Investigating the Representation of Heatwaves from an Ensemble of Km-scale Regional Climate Simulations within CORDEX-FPS Convection

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Abstract

Heatwaves (HWs) are high-impact phenomena that stress both societies and ecosystems. Their intensity and frequency are expected to increase in a warmer climate over many regions of the world. While these impacts can be wide ranging, they are potentially influenced by local to regional features such as topography, land-cover, urbanization. Here, we leverage recent advances in the very high resolution modelling required to elucidate the impacts of heatwaves at these fine scales. Further we aim to understand how the new generation of km-scale regional climate models (RCMs) modulates the representation of heatwaves over a well-known climate change hot spot. We analyze an ensemble of 15 convection-permitting regional climate model (CPRCM, $\sim 2\text{--}4$ km grid spacing) simulations and their driving, convection-parameterized regional climate model (RCM, $\sim 12\text{--}15$ km grid spacing) simulations from the CORDEX Flagship Pilot Study on Convection. The focus is on the evaluation experiments (2000–2009) and three subdomains with a range of climatic characteristics. During HWs, and generally in summer season, CPRCMs exhibit warmer and drier conditions than their driving RCMs. Higher maximum temperatures arise due to an altered heat flux partitioning, with daily peaks up to $\sim 150\text{ W/m}^2$ larger latent heat in RCMs compared to the CPRCMs. This is driven by a 5–25% lower soil moisture content in the CPRCMs, which is in turn related to longer dry spell length (up to double). It is challenging to ascertain whether these differences represent an improvement. However, a distribution-based maximum temperature evaluation, suggests that this CPRCMs warmer/drier tendency is likely more realistic compared to the RCMs, with $\sim 70\%$ of reference sites indicating an added value compared to the driving RCMs. Certainly, CPRCMs enhance dry conditions, with knock-on implications for summer season temperature overestimation, especially over flat terrains. Whether this improved physical representation of HWs also has implications for future changes is under investigation.

1. Introduction

Heatwaves (HWs) represent a particular category of weather extremes defined by persistently anomalous high temperature (Perkins and Alexander 2013). Often studied from a climatological perspective, the governing spatial and temporal scales place HWs as meteorological extreme events. These phenomena may have devastating impacts on nature and society, causing both a sharp mortality rate increase and limiting ecosystem functioning and services.

During recent decades, Central Europe and in general mid-latitudes, witnessed HWs with unprecedented severe impacts (Black et al. 2004; Miralles et al. 2014). Observed trends indicate a region-specific increase of frequency and magnitude of heat waves (Fischer and Schär 2010). Though it is complicated to attribute a cause-effect relationship between anthropogenic climate change and a specific event, several studies point out how a warmer background climate state increases the likelihood of high-intensity HW events (Fischer and Schär 2010; Seneviratne et al. 2012; Zscheischler et al. 2018; Seneviratne et al. 2021).

HW occurrence generally relies on two main underlying drivers: (i) A large-scale circulation component consisting of different high-pressure synoptic systems advecting warm-to-hot air masses toward the affected region (Black et al. 2004; Feudale and Shukla 2007; Dole et al. 2011; Horton et al. 2015; Perkins 2015; Hong et al. 2018; Woollings et al. 2018; Kornhuber et al. 2019; Wehrli and Guillod 2019), and (ii) local-scale forcing mainly associated with soil moisture. The latter is of particular importance in extreme events such as

droughts and heatwaves and even manifests as a local source of predictability (Fischer et al. 2007; Hohenegger et al. 2009; Seneviratne et al. 2010; Taylor et al. 2013; Knist et al. 2017; Careto et al. 2018; Myhre et al. 2018; Soares et al. 2019; Zhou et al. 2019).

Soil moisture constrains the surface energy balance and the partitioning of latent and sensible heat fluxes, impacting air surface temperature (Koster et al., 2004; Santanello et al., 2018). Land-atmosphere coupling can control HWs, amplifying intensity and persistence in the case of a combination of persistent blocking highs and dry soils, where the sensible heat is the dominant flux. A typical situation is represented by the well documented 2003 HW over central and Western Europe. In this event, particularly dry conditions triggered a positive feedback between soil moisture and temperature extremes which exacerbated the HW intensity by about 40% with a secondary impact on the resulting synoptic circulation (Fischer et al. 2007, Miralles et al. 2014).

Regional Climate Models (RCMs) are a well-established tool to explore the interplay of HWs driving mechanisms, and their response to projected anthropogenic forcing (Molina et al., 2020; Vautard et al., 2013). RCMs bridge the gap between the coarse resolution projections from driving Global Climate Models (GCMs) and local climate information. In this regard, the latest generation of Convection Permitting RCMs (CPRCMs, < 4 km grid spacing) is considered as a step change toward temporal/spatial resolution directly usable in regional-to-local scale climate impact studies (Kendon et al. 2012, 2020; Prein et al. 2013; Fosser et al. 2017; Prein et al. 2017; Berthou et al. 2018; Coppola et al. 2020; Adinolfi et al., 2021; Ban et al. 2021; Pichelli et al. 2021). Compared to previous RCM generations (Déqué et al. 2005; Giorgi et al. 2009; van der Linden and Mitchell 2009), km-scale modeling allows for an explicit treatment of relevant physical processes like deep convection without relying on parameterization schemes. Beyond the expected added value in short-duration precipitation extremes, km-scale modeling captures many small-scale mechanisms (e.g., hail, cloud processes, local-scale circulation patterns, coastal region dynamics and tropical cyclones) underlying many high-impact phenomena, leading to more reliable projections, especially over complex orography (Kendon et al. 2020).

Another key aspect when moving to km-scale is the improved representation of land-atmosphere feedbacks (Knist et al. 2017, 2020; Jiang et al. 2019). In the present context, the feedback between soil moisture and precipitation is important for amplifying extreme events such as droughts and heatwaves.

A key factor leading the onset of a positive or a negative soil moisture precipitation feedback, is mesoscale circulations developing in response to horizontal gradients in surface heat fluxes ultimately driven by soil moisture spatial variability and orography (Findell and Eltahir 2003; Hohenegger et al. 2009; Cioni and Hohenegger 2017; Imamovic et al. 2017). In this regard, simulation-based studies demonstrate that a more realistic representation of the deep convection can present an essential advantage in reproducing soil moisture variability and consequent soil moisture precipitation feedback. (Hohenegger et al. 2009; Taylor et al. 2013). Differently, in parameterized-convection simulations, soil moisture precipitation feedback is dominated by grid column vertical exchange processes, generally combined to a rapid response to the increase of moist static energy over wet soils. This may overemphasize land-atmosphere interactions resulting in prevailing positive soil moisture precipitation feedback (Pielke 2001; Taylor et al. 2012, 2013).

Different soil moisture content between convection-parameterized and convection-permitting simulations has a potential influence on temperature. For example, in the case of transition regions between wet and dry climates, considered as regions of strong land-atmosphere coupling, a large part of temperature variability is driven by the soil moisture-temperature feedback (Koster et al. 2004, 2009; Miralles et al. 2012; Yang et al. 2018). When radiative fluxes increase, and soil moisture decreases over time, flux partitioning changes in favor of the sensible heat flux, fostering anomalous high surface temperatures (Miralles et al. 2012, Miralles et al. 2019).

In this study, we present a first ensemble-based investigation on the modulation of HWs and related processes when moving from a convection-parameterized to a convection-permitting scale (km-scale). We take advantage of a multi-model ensemble of decade-long climate evaluation simulations at convection-permitting scale and the corresponding driving convection-parameterized RCMs from the CORDEX-FPS Convection initiative (Coppola et al. 2020, Ban et al. 2021, Pichelli et al. 2021). We analyze the modulation introduced by km-scale modeling over three subdomains of the greater Alpine region with specific topographic and climatic features, following four analysis steps: first a description of the main HWs characteristics, temperature, timing, and persistence; followed by a cause and effect analysis on the surface energy balance; soil moisture; and summer season dry spell length.

In section 2.1 the ensemble simulations and reference products considered are presented. In section 2.2 the experimental setup is described. Results follow in section 3. A discussion with a summary of the main findings and future research perspectives are presented in section 4.

2. Data And Experimental Design

2.1. Model simulations

In this study, we analyze an ensemble of 15 CPRCMs simulations representing a subset of the evaluation simulations performed within the CORDEX Convection Flagship Pilot Study (Coppola et al. 2020). These simulations consist of high-resolution convection-permitting simulations (2–4 km grid-spacing) performed with 5 different RCMs (Table 1). Except for simulations run by UK Met Office (MOHC) and Justus-Liebig-University Giessen (JLU), all the CPRCMs are driven by the corresponding RCMs at an intermediate resolution (~ 12 – 15 km grid-spacing). Although the MOHC group is not using the intermediate step, they are providing the data from the UM model at the resolution of 12 km used for comparison in Berthou et al. (2018). Concerning the COSMO consortium, KIT, CMCC and JLU use the same RCM COSMO-CLM and CPRCMs share the same numerical configuration but a different downscaling approach: JLU has a direct downscaling from ERA-Interim, KIT uses a 0.22° resolution simulation for nesting and CMCC uses a 0.11° resolution simulation over EUR-CORDEX domain for nesting. Moreover, CMCC adopts the urban scheme TERRA-URB (Wouters et al. 2016) for the CPRCM, accounting for the urban heat with expected impact on temperature modulation, heat fluxes partitioning, radiation, relative humidity, over urban and surrounding areas.

Table 1

List of ERA-Interim driven simulations from the different institutions and models used in this study

Institution		CPRCM	Resolution (km)	Driving RCM/domain ^a	Resolution (km)
BCCR	The Bjerknes Centre for Climate Research (Norway)	WRF381BF	3	WRF (EURO-CORDEX)	15
CICERO	Center for International Climate and Environmental Research (Norway)	WRF381BJ	3	WRF (EURO-CORDEX)	15
IDL	Instituto Dom Luiz (Portugal)	WRF381BH	3	WRF (EURO-CORDEX)	15
UCAN	Universidad de Cantabria (Spain)	WRF381BI	3	WRF (EURO-CORDEX)	15
FZJ	Research Centre Jülich (Germany)	WRF381BB	3	WRF (EURO-CORDEX)	15
UHOH	University of Hohenheim (Germany)	WRF381BD	3	WRF (EURO-CORDEX)	15
AUTH	Aristotle University of Thessaloniki (Greece)	WRF381BG	3	WRF (EURO-CORDEX)	15
IPSL	Institut Pierre-Simon-Laplace (France)	WRF381BE	3	WRF/ EURO-CORDEX	15
ICTP	International Centre for Theoretical Physics (Italy)	RegCM4	3	RegCM4 (Europe)	12
MOHC	Met Office Hadley Centre Exeter (UK)	UM	2.2	No ^b	No
KNMI	Royal Netherlands Meteorological	HCLIM38-AROME	2.5	RACMO (Europe)	15
HCLIM	HARMONIE-Climate community Danish Meteorological Institute (Denmark), MET Norway and Swedish Meteorological (Norway), Hydrological Institute (Sweden)	HCLIM38-ALADIN	3	ALADIN (Alps)	12

^aNote that many groups are using European domain as an intermediate step. However, this domain is not necessarily the same between the groups, except for the EURO-CORDEX domain.

^bAlthough, UKMO group is not using the intermediate step, they are providing the data from the UM model at the resolution of 12 km. This data was also used for comparison in the work of Berthou et al. (2018)

Institution		CPRCM	Resolution (km)	Driving RCM/domain ^a	Resolution (km)
CMCC	Centro Euro-Mediterraneo sui Cambiamenti Climatici (Italy)	COSMO-CLM	3	COSMO-CLM (EURO-CORDEX)	12
KIT	Karlsruhe Institute of Technology (Germany)	COSMO-CLM	3	COSMO-CLM (Europe)	25
JLU	Justus-Liebig-University Giessen (Germany)	COSMO-CLM	3	No	
^a Note that many groups are using European domain as an intermediate step. However, this domain is not necessarily the same between the groups, except for the EURO-CORDEX domain.					
^b Although, UKMO group is not using the intermediate step, they are providing the data from the UM model at the resolution of 12 km. This data was also used for comparison in the work of Berthou et al. (2018)					

The main difference between the CPRCMs and driving RCMs lies in the deep convection parameterization used to treat deep convective processes in the RCMs. The latter provide driving fields and act as reference for comparison to km-scale simulations. In this regard, it is noteworthy that, for HCLIM and KNMI simulations, the driving RCMs are different from the nested CPRCMs. In those cases, it is not possible to disentangle the signal generated by the km-scale from other factors (e.g., differences in numerical schemes and dynamical configuration) which could affect nested simulations as well. Convection-parametrized RCMs are in turn forced by ERA-Interim initial and boundary conditions (Dee et al. 2011) along the CORDEX-FPS Convection evaluation period 2000–2009. Details regarding different RCM configurations in terms of main numerical schemes adopted and how multi-physics ensemble variability is generated within the individual modeling consortia can be found in the recent study from Ban et al. 2021.

To isolate km-scale modulation over specific topographical contexts, three subdomains of the greater Alpine region, shown in Fig. 1, are selected. The first domain consists of some of the most complex topography of the Alpine region. The second domain presents opposite features, consisting of a totally flat-terrain portion of the Po valley. The third domain, the Adriatic region, has multifaceted orography, and a large portion is represented by coastal areas.

2.2 Reference datasets

We use several reanalysis and observation-based reference products. For the daily maximum temperature these are:

- UERRA HARMONIE-MESCAN SURFACE which combines UERRA HARMONIE reanalysis (Bazile et al. 2017) with a spatial resolution of 11 km over the entire Europe driven by ERA-Interim, to a surface analysis system, MESCAN SURFACE (Ridal et al. 2017) producing surface analysis over Europe with a spatial resolution of 5.5 km available over the period 1961–2018

- ERA5-Land (Muñoz-Sabater et al. 2021), the European Centre for Medium-Range Weather Forecasts (ECMWF) enhanced global dataset for land component and surface variables of ERA5 reanalysis (9 km resolution, 1981 to present).
 - The gridded EOBS 23.0e dataset (Haylock et al. 2008) at ~11 km resolution over Europe (available from 1950-01-01 to 2020-06-30).
 - Underlying local-scale measurement stations datasets ECA&D V24 (Klein Tank, A.M.G. et al. 2002) provided by the European Climate Assessment & Dataset observational stations (<http://www.ecad.eu>).
- For the soil moisture:
- ESSMRA reanalysis (Naz et al. 2020) consisting of 16 years (2000–2015) daily high-resolution surface soil moisture dataset (3 km resolution) over Europe based on coarse-resolution satellite derived soil moisture data assimilated into the community land model (CLM3.5).
 - ERA5-Land (see above).

For the precipitation:

- EURO4M-APGD (Isotta et al. 2014) daily precipitation gridded dataset (5 km resolution) over the Alpine region, available for the 1971–2008 period (here considered for the 2000–2008 period).
- GRIPHO (Fantini, 2019) hourly gridded precipitation dataset over Italy based on surface station observations (3 km resolution) covering 2001–2016 period (here considered for the 2001–2009 period).

2.3. Analyses

Scientific literature reports a broad number of HW definitions and measures (Perkins and Alexander 2013). A general framework tends to identify at least three days in a row exceeding a certain percentile-based threshold (Perkins et al. 2012; Russo et al. 2015) allowing for a comparison of HW events on different climate types. In this study, we define a HW event as a hot-day spell lasting for at least five days, similar to Fischer and Schär (2010) and Vautard et al. (2013). A hot day is here defined as a day with maximum temperature (T_{max}) equal or larger than the 90th percentile of the evaluation period summer season statistical distribution. Within the evaluation experiment period, we selected three major HW events (2003, 2006, and 2007). Their general

features and atmospheric circulation anomaly patterns are shown in the supplementary materials Fig. SM1, based on ERA5 reanalysis.

As already mentioned, HWs forcing can be mainly discerned in local-scale forcing and large-scale forcing (Hong et al. 2018). In this study, we only evaluate local-scale forcing, postulating that large-scale patterns are simulated similarly between CPRCMs and RCMs during HW events. This is supported by a preliminary analysis of large scale forcing variable distributions during HWs considering a small subset of models (Fig. SM 2).

Four main analyses are performed.

(i) First analysis regards a temperature-based characterization of HWs represented by CPRCMs and RCMs. HWs magnitude, timing, and persistence at the two resolutions are shown. Then, statistical distribution properties of daily maximum and daily mean temperature at the two resolutions are assessed, considering only HWs and the whole summer season. These analyses, including the selection of HW events, consider spatial averages computed on native simulations grid resolution. Then, we compare HWs Tmax RCM and CPRCM ensemble mean; corresponding differences with a reference product (EOBS) and finally a HW distribution-based magnitude (or intensity) metric is derived for RCM and CPRCM ensembles. To characterize spatial patterns, in this latter set of analyses is followed a grid-node by grid-node approach over a domain encompassing the three subdomains previously described. To make results comparable, all CPRCMs are remapped into a common 3 km resolution grid and the same done for the RCMs over a common 15 km grid.

When compared to the reference product, both the CPRCMs and RCMs are remapped into the ~ 11 km resolution EOBS grid. Here, the three HWs reported (2003, 2006, and 2007) have been selected considering temporal segments with the largest number of models and reference products reproducing a HW (2–14 Aug., 20–30 Jul., 15–25 Jul. respectively, see Fig. 2). However, this approach presents the limitation of disregarding grid-node specific differences in terms of HWs occurrence and duration, that are a function of the grid node Tmax distribution properties. Regarding the HW magnitude metric, it consists of a cumulative anomaly of Tmax during a given HW, quantifying how a HW has been anomalous in function of the corresponding statistical distribution properties. The HW magnitude formulation, originally presented in Russo et al. 2015 and adapted for our study, is the following:

$$M = \sum_{d=1}^n \frac{Tmax(d) - P25}{P75 - P25}$$

equation 1

Where Tmax(d) represents the Tmax of a HW day and n is the duration of the HW in days. The interquartile range (IQR) at the denominator is a measure of the variability of the (grid-node-specific) time series and composed by summer season daily Tmax in 2000–2009. In our case, differently from Russo et al. 2015, who derived the IQR of a 30-year period yearly Tmax, the IQR refers to the 2000–2009 JJA daily Tmax statistical distribution.

The results from all models are averaged to obtain the ensemble mean value. Concerning the unit, if the magnitude on HW day d is for example x , then the T_{max} anomaly from the evaluation period 25th percentile is x times the IQR which represents the HW magnitude unit.

Finally, we present a JJA T_{max} station-scale evaluation to assess the potential added value of CPRCMs in comparison to their driving RCMs. This analysis relies on local-scale ECA&D V24 dataset as a reference product. Only the measurement stations providing the highest quality code and with more than 90% of data available during the evaluation period 2000–2009 are selected. Observed time series are compared to the nearest neighborhood grid nodes of RCM and CPRCMs. Original resolutions are here considered, with no interpolation performed. The unique longitude-latitude couples, identifying the i^{th} reference site common to the two resolutions are processed. Potential added value provided by higher resolution CPRCMs compared to the driving lower resolution RCMs is assessed through a Distribution-based Added Value (DAV, Soares and Cardoso (2018)) metric, derived at each reference site. This metric measures the common area between a simulated and an observed statistical distribution and is developed from a PDF skill score (S score) introduced by Perkins et al. (2007). For each observed and simulated time series frequency histograms (FHist) are defined with bins width of 1°C and encompassing all the observed values range. For the two resolutions the common area between observed and simulated distributions is computed, representing an integral of the curve defined by the minimum between observed and simulated frequencies of each distribution bin.

$$S_{rcm} = \sum_1^n \min(Z_{rcm}, Z_{obs})$$

$$S_{cprcm} = \sum_1^n \min(Z_{cprcm}, Z_{obs})$$

equation 2

Where S is the integral of the correspondence between the simulated and observed frequencies (Z) and n is the number of distribution bins. Finally, the DAV value is derived as a percentage difference of the S value resulting from the two resolutions (S_{rcm} and S_{cprcm}).

$$DAV = \frac{S_{cprcm} - S_{rcm}}{S_{rcm}} * 100$$

equation 3

(ii) In a second analysis section, the focus is on the surface energy balance at the two resolutions during HW events. Spatially averaged hourly time series of heat fluxes produced by CPRCMs and RCMs during HW events are compared, and the modulation of HWs maximum temperature as function of the Bowen ratio (ratio between sensible and latent heat fluxes) is assessed.

(iii) The third analysis section focuses on soil moisture during HW events, summer months and the entire annual cycle. Here, both spatially averaged time series and grid-node by grid-node spatial patterns are

presented. The latter consider all the RCMs remapped into a ~ 15 km resolution grid, whereas CPRCM into a ~ 3 km resolution grid.

(iv) Finally, we explore the mean and different statistics of summer season dry spell length (DSL) as reproduced by CPRCMs and RCMs. This is considered a key factor driving soil moisture content differences between the two resolutions. As for the previous analysis, RCMs and CPRCMs are respectively remapped into common resolution grids and, for the RCMs-CPRCMs comparison, CPRCMs are remapped into the common RCMs grid (~ 15 km) beforehand DSL computation.

3. Results

3.1. Temperature

Figure 2 shows an initial characterization of physical intensity, timing and persistence of HWs produced by CPRCMs, driving RCMs, and three reference products considering their own Tmax statistical distributions. Each panel consists of a daily-based comparison of spatially averaged Tmax at the two resolutions. Along the x-axis are reported summer days (JJA months) whereas along the left y-axis models at CP and non-CP resolution (JLU only provides CP runs through a direct downscaling). In the right y-axis are reported the mean of HWs Tmax. In case of multiple events this value refers to the most intense event (i.e., the largest cumulative number of Celsius degrees above the 90th percentile). Results for the reference products UERRA, EOBS, and ERA5-Land are reported in the bottom lines. Different panels show results for different HWs (rows) and domains (columns). The three summer seasons shown (2003, 2006, and 2007) are selected as characterized by the largest number of events common to simulations and reference products. Horizontal thick black lines distinguish different modeling consortia.

The HW of 2003 generally stands out for magnitude, persistence and number of events. Over the Alps domain, CPRCMs and RCMs produce HWs Tmax close to the reference products mean value or slightly higher. CICERO and KIT simulations stand out with mean HW Tmax warm biases up to $\sim 4^\circ\text{C}$. Over Po valley, regardless of the HW considered, both CPRCMs and RCMs show large hot biases up to $6\text{--}8^\circ\text{C}$. Adriatic region domain shows intermediate biases between Alps and Po valley domains. However, the robustness of deviation between simulations and reference products is hindered by the large discrepancies among these latter, up to $\sim 2.5^\circ\text{C}$ over the Po valley and large differences in HWs persistence in the Adriatic. For this latter subdomain it has to be taken into account that spatially-averaged EOBS temperature, differently from reanalysis and simulations, does not include temperature over the sea portion of the domain.

It can be observed that CPRCMs and corresponding RCM show similar timing and persistence for 2006 and 2007 events. Larger differences, up to cases where a short event is reproduced only in one of the two resolutions (e.g., MOHC Alps 2003), can be observed in the 2003 summer season and also in the 2006 HW over Po valley and Adriatic. For what concerns Tmax values, excluding KNMI (over the Alps) and CMCC runs (over the three domains), CPRCMs tend to produce higher values than the RCMs. Considering the mean of the HW Tmax, CPRCMs-RCMs differences are generally around 1.0°C . However, in some cases like IPSL, ICTP, MOHC and KNMI, differences over Po valley can exceed 3°C in 2003 and 2006 HWs. These higher temperatures represent an improvement for IPSL and, though to a lesser extent, for the ICTP CPRCMs. Over Po

valley, MOHC CPRCM higher temperature signals a worsening compared to the RCM. It is peculiar the case of KNMI showing similar CPRCMs and RCMs mean Tmax over Alps and CPRCM 3°C warmer than the RCM over Po valley. Also in this case, this modulation leads to an increased warm bias over reference products. Within the WRF multi-physics ensemble, differences between CPRCMs and RCMs typically do not exceed 1°C with UHOH RCM showing higher Tmax than the CPRCM in the 2006 event over the Po valley. In this context, as previously mentioned, IPSL CPRCM stands out with a larger warm modulation of the RCM signal over Po valley. It is noteworthy highlighting that IPSL and UHOH WRF simulations share the same combination of physics schemes except for the microphysics scheme (i.e., Thompson and the aerosol-aware Thompson respectively).

In Table 2 summarizing statistics (mean and standard deviation) are reported for CPRCM and RCM HWs Tmax. Statistics consider the series of HWs mean Tmax (right y- axis Fig. 2) produced by each model at the two resolutions during the three HWs over the three subdomains. Besides generally higher Tmax, CPRCMs are also characterized by lower inter-model spread, especially over Po valley.

Table 2
Mean and standard deviation of HWs mean Tmax series considering the three events. Units are °C

HWs mean Tmax (2003, 2006, 2007)	Alps	Po valley	Adriatic
Mean CPRMCs	25.7	39.3	33.1
Mean RCMs	24.9	38.1	32.4
Std CPRCMs	1.6	1.9	1.8
Std RCMs	1.8	2.7	2.2

We now assess if the resulting HWs timing, duration and CPRCMs-RCMs differences are influenced by the metric chosen to select HW events. Supplementary material Fig. SM 3 shows the same analysis but with HWs selected considering the 90th percentile of the daily mean temperature distribution instead of Tmax. Here, the right y-axes values are the mean of HWs daily mean temperature. HW temporal patterns (timing and persistence) are mainly preserved compared to Fig. 2. Only in 2003, over the Po valley, an increased number of events and a larger persistence for some models (e.g., CICERO, UHOH, FZJ, ICTP runs) resulted. The km-scale Tmax modulation is consistent with what results considering daily mean temperature. This fact suggests that when a km-scale temperature amplification occurs, it regards not only daily temperature peaks but also mean temperature, which implicitly includes nighttime minimum values.

Box plots in Fig. 3 summarize statistical properties of the spatially averaged HWs daily Tmax. In the upper panels, distributions are built on HW events daily Tmax shown in Fig. 2. Bottom panels show daily Tmax distribution for the summer months considering the whole evaluation period. According to the median of the ensembles (black dot within the boxes), CPRCMs Tmax are ~ 1°C higher than the corresponding RCMs ensemble. However, relevant inter-model and intra-model differences can be observed. Firstly, considering the HWs box plots median differences about 6°C result among different models. Regarding the intra-model differences, within the WRF ensemble, IDL and UCAN WRF show CPRCMs Tmax ~ 1.5°C higher than the

corresponding RCMs over the Alps and Adriatic domains. As previously mentioned, ICTP, MOHC and KNMI (over the Po valley) show CPRCMs Tmax up to more than 3°C higher than the RCMs.

Within COSMO simulations a different tendency between CMCC and KIT results with the former showing higher Tmax in the RCM than the CPRCM over the Alps domain. Noteworthy are the differences between KIT and JLU with this latter generally closer to reference products. The two CPRCMs share the same numerical configuration but different downscaling approach (a direct downscaling of ERA-Interim for the JLU). This aspect points out that downscaling strategy can modulate temperature extremes as well, representing a further level of uncertainty.

Over the whole evaluation period (bottom panels of Fig. 3), simulated and reference products distribution get much closer than when only HW days are considered. Also, a consistent reduction of differences among the reference datasets can be observed. However, it has to be noticed that, when considering the entire evaluation period, substantial differences among domains come up. While in the Alps we can observe similar CPRCMs and RCMs Tmax, conversely, in the Po valley we can still observe consistently higher CPRCMs Tmax compared to the RCMs. Differently from the other subdomains, over Po valley, also CMCC shows higher Tmax in the CPRCM. Considering the high concentration of Po valley urbanized areas, this could be regarded as the cumulative effect of urban scheme adopted in the CPRCM. Here, the median of the CPRCMs ensemble is higher than the corresponding RCM ensemble by about 2°C. It is noteworthy that IPSL, ICTP, MOHC and KNMI CPRCMs runs produce Tmax up to more than 3°C higher than the driving RCMs, even when the entire evaluation period distribution is considered. The Adriatic region domain shows intermediate results between the Alps and Po valley domains.

Similar CPRCMs-RCMs difference patterns can be observed considering mean daily temperature instead of the daily maximum temperature. Related results, reported in the supplementary materials (Fig. SM 4) show similar patterns, except a further amplification of differences between the CPRCM and RCM for the MOHC model.

A spatial patterns analysis over a domain encompassing the three subdomains is presented in Fig. 4. This consists of reference products and simulation ensemble means (panels a and b respectively) physical values, differences between RCM and CPRCMs ensembles and EOBS (panels c), and RCM and CPRCM ensembles HWs magnitude metric as derived in Eq. 1 (panels d). Results for the representative 2003 HW are shown, whereas 2006 and 2007 results are reported in the Figs. SM 5 and SM 6. A comparison between the two reference products confirms how ERA5-Land produces lower Tmax than the EOBS dataset. Moving to simulations, CPRCMs ensemble generally shows higher temperatures than the nonCP ensemble mean, especially over flat terrain (up to ~ 2°C). Higher CPRCMs ensemble Tmax translates into a general reduction of the RCM ensemble cold bias, aside from the upper Po valley, where warm Tmax bias is increased in the CPRCMs ensemble. Considering 2006 HW, a warmer CPRCMs ensemble signals an increase in warm bias. This can be mainly observed again over flat terrain of the Italian peninsula. Over the northern part of the domain, RCMs ensemble cold bias shifts into a similar magnitude warm bias in the CPRCMs ensemble. Similar modulation patterns can be observed also in the 2007 event.

HW magnitude index shows, despite the higher CPRCMs ensemble Tmax, a similar cumulative anomaly, namely the HW has, in statistical terms, a similar location in the two resolution distributions. This feature, confirming results of Fig. 4 (bottom panels), suggests a shift toward warmer values of the CPRCMs PDF instead of a shift limited to the distribution right tail.

We conclude temperature-based analysis presenting the results for a point-scale evaluation of JJA Tmax for each model and corresponding ensemble mean. In Fig. 5 results from 146 reference sites are shown. Considering original model grids this number can slightly vary across models as a function of the different resolutions and if the specific reference site is seen as a land or a sea node by the specific model grid. The ensemble consists of an average of all the model results for the specific reference site. Maps in the right subplots show geographical distribution of the reference sites and corresponding DAV values (Eq. 3). The percentage of reference sites characterized by $DAV > 0$, i.e. the 3km CPRCM run adds value on the driving RCM, is indicated on the lower left corner of each map panel. In the left subplots, violin plots show a direct comparison of how well observations are captured by the two resolutions in terms of observed-simulated statistical distributions matching. Here if a model perfectly simulates the observed station conditions, the S skill score will equal one, which is the total sum of the frequency at each bin. A S skill score PDF is built simply considering S scores from all the reference stations. Considering the ensemble mean, 69% of reference sites present a $DAV > 0$ indicating an improved representation of the observed JJA Tmax performed by km-scale simulations. Larger positive DAV values can be found in areas of complex-topography alpine region sites and Croatian coastline sites. Analyzing results from individual ensemble members, largely different responses result. The positive DAV percentage varies from 25% for the HCLIM to 94% for the ICTP. In this regard it is however essential taking into account, beside the mere CPRCM improvement measure, also the S score performed by the driving RCM. In fact, where large positive DAVs result (e.g. ICTP and IPSL) we can see poorer S scores characterizing the driving RCMs (median ~ 0.7) compared to the cases where a detrimental impact of the CP-scale results. In these latter cases, the driving RCMs already show satisfactory performance with high S score median, sometimes close to 0.9, as for HCLIM, AUTH and IDL models.

It is now interesting to explore if, and to what extent, the added value in CPRCMs is due to a grid cell height closer to that of the reference station, as a result of the increased resolution. Since the systematic height difference shifts frequency histograms, affecting DAV, the same analysis is performed taking into account nearest neighbors height difference of both RCMs and CPRCMs with reference to station height. A first order approximation is used according to a standard lapse rate of $0.0065^{\circ}\text{C}/\text{m}$. As expected, a height correction reduces the CPRCMs added value in the sites located at higher elevation (Fig. SM 7). Height correction leads to a reduction of a few percentage points of the ensemble DAV moving from 69–66% of reference sites with positive DAV, with a similarly modest shift exhibited by the vast majority of models. Thus, there is an indication of genuine added value by the CPRCMs, not just related to the better representation of the station height. Though a height correction is commonly proposed in the evaluation of different resolution simulations, it should be mentioned that this does not systematically ensure a more sensible comparison. Lapse rate is consistently and non-linearly affected by local-scale features. Furthermore, the added value of higher resolution cannot be considered only belonging to improved representation of topography; it entails changes in simulation thermodynamic and dynamic features. These aspects make it challenging to fully disentangle the role of increased resolution vs. the role of improved physics, as they are inextricably linked.

3.2. Surface energy balance

In this section, we assess km-scale modulation on HWs heat fluxes partitioning. Figure 6 shows spatially averaged hourly time series of latent heat flux differences between RCMs and CPRCMs during HWs. Time steps where at least one of the two represent a HW are selected. In cases where hourly time resolution is not available (i.e., CMCC and KIT RCMs) a 3-hourly mean is performed on the corresponding hourly CPRCM time series. In this analysis, HWs from 2000 are also included; these were not considered in the previous analyses as no HW was reproduced in the reference products. Figure 6 shows positive differences indicating larger latent heat in the RCMs excluding CMCC and KNMI (over Alps) and UHOH (over Po valley). These patterns are consistent to those resulting from previous temperature analysis.

In fact, RCMs showing large $T_{\max}$ increases moving to the km-scale show also remarkable differences in latent heat flux. Namely, for IPSL, ICTP, MOHC, KNMI, KIT simulations the difference between RCMs and CPRCMs can be as large as about 150 W/m^2 . This latter value in relative terms signals a consistent modification, considering that summer season latent heat flux peaks rarely exceed 350 W/m^2 . This aspect can be exemplarily seen for three representative models over the Po valley in Fig. SM 8, showing hourly time series of latent heat physical values produced at the two resolutions. Consistently with temperature, latent heat flux modulation tends to characterize not only HW events but also the whole summer season.

Regarding the sensible heat flux, as expected, an opposite difference sign results (Fig. SM 9). It is however noteworthy that the magnitude of differences is smaller compared to the latent heat. This indicates an asymmetry in the km-scale modulation, with larger modification of latent heat than that of sensible heat flux. Figure 7 summarizes the relationship between HWs $T_{\max}$ and heat fluxes as represented by the Bowen ratio ($Br = \text{sensible heat} / \text{latent heat}$) for CPRCMs and RCMs. Br gives a basic idea about the different partitioning of heat fluxes, which is mostly, but not only, driven by different soil moisture availability. In the different panels of Fig. 7 we show $T_{\max}$ vs. Br scatterplots for the different domains and for the different HW events. Spatially averaged $T_{\max}$ and Br time series are temporally averaged over the specific HW for the two resolutions. Comparing CPRCMs and RCMs, despite the large inter-model variability, drier-warmer conditions generally characterize CPRCMs. In the presence of drier soils (i.e., Po valley) with higher Br , we observe a smaller sensitivity of temperature alterations to differences in Br . This feature can be explained by a stronger land-atmosphere coupling over dry soils, where sensible heat flux largely prevails over latent heat flux. Finally, it is noteworthy how temperature alteration shows a sensitivity to Br largely model- and event-dependent. This suggests that km-scale HWs temperature modulation can be only partially explained by considering differences in heat flux partitioning. Other relevant non-local scale mechanisms (e.g., horizontal advection of heat) are likely to play a role as well (Miralles et al. 2019).

3.3. Soil moisture

In this section, we explore differences in soil moisture content between CPRCMs and RCMs. Figures 8a and 8b show representative 2003 HW mean volumetric soil moisture for the CPRCMs and RCMs, respectively. All the simulated soil moisture values belong to the top-soil layer, excluding ICTP RegCM. For this latter, which provides several soil layers, is selected the depth closest to the 0.10 m (0.12 m) characterizing the majority of models. Simulated soil moisture datasets have been interpolated on a common grid of 3 km resolution for

CPRCMs and 15 km resolution for the RCMs. The reference products ESSMRA and ERA5-Land reanalysis (top-left and top-central panels respectively) are shown on their native grid resolution (3 km and 9 km respectively). These two products show substantially different soil moisture values during the 2003 event, and even more when considering the summer (JJA) climatology for the reference period (Figs. SM 10). It is a challenge to disentangle to what extent differences are driven by different soil layer depth (0–3 cm and 0–7 cm for ESSMRA and ERA5-Land respectively) or by structural land surface modeling system differences. For sake of comparability between simulated and reference values, soil moisture in models, originally provided in $\text{kg}\cdot\text{m}^{-2}$, is converted to volumetric soil moisture ($\text{m}^3\cdot\text{m}^{-3}$) according to Bauer-Marschallinger and Stachl (2019):

$$\text{SM}[\text{m}^3/\text{m}^3] = \text{SM}[\text{kg}/\text{m}^2] * 0.001 * 1/d$$

where d is the thickness of the soil layer in meters. The factor 0.001 is due to the assumption that 1 kg of water represents 1000cm^3 , which is 0.001m^3 . However, even with the same units, a direct comparison between model's soil moisture and reference products is hindered by different top-soil layer depth between models and reanalysis. Also, top-soil layer depth varies among models as a result of different land surface models employed by the different modeling consortia. Taking into account these limitations, it is possible to compare soil moisture among a large part of the models. These do not include KNMI, for which soil moisture data is not available, KIT runs, having a different top-soil layer depth between the CPRCM and RCM and the already mentioned case of JLU performing a one-step downscaling. Excluding the CMCC, all the CPRCMs tend to get drier in respect to the RCMs (cf. Figures 8a and 8b). CICERO and to a lesser extent UHOH and AUTH WRF runs present evident dry conditions already on the RCM especially over the flat terrain of Po valley. In these cases, CPRCMs tend to preserve almost totally dry conditions, with a subsequent irrelevant alteration of HW maximum temperature (Fig. 2). Supplementary materials Figs. SM 10a and SM 10b show the same analysis, but averaging JJA daily soil moisture data over the entire evaluation period. Here, similar km-scale modulation patterns can be observed for the majority of models, confirming that CPRCMs modulation is not limited to HW events. In Fig. 9, we show the temporal evolution during the evaluation period of percentage differences between CPRCMs and RCMs soil moisture. Again, we only consider comparable models in terms of soil layer depth. With respect to Figs. 8a and 8b, Fig. 9 excluded CMCC runs providing a very shallow top-soil layer with a day-to-day variability not comparable to the other models; KIT runs which have two different soil layer depths between CPRCM and RCM, and MOHC runs are excluded because of too large differences between CP and non-CP runs despite employing the same land surface model parameterization but different configurations. These large differences in MOHC come from the non-CP run being closer to the UK Met Office global climate configuration and the CP run closer to the weather-like configuration of the same model. The CP run has too much runoff due to this configuration difference plus too little canopy interception, which makes it very dry in the summer months (Halladay et al. 2021).

Over the Alps domain, CPRCMs show lower soil moisture than corresponding RCMs with an ensemble mean difference ranging from – 5% to -15%. Two main peaks reporting larger differences can be observed during the 2003 and 2006 summer seasons, characterized by the two most intense HW events. Larger differences combined with noisier patterns can be observed over Po valley. Here, very low soil moisture values can contribute to this large variability in percent differences, which are amplified by combining very small

numbers to fractions. Negative differences between RCMs and CPRCMs prevail, with some positive values resulting from the driest CICERO runs. In correspondence of 2003 and 2006 summer seasons' ensemble mean shows a negative difference reaching about - 25% with some models down to -40%. The Adriatic region domain shows intermediate characteristics between the Alps and Po valley domains.

Results obtained so far suggest an enhancement of the heatwaves by the CPRCMs compared to the RCMs. However, it is difficult to state if these signals constitute an improvement. This is because HW events are rare and inferences are constrained by the small sample size. For better framing soil moisture modulation occurring during HWs, we depict in Fig. 10 the annual cycle of soil moisture in the CPRCMs vs. the RCMs. In the case of a more realistic soil moisture annual cycle, it can be argued that the heatwave representation is also improved. In the Fig. 10 are shown CPRCMs and RCMs volumetric soil moisture monthly means over the three domains. Simulations are compared to the topsoil layer (7 cm depth) of ERA5-Land, and ESSMRA (3 cm depth) considered as reference products. The majority of models have a 10 cm depth topsoil layer (see Figs. 8), and in those cases ERA5-Land better matches than the ESSMRA (3 cm depth). For COSMO (CMCC, KIT (CP), and JLU) and HCLIM simulations, ESSMRA represents the best matching reference product.

Over the Alpine domain, ERA5-Land shows an annual cycle characterized by a dry peak in late winter and a wet peak in late spring. A similar annual cycle with smaller values is shown by ESSMRA reanalysis. Compared to ERA5-Land, All models (except HCLIM) miss the spring peak, leading to a too dry summer (relative to their corresponding winter level) likely driven by a misrepresentation of snow melting. Simulated annual cycles show dry conditions peaking during summer months and wettest conditions in correspondence of winter months. HCLIM model, having a shallower topsoil layer depth (1.0 cm) reproduces the reference annual cycle, but it exaggerates annual variability. Considering the ensemble means, small differences between CPRCMs and RCMs characterize winter and spring months. Differences get larger during summer. In this regard, it can be observed how the drier CPRCMs ensemble means would be mostly determined by the particularly dry KIT and JLU simulations. It is worth recalling that KIT CPRCM and RCM soil moisture are not comparable (1 cm vs. 1 m soil layer depth, respectively). Besides these two models, the MOHC model is the one showing the largest difference between the two resolutions, with a drier summer season and an early dry peak (from August to July) at the CP scale. The WRF ensemble shows a small spread across members and a reduced summer season drying when moving to the km-scale. In this regard, there is a clear model-specific behavior, especially for the Alps, where different layer thickness can be seen as at least partially contributing to this model-based differentiation.

Po valley and Adriatic domains show similar soil moisture annual cycles characterized by an evident summer dry peak. ERA5-Land and ESSMRA show the driest conditions in July, whereas CPRCMs and especially RCMs show dry conditions peaking in August. Both the CPRCMs and RCMs show dry biases during the entire annual cycle, exacerbated from late spring throughout summer by the CPRCMs. Especially over Po valley, CPRCMs are also characterized by a steeper increase of monthly values during autumn and early winter. Confirming previous results, the CMCC model is generally very close to the ESSMRA reference product (especially over flat territories) and shows a different modulation between the two resolutions, with a more emphasized summer drying in the RCM compared to the CPRCM. In July and August, CPRCMs shows higher soil moisture, closer to ERA5-Land but too wet considering the ESSMRA dataset. In conclusion, also considering the whole annual cycle, CPRCMs are still drier than their non-CP counterparts and their spread is large. This is a source of

uncertainty that requires deeper investigations also considering potentially relevant knock-on implications for precipitation via the soil-moisture precipitation feedback.

Nonetheless, a large source of uncertainty comes also from reference products considered, presenting a large spread and being characterized by considerable structural differences.

3.4. Dry spell length

Figures 11a and 11b present a comparison between CPRCMs and RCMs summer months mean dry spell length (DSL) considering the entire evaluation period. As a reference, two different observational-based precipitation datasets are considered: EURO4M (Isotta et al. 2014) from $\sim 43^\circ\text{N}$ northward and GRIPHO (Fantini 2019) from $\sim 43^\circ\text{N}$ southward.

Dry spell length (DSL) is derived considering daily accumulated precipitation, where a dry day is characterized by precipitation lower than 1 mm.

Consistent with what is observed for soil moisture, substantial differences can be observed. CPRCMs ensemble mean introduces, on the one hand, an improved representation of the topography-driven spatial patterns, on the other hand, it also introduces a remarkable extension of DSL compared to the RCMs ensemble mean. Compared to reference products, this consists of a substantial overestimation of the observed DSL. RCMs ensemble mean shows DSL values closer to the observations. Large differences between CPRCMs and RCMs DSL are particularly evident over flat terrain and coastline, where CPRCMs DSL doubles RCMs DSL. In Fig. SM 11 are shown grid-node by grid-node percentage differences between CPRCMs and RCMs DSL. Here, CPRCMs have been preliminarily remapped into the common RCMs grid.

Even with large differences, all the models, excluding CMCC runs, present the km-scale version characterized by longer DSL. Focusing on the two models showing the largest temperature modulation between the two resolutions (ICTP and MOHC), ICTP shows also the largest difference between CPRCM and RCM DSL (Fig. SM 11). Differently, the MOHC model does not present particularly high DSL alteration between the two resolutions. This fact suggests potentially different mechanisms underlying temperature alteration resulting in the two models. Moreover, unlike other models, ICTP km-scale runs show an improvement compared to the RCM where a consistent wet bias is moved to a dry bias but of smaller magnitude. Figure 12 shows DSL alteration between the two resolutions and related deviation from the observations for the three domains and over the entire statistical distribution (empirical cumulative distribution function, ECDF). Here, to preserve as unaltered as possible the original daily precipitation statistics, no interpolation is performed. ECDFs are defined considering grid node-by-grid node DSL time series along the entire evaluation period summer seasons. Distinct modulation tendencies can be observed in the different domains. Again, the largest modulation signal appears over the flat terrain of the Po valley, where almost all members of the km-scale ensemble are shifted on the right side of the observed ECDF, indicating longer DSL over the entire statistical distribution. In contrast, we observe ECDF evenly distributed within the variability of RCMs ensemble. A similar modulation pattern, though with consistently lower magnitudes, is evident over the Alps. The Adriatic region shows the smallest differences between the CPRCMs and RCMs ensembles. In the upper part of the panels, we report DSL simulated and observed values for representative statistical moments. As already mentioned,

the CPRCM ensemble shows statistics roughly doubling the observed values. The RCM ensemble presents more comparable values to the reference products, especially over the Alps and Po valley domains.

4. Discussions And Conclusion

In recent years, several studies investigated historical period performance and projected climate change signal generated by the latest generation of very high-resolution (km-scale or convection-permitting scale) climate models. These studies have been largely focused on precipitation (Kendon et al. 2012, 2016; Ban et al. 2015, 2021; Fosser et al. 2017; Berthou et al. 2018; Coppola et al. 2020; Knist et al. 2018; Vanden Broucke et al. 2019; Lenderink et al. 2019; Pichelli et al. 2021; Adinolfi et al. 2021). Feedbacks from a km-scale representation of land-atmosphere interactions on the temperature are still largely unexplored (Knist et al. 2020; Soares et al. 2022 (submitted)). This present study explores whether and why km-scale modeling modulates HWs and underlying processes representation, taking advantage of a multimodel ensemble from CORDEX-FPS Convection initiative. In this regard, past studies highlight soil moisture-precipitation feedback modifications (Pielke 2001; Koster et al. 2004), up to the sign change in wet-arid transitional areas, when moving from a parameterized to an explicit treatment of deep-convection processes (Hohenegger et al. 2009; Taylor et al. 2013). A different soil moisture-precipitation feedback impacts the heat flux partitioning, which can in turn consistently affect temperature, in particular, summer extremes.

We summarize the main results as follows:

- Regarding the temperature, our results show warmer conditions during HWs, and generally in the summer season, in CPRCMs compared to the driving RCMs. From a multi-model perspective, km-scale modulation toward warmer-drier conditions seems to be more scale-dependent than model-dependent. This modification is generally observed in all models (except one) although with substantial inter-model spread. Considering all the HWs occurred in the evaluation period, the CPRCMs ensemble shows about 1°C higher temperature than the corresponding RCMs ensemble. IPSL, ICTP, MOHC, and KNMI (this latter only over Po valley) models show the largest HWs temperature modulation, exceeding in some cases 3°C. Considering gridded reference products, CPRCMs tendency of simulating higher temperatures mainly represents a reduction of cold biases and an exacerbation of warm biases generated by the RCMs. This latter result is especially evident over the flat terrain of the Po valley domain. Similarly, CPRCMs temperatures are higher over the Alps and Adriatic domains, but with smaller biases. However, considering JJA Tmax, a distribution-based local-scale evaluation shows an ensemble mean added value of CPRCMs compared to the driving RCMs (positive DAV) over the 69% of reference sites. This suggests the CPRCMs tendency toward warmer/drier conditions is likely more realistic and more accurate than the RCMs.
- Behind temperature modulation, we found lower (higher) latent (sensible) heat fluxes in the CPRCMs. However, a slight asymmetry of heat fluxes modulation results in larger modifications of latent heat flux compared to the sensible heat flux with diurnal peaks up to 150 W/m² over the Po valley domain. In both RCMs and CPRCMs HWs take place despite the absence of net radiation anomaly (not shown). Hence, the partitioning of heat fluxes, largely driven by soil moisture level, plays a key role in determining temperature extremes (Fischer et al. 2007).

- In this regard, CPRCMs present drier conditions than the corresponding RCMs (excluding the CMCC model). This feature results in all the three domains (up to -25% considering ensemble mean) and not only during HWs but in general during the summer months.
- Drier conditions correspond to consistently longer DSL in the CPRCMs ensemble. A doubling of CPRCMs DSL results over flat terrains and coastal areas. Compared to the observations, this km-scale DSL extension corresponds to a dry bias, especially over the Po valley domain. An extension of dry spells in km-scale simulations, is in agreement with other studies involving different areas and different models (Kendon et al. 2016, 2019; Berthou et al. 2018; Barlage et al. 2021).

It is difficult to disentangle interacting mechanisms driving km-scale modulation. However, insights can be retrieved considering the two models showing the largest temperature modulation (ICTP and MOHC). MOHC model shows larger modulation of soil moisture with respect to the ICTP model considering both the HW event of 2003 (Fig. 8a and 8b) and the summer seasonal mean for the whole evaluation period (Fig. SM 10a and SM 10b). Differently, the ICTP model shows a larger modification of DSL than the MOHC model (Fig. SM 11).

In the case of the MOHC model, arguments can be made over a larger role played by a different configuration of land surface model in determining alteration of land-atmosphere interactions between the two different resolutions observed in recent studies (Berthou et al. 2018; Halladay et al. 2021). Different from MOHC, the ICTP model presents the same land surface model configuration in the two resolutions. Here, a relevant role could be played by different PBL and cloud microphysics schemes, resulting in different sensitivity to the convection triggering processes in the two resolutions. Further, the entrainment of environmental drier air in convective plume is parametrized in RCMs, which may partially explain the spread between models. In CPRCMs, the mixing is explicit, and this affects the triggering of precipitation (and also dissipative effects). In related research (Ha et al. 2022, under review) it has been observed that for similar temperature ranges, the triggering is suppressed in CPRCMs. It is another factor explaining the differences between RCMs and CPRCMs in the dry spell length. The relevance of microphysics scheme choice is also evident, considering the differences between WRF IPSL and UHOH models sharing the same physics schemes combination except for the microphysics scheme.

Hence, land-atmosphere interactions and microphysical parameterization schemes could be regarded as key factors behind modifications introduced by km-scale modeling (e.g., Milovac et al. 2016).

Nevertheless, soil moisture constitutes a key variable for temperature extremes and different aspects can contribute to its alteration when moving to a km-scale. In this context robust evidence pertains the modified summer convective precipitation diurnal cycle resulting in less frequent and more mid-to-high intensity events, explored in recent studies (Berthou et al. 2018; Kendon et al. 2019; Prein et al. 2021). At the same time, large uncertainty affects the representation of soil moisture-precipitation feedback, which still remains a challenge (e.g., Yang et al. 2018, Kendon et al. 2020 Leutwyler et al. 2021). The lower part of this feedback loop (i.e., soil and land-surface processes) is parameterized by the land surface models, which are typically developed offline and coupled to the atmospheric part of weather and climate models. With an increase in the horizontal resolution, these models are becoming more complex with more parameterized sub-grid scale processes, and they start to play a significant role, especially in representing land surface-atmosphere feedbacks.

Furthermore, it has been recognized that these feedbacks represent a large source of uncertainty in the models (Kendon et al. 2020). A good example is represented by the increasingly relevant inclusion of ground water when resolution lower than 3 km are considered. Ground water can represent an additional water source critical to replenish upper layers soil moisture and identified as an effective pathway to mitigate warm summer season biases thanks to an increased evapotranspiration (Barlage et al. 2021). With the increase in spatial resolution, the role of the accurate representation of these feedbacks is becoming crucial, especially considering cumulative effects in climate time scales (e.g., Seneviratne et al. 2010). In fact, in the next decades, vast continental areas are projected to shift toward wet-dry transitional conditions, characterized by a strong land-atmosphere coupling, where atmospheric variables are largely constrained by soil conditions (Knist et al. 2017; Careto et al. 2018; Soares et al. 2019).

In this study we presented a first km-scale ensemble-based temperature analysis, highlighting that km-scale effects go beyond the well documented modifications of precipitation extremes introducing a modification of summer temperature and HW events.

A local-scale evaluation of summer maximum temperature suggests the warmer/drier signal moving to a km-scale is likely more realistic and more accurate than the RCMs. It is in any case not possible to fully disentangle the role of resolution increase vs. the role of improved physics that are inextricably linked. Further process-based studies are needed to confirm that these modifications are physical plausible signaling an improvement. Particular attention is recommended on summer convection inhibition at km-scale and on to disentangle the role of different mechanisms underlying km-scale modification, e.g., land-atmosphere interactions but also the PBL, shallow convection and microphysical parameterization schemes. These aspects can be of particular relevance considering cumulative effects on multi-decadal climate temporal scales and future projections. In this context, next research will focus on potential implications of evaluation experiment findings on HWs future changes, exploring if future changes in soil moisture will show a resolution dependency and if the summer km-scale warmer-drier tendency can be expected time-stationary or amplified/reduced in a future warmer climate.

Declarations

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Figures

Figure 1

Geographical domains considered in this study and corresponding to the Alpine region, Po valley, and Adriatic region respectively

Figure 2

Spatially averaged HWs daily maximum temperature produced by RCM and CPRCM simulations and the reference products UERRA, EOBS, and ERA5-Land (left y-axis). The x-axis reports summer days. Gray-shaded cells indicate daily Tmax exceeding the evaluation period summer 90th percentile, but not included within a HW event. Panels from left to right columns show results for different domains, whereas different summer seasons (2003, 2006, and 2007) are reported along the lines

Figure 3

Upper panels: box plots summarizing statistical distribution built on spatially averaged HWs daily maximum temperature for the reference products (UERRA, EOBS, and ERA5-Land) and models at the two resolutions. Filled boxes are representative of CPRCMs while boxes white filled are for RCMs. Bottom panels: same as upper ones, but with statistical distributions built on daily maximum temperature of the entire evaluation period (2000-2009) summer seasons. Left to right panels show results for the different domains. Unfilled boxes with dashed lines represent RCMs and reference products. Filled boxes with solid lines for whiskers represent CPRCMs. On each box, quartiles (central mark and box edges), extreme values within the 1.5 interquartile range from the box edges (whiskers) are represented

Figure 4

Mean of the daily Tmax during the 2003 HW, for the two reference products, EOBS and ERA5-Land panels (a); for the RCM and CPRCM ensemble means panels (b). Differences (°C) between RCM and CPRCM ensemble means and EOBS mean HW Tmax (c). HW magnitude (intensity) index for the RCM and CPRCM ensembles (d). This latter represents the average of the index results from each individual model

Figure 5

Subpanels show percentage DAV in correspondence of the selected reference sites (right) and RCMs and CPRCMs S score PDFs comparison built on all the site-specific S scores (left). Ensemble means (upper left panels) represent the average of values resulting from all the models for each reference site

Figure 6

Spatially averaged hourly (3-hourly if hourly not available) time series of differences in latent heat flux between RCMs (nonCP) and CPRCMs (CP) during HW events. Panels from left to right show the different domains whereas along the lines results for different HW events are shown. For each model, only time steps where at least one of the two resolutions reproduced a HW event are considered. Only time steps with heat fluxes > 0 are shown

Alps

Po valley

Adriatic

Figure 7

HWs maximum temperature as a function of the Bowen ratio (ratio between sensible and latent heat fluxes) for the RCMs (squares) and CPRCMs (triangles). Left-to-right panels display different HWs and top-down panels the three different domains. Values consist of spatial averages. The Bowen ratio is defined only considering time steps with heat fluxes > 0

Figure 8

Spatial patterns of mean volumetric soil moisture for the representative HW of 2003 over a representative domain including the Alps, Po valley, and Adriatic region for the CPRCMs (a) and RCMs (b) and related ensemble mean. In the upper part of each panel is reported the depth of the soil layer providing the soil moisture for the different models and reference products (ESSMRA and ERA5-Land reanalysis). Units are m^3/m^3

Figure 9

Spatially averaged time series of the percentage difference between CP and nonCP simulations volumetric soil moisture content for the three domains. Time series consist of running means with a temporal window of 15 days and consider the entire evaluation experiment period (2000-2009)

Figure 10

Volumetric soil moisture content annual cycles over the three domains. Reference products ERA5-Land (0.07m soil layer depth) and ESSMRA (0.03m soil layer depth) overlaid to CPRCMs (left) and RCMs (right) and related ensemble means. Values represent monthly means of the period 2000-2009. Note that for FZJ WRF, soil moisture is available only for the summer season

Figure 11

Spatial pattern of mean dry spell length (DSL) over a representative domain including the Alps, Po valley, and Adriatic region for the CPRCMs (a) and RCMs (b). DSL considers summer season daily precipitation from 2000 to 2009. In the top-left panel results from the reference product (a merge of EURO4M and GRIPHO datasets) are shown. Units are days

Figure 12

Grid-node specific DSL empirical cumulative distribution functions (ecdfs) for CPRCMs (left panels), RCMs (right panels), and reference products (EURO4M for the Alpine and Po valley domains, GRIPHO dataset for the Adriatic domain). The ecdfs are built considering the 2000-2009 summer season daily precipitation time series from each grid node with no interpolation performed. The main statistics (mean, median, 95th, and 99th percentile) of the observed and simulated DSL are shown in the upper part of each panel

Supplementary Files

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