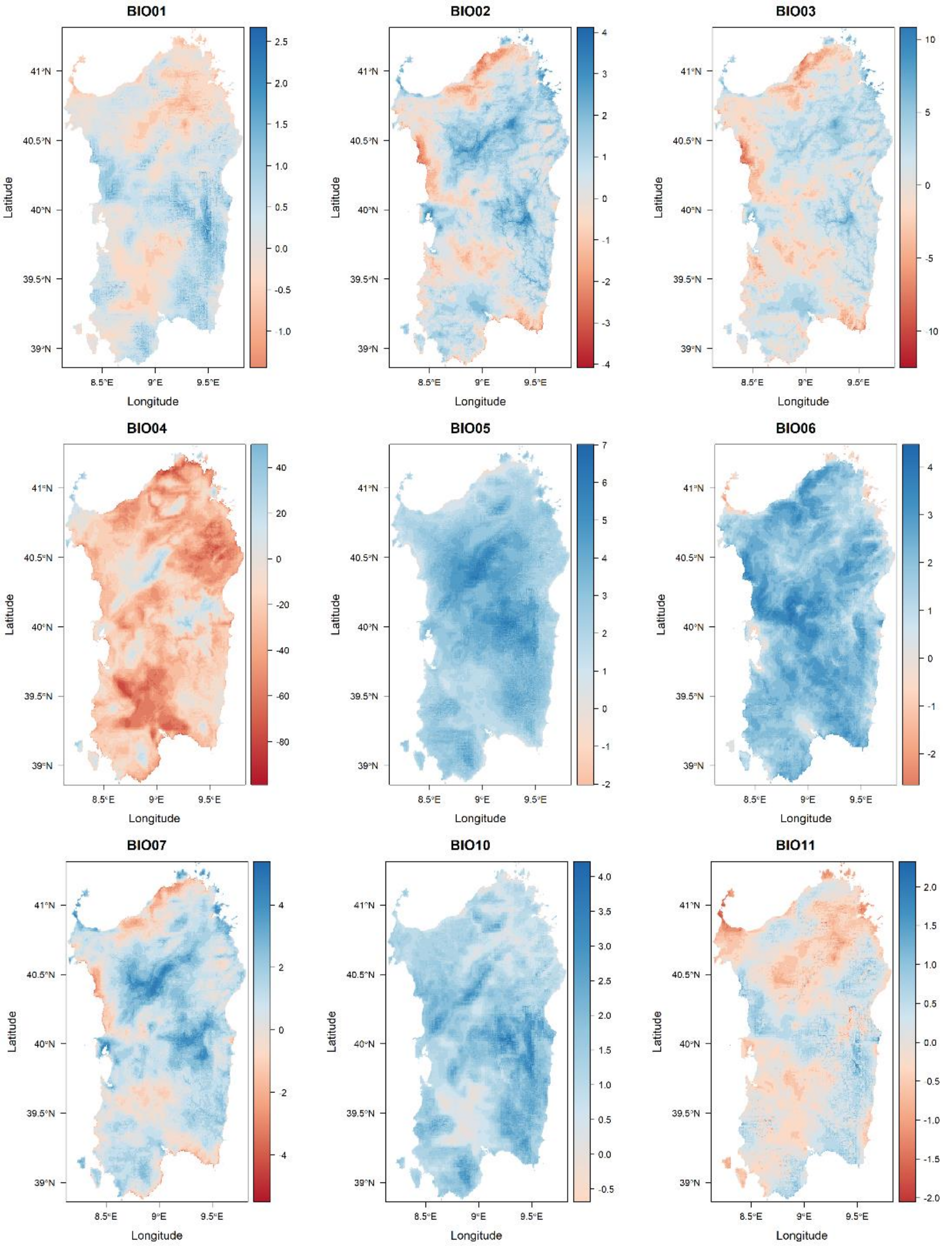


Fig. 6. Spatial distribution of the differences between all pairs of the new high spatial resolution dataset and WorldClim 2 rainfall-related bioclimatic variables (BIO12-BIO17). Red colours indicate overestimated areas by Worldclim2, blue colours the underestimated ones.

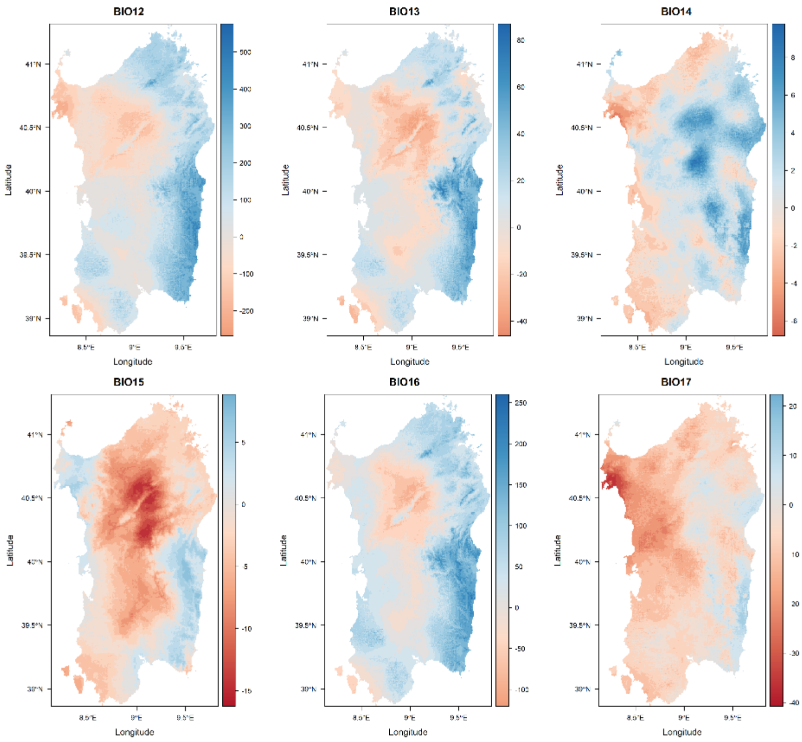
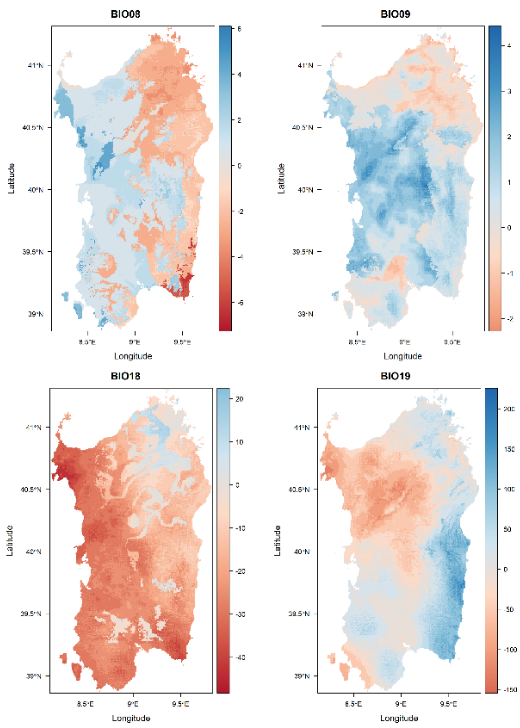


Fig. 7. Spatial distribution of the differences between all pairs of the new high spatial resolution dataset and WorldClim 2 bioclimatic variables related to both temperature and precipitation (BIO08-BIO09 and BIO18-BIO19). Red colours indicate overestimated areas by Worldclim2, blue colours the underestimated ones.



5 Discussions

Bioclimatic variables are fundamental for understanding and modelling the ecological processes and the distribution of biodiversity of earth (Jennings and Harris, 2017; Rivas-Martínez et al., 2011). Nevertheless, our study demonstrated that comparing the global dataset to a high spatial resolution one, revealed that we should pay attention on the accuracy of coarse spatial resolutions data, especially in areas of high heterogeneity where weather stations are few and sparsely distributed (Sandoval et al. 2020), like the Mediterranean area.

We observed that the discrepancies existing among our high spatial resolution dataset and WorldClim 2 are evident and each bioclimatic variable behaved in a different way: we did not detect a general over/underestimation pattern (or trend) of the bioclimatic variables, but we rather observed variable-specific patterns mainly linked to the local orographic conditions and to the direction of the dominant winds driving weather perturbations.

The new high spatial resolution dataset compared to WorldClim 2 showed that the larger discrepancies were spotted in the bioclimatic variables related to precipitation. Those inconsistencies are not evenly distributed in the territory: the greater differences between the two datasets correspond to the areas characterized by complex orographic systems. Moreover, since the dominant air mass perturbations in Sardinia come from west and the rain shadow effect is not considered in the model, the global dataset, probably limited by an uneven distribution of meteorological stations, strongly underestimated the annual precipitation in the eastern zones and overestimated the annual and the summer precipitations (i.e. driest and warmest quarter) in the western zones (up to 40 mm). These discrepancies, if applied, for example, to vascular plant species distribution models, can cause biases in the comprehension of the distribution of thermo-xerophilous species particularly (or exclusively) abundant in the western coast of the island (like *Chamaerops humilis, Polygala rupestris, Viola arborescens*, among the others (Biondi et al., 2001), and, contrarily, of mesophilous species of non-Mediterranean origin that can surprisinglycolonize low elevation (down to the sea level) in the eastern coast, like *Ostrya carpinifolia* Scop.(Bacchetta et al., 2004a) and *Taxus baccata* (Farris et al., 2012).

Similar limitations of the WorldClim spatial dataset accuracy, especially in isolated mountainous areas, were indicated for the first and second versions of this dataset by Hijmans et al. (2005) and Fick and Hijmans (2017), respectively. In particular for Italy, Pesaresi et al. (2014, 2017) highlighted that the lower accuracy in precipitation spatialization of WorldClim, could be explained by the scarcity of meteorological stations density respect to the topographic complexity and heterogeneity of the Italian territories. Bedia et al. (2013) highlighted that the discrepancy in precipitation-related variables between local and WorldClim datasets could determine a lack of robustness of the species distribution models leading, for example, to artifacts in the projections of climate change scenarios at regional or local scales. This can eventually compromise the successful use of models in biodiversity conservation and management actions.

The maximum/minimum temperature of the warmest/coldest month are underestimated, i.e. compared to the high spatial resolution dataset, the global dataset generally models cooler summer maximum (up to 7°C) and colder winter minimum (more than 4°C). Accordingly, the coarse scale dataset models a smaller temperature annual range in the mountains and a wider one on the coasts, underrating the continentality values in the internal areas and exaggerating it on the coasts. These discrepancies are particularly important in the Mediterranean climate, since the seasonal distribution of rainfall and the extreme temperatures determine the limits for species survival. Since Sardinia shows many plains and depressed areas in the internal parts of the island, often surrounded by hills or mountains, it is of crucial importance to discriminate areas with higher temperature annual range (i.e. more continental) from those characterized by a smaller temperature annual range (i.e. more oceanic). In the more continental areas, no matter the altitude above the sea level, species like *Arbutus unedo* L.*,* *Laurus nobilis* L. and *Myrtus communis* L., among the others, are very rare if not completely absent (Bacchetta et al., 2007; Farris et al., 2007), whereas species more tolerant to continentality like *Quercus* gr. *pubescens* Willd. are relatively abundant even at lower elevation (Bacchetta et al., 2004b).

The observed differences related to the precipitation of driest/warmest periods also influence the delimitation between Mediterranean and Temperate macro-bioclimates (Rivas-Martínez et al., 2011).The definition of this ecological boundary can be particularly important in a Mediterranean island where zones with a Temperate bioclimate are crucial for the conservation of small, isolated populations of plant species of boreal-temperate origin, often living at their rear edge and therefore with important conservation concerns such as *Daphne laureola* L., *Isopyrum thalictroides* L., *Lotus alpinus* (DC.) Schleicher, and *Sanicula europaea* L. (Farris et al., 2018; Rosati et al., 2020) but also characterized by a high evolutionary potential (Hampe and Petit, 2005). In the same way, those Temperate areas in a Mediterranean context host non-sclerophyllous plant communities like woods with *Quercus* gr. *pubescens* Willd., *Ostrya carpinifolia* Scop., *Taxus baccata* L. and *Ilex aquifolium* L., as shrubs with *Sorbus torminalis* (L.) Crantz, *Malus pumila* Mill., *Pyrus communis* L. and *Juniperus nana* Willd. (Bacchetta et al., 2009; Farris et al., 2012) and perennial pasturelands with *Anthoxanthum odoratum* L. and *Cynosurus cristatus* L. (Farris et al., 2013), identified as habitats of European concern.

Treating the bioclimatic indices individually helps us to understand which are more reliable, indicating the critical issues to be faced when one is forced to use global datasets such as Worldclim2 in a Mediterranean territory. According to our results, in Sardinia the most consistent indices regard temperature, with the Annual Mean Temperature being the most reliable one. Yet, the spatial distribution of the variables highlights that mountain areas are difficult to model; in fact, even the annual mean temperature shows some variations.

On the contrary, WorldClim 2 does not seem to be reliable on the precipitation indices, influencing the combined indices too: among the least performing variables we can identify Minimum Temperature of Coldest Month (BIO06) and the Precipitation of Warmest Quarter (BIO18).

Given the high discrepancy identified in several sectors of our study area, we recommend being cautious in making ecological assessments based on bioclimatic variables derived from global data with coarse spatial resolutions. The high degree of variability of the new high-resolution bioclimatic variables of the island underlined the need to use fine spatial resolution data to capture the ecological response in physiographically complex landscapes (Hijmans et al., 2005).

6 Conclusions

In this paper we present and make available the first high spatial resolution dataset for the second largest island in the Mediterranean (Sardinia, Italy), including the 19 bioclimatic variables proposed in WorldClim and widely used for ecological studies (e.g. Iannella et al., 2019; Sýkora et al., 2017).

Increasing the availability of high spatial resolution data to improve ecological understanding of variation at finer scales is extremely important, especially in the Mediterranean regions where past geographical and climatic changes and current environmental heterogeneities have determined high levels of biodiversity and biogeographical complexity (Medail, 2017; Thompson, 2020). Tree species composition and richness in Europe is shaped and strongly influenced by both historical and environmental conditions, in particular climate (Svenning and Skov, 2005): high levels of divergence have been highlighted, particularly on islands, which have been attributed to the combined effects of climatic changes, current ecological conditions, and anthropogenic factors, that have originated a long history of population isolation (González-Martínez et al., 2010).

These new data will support a new generation of research studies in a broad array of ecological applications at a much finer scale than previously possible. This sharpening of analysis is particularly urgent in those areas considered as climate-change hotspots (Giorgi, 2006), like the Mediterranean basin (Giorgi and Lionello, 2008): in southern European mountains boreo-temperate species are suspected to undergo a serious decline in future decades, as a consequence of the climatic change (Erschbamer et al., 2009; Normand et al., 2007; Stanisci et al., 2005).

Coarse-scale data is certainly useful for studying patterns on a global scale, but to model in order to obtain reliable results for planning conservation actions and biodiversity management, we need data with good spatial resolution (Sandoval et al. 2020), showing the variability of our territories.

Annex I. GeoTIFF rasters of all 19 bioclimatic variables of Sardinia (Italy) are included. Metadata files include file name, thumbnail, tags and description for all rasters. Rasters are provided at roughly 1.69 arcsec (40 m cell size) resolution, WGS84 geographic coordinate system (EPSG code of 4326).

Competing interests. The authors declare that they have no conflict of interest.

Author contributions. EB designed the study, developed the new high-resolution biologically meaningful variables, and drafted a first version of the manuscript. MM, LR, MF, EF and SC designed the study and helped draft the manuscript. All authors revised the manuscript and approved the final version of the manuscript for publication.

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