A statistical–dynamical downscaling methodology for the urban heat island applied to the EURO-CORDEX ensemble

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Abstract

Regional Climate Models (RCMs) are the primary climate information available to public stakeholders and city-planners to support local adaptation policies. However, with resolution in the order of ten kilometres, RCMs do not explicitly represent cities and their influence on local climate (e.g. Urban Heat Island; UHI). Downscaling methods are required to bridge the gap between RCMs and city scale. A statistical–dynamical downscaling methodology is developed to quantify the UHI of the city of Paris (France), based on a Local Weather Types (LWTs) classification combined with short-term high-resolution (1-km) urban climate simulations. The daily near-surface temperature amplitude, specific humidity, precipitation, wind speed and direction simulated by the RCMs are used for the LWTs attribution. The LWTs time series is associated to randomly selected days simulated with the mesoscale atmospheric model Meso-NH coupled to the urban canopy model Town Energy Balance to calculate the UHI corresponding to the successive LWTs. The downscaling methodology is applied to the EURO-CORDEX ensemble driven by the ERA-Interim reanalysis, and evaluated for the 2000–2008 period against station observations and a 2.5-km reanalysis. The short-term dynamical simulations slightly underestimate and overestimate near-surface minimum and maximum air temperature respectively, but capture the UHI intensity with biases in the order of a tenth of a degree. RCMs show significant differences in the variables used for the LWTs attribution, but the seasonal LWT frequencies are captured. Consequently, the reconstructed temperature fields maintain the small biases of the Meso-NH simulations and the statistical–dynamical downscaling greatly improves the UHI compared to the raw data of RCMs.

Keywords Urban heat island · Downscaling · EURO-CORDEX · Mesoscale modelling · Model evaluation

1 Introduction

Anthropogenic global warming (Stocker et al. 2013) is expected to cause regional climate changes (Christensen 2013), which will have in turn, several local impacts (e.g. on the urban environment; Wilby 2007). Urban areas are already the most densely populated and economically active places in the world and are expected to grow further in the future (UN DESA 2019). Moreover, due to their specific characteristics (e.g. artificialisation of surfaces) and the activities they host, they are already subject to specific hazards (e.g. air pollution; Duh et al. 2008; Landrigan et al., 2018; Salmond et al. 2018, heat waves and thermal stress;

Kovats and Hajat 2008; Gosling et al. 2009; Dousset et al. 2011, and floods; Hammond et al. 2015; Mignot et al. 2019). Consequently, decision makers and stakeholders need information in order to be able to think the city of tomorrow and to develop the necessary adaptations to future changes (Revi et al. 2014; IPCC 2018). As a response, scientists conduct impact studies focused on the regional or local scale in many different fields such as air pollution (Künzli et al. 2000; Vautard et al. 2003), energy consumption (Santamouris et al. 2001; Ewing and Rong 2008; Kolokotroni et al. 2012), thermal comfort and heat stress (Patz et al. 2005; Lemonsu et al. 2013, 2014, 2015; Lauwaet et al. 2020; Viguié et al. 2020), urban ecology (Muratet et al. 2007; Hope et al. 2008; Buyantuyev and Wu 2009; Wu 2014) or hydrology (Foster et al. 1994; Mitchell et al. 2001; Berne et al. 2004; Barles 2007; Fletcher et al. 2013). Impact models are driven by climate information either coming from Earth System Models (ESMs) or Regional Climate Models (RCMs). The RCMs horizontal spatial resolution is in the order of the

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ten of kilometres which enables them to directly provide climatic forcings for some impact studies (e.g. air quality; Hogref et al. 2004; Leung 2005; Menut et al. 2013, heat-waves; Vautard et al. 2013, hydrology; Graham et al. 2007, energy production; Tobin et al. 2015; Gutiérrez et al. 2020). However, urban related studies present two main challenges. The size of the urban areas and the high heterogeneity of urban surfaces require a fine spatial resolution and a detailed representation of land covers and their physical properties. In addition, climatic conditions, especially air temperature in the atmospheric boundary layer, are locally modified by the presence of the city (i.e. the Urban Heat Island, UHI; Oke 1973; Arnfield 2003). In most cases, the spatial resolution and surface parameterisations of RCMs are not sufficient and adapted to represent those high resolution processes and feedbacks, and therefore the RCM results need to be downscaled (Rummukainen 2010). In order to derive higher spatial resolution information from RCMs, two types of downscaling exist, each with advantages and disadvantages: Statistical and Dynamical Downscaling (SD and DD, respectively; Wilby and Wigley 1997). SD approaches link large scale meteorological variables (i.e. predictors) with local ones (predictands) to find statistical relationships. These relationships are then applied to the same resolution of RCM output in which they were calibrated to obtain higher resolution meteorological variables. SD is computationally cheap as it does not require additional numerical simulations, but it can make strong assumptions regarding the universal validity of the statistical relationships and especially their stationarity in future climate conditions. On the other hand, DD approaches use the outputs from lower resolution climate models to drive finer resolution models. They assume no statistical relationships and provide physical consistency of the results, however, the finer the resolution is, the more computationally expensive the DD approaches become. These studies are often limited to a single GCM or RCM ensemble member and a single emission scenario, as well as reduced time slices that might call into question the reliability of resulting impact analysis. Statistical–dynamical downscaling methodologies (SDD; Frey-Buness et al. 1995; Boé et al. 2006) have been developed to combine the advantages of both approaches. For the SDD of the UHI, weather typing approaches have been developed with the aim to add the high-resolution UHI field to coarse resolution RCM results. The postulate that supports this approach is that the UHI phenomena is highly dependent on meteorological conditions, varying in intensity according to wind speed and cloudiness conditions, and in spatial structure according to regional flow. Using large-scale or local meteorological variables they determine specific weather situations associated with a particular response of the urban climate to the local meteorological conditions. The UHI effect is then explicitly represented by conducting high-resolution urban

climate simulations, whose results are combined with the RCM output.

Duchêne et al. (2020) developed an analogs' based SDD methodology to reconstruct Brussels' (Belgium) UHI in regional climate projections using the ALARO model at 4-km resolution coupled with the state-of-the-art 3D Urban Canopy Model (UCM) Town Energy Balance (TEB; Masson 2000). Their approach relies on a 4-years continuous simulation of the city's UHI whose duration necessarily constraints the spatial resolution that can be achieved. By statistical analogy, they link each day of a given regional climate projection according to its daily atmospheric variables with the most similar day of the 4-years high-resolution urban simulation. The RCM fields are then corrected by integrating the UHI signature of the city of the day considered. Hoffmann et al. (2018) reconstructed Hamburg's (Germany) UHI in future climate projections by combining a weather pattern classification and 1-km resolution urban climate simulations with the mesoscale model METRAS. Compared to the previous method, they free themselves from the resolution limitations related to the computation time since they only simulate selected meteorological situations discriminating the UHI's intensity and spatial pattern. However, METRAS does not include an UCM. Instead, the specifics of the urban surfaces are taken into account by the modification of the surface parameters related to radiative, energy, and water exchanges.

The method presented here follows a weather typing approach similar to that of Hoffmann et al. (2018) rather than the analogue approach of Duchêne et al. (2020) with two main improvements: (1) the high resolution urban climate simulations are done for a limited number of days that are representative of the weather types, and not in a continuous way, thus limiting the computational cost; (2) these urban climate simulations are performed with the same UCM TEB used by Duchêne et al. (2020) but with a higher horizontal resolution of 1 km and a more sophisticated version of the model including in-canyon urban vegetation (Lemonsu et al. 2012) and a building energy model (Bueno et al. 2012; Pigeon et al. 2014).

The present study describes the SDD method which consists in processing time series of meteorological variables simulated by RCMs and representative of the meteorological conditions in the rural areas surrounding the city (Fig. 1a). Local day-to-day weather types discriminating the UHI's intensity and spatial pattern are determined based on the RCM output (Fig. 1b). High resolution urban climate simulations for these weather types are performed using a mesoscale atmospheric model and the results are combined with the rural background RCM data to obtain a climatological time series of high-resolution temperature maps (Fig. 1c). For the weather types classification, a database developed by Hidalgo et al. (2018)

Fig. 1 Simplified flow chart of the employed statistical–dynamical downscaling methodology

for 51 French cities and a set of high resolution urban simulations already performed and presented in detail by Schoetter et al. (2020) and Gardes et al. (2020) are available. The method is here applied and evaluated for the city of Paris (France) with the aim of correcting daily temperature values from RCM projections for the urban influence on air temperature and for producing daytime and nighttime UHI diagnostics. The SDD methodology aims to bring high resolution information in climate projections to addresses UHI issues and their impacts. Accordingly, it is used to the spatial downscaling of air temperature and related variables (humidity and atmospheric radiation), but is not suitable for the reconstruction of the city's effect on wind speed, precipitation, and other indicators that are not strongly related to air temperature.

The aim of the study is to evaluate the capacity of the SDD methodology to reconstruct the seasonality of UHIs both in terms of intensities and spatial extent. The weather type climatology, the high resolution urban climate simulations, and the SDD methodology are presented in Sect. 2. Then, the different steps of the approach are evaluated in Sect. 3. The final results are presented in Sect. 4 and completed by a discussion on the possible limitations of the approach.

2 Data and method

This section presents the successive steps of the SDD methodology and the different databases it relies on.

2.1 Local weather type climatology

Weather type classifications used for statistical downscaling are developed to link large scale predictors such as atmospheric circulation regimes with local scale predictands (Cassou et al. 2005). For the present case study over the Paris region, we use the existing Local Weather Types (LWTs) classification developed by Hidalgo and Jougla (2018) for 51 French cities, because it meets the specific needs of urban climate studies. Unlike traditional classifications related to the synoptic-scale meteorological situation (Philipp et al. 2010; Beck and Philipp 2010), the LWTs are related to the different states of the planetary boundary layer in the rural areas adjacent to the city and are attributed based on near-surface meteorological variables (Hidalgo and Jougla 2018). Applied in the vicinity of cities, the LWTs make it possible to link the evolution

of meteorological situations to the day-to-day variability of the UHI phenomenon.

Based on the previous work of Hidalgo et al. (2014), Hidalgo and Jougla (2018) developed a statistical methodology to produce a LWTs classification. They used the “Partition Around Medoids” clustering algorithm (PAM; Kaufman and Rousseeuw, 1990) in combination with Gower’s distance (Gower 1971) as a measure of dissimilarity for a set of five daily variables: the daily near-surface (2 m above the ground) thermal amplitude (dT) computed from the minimum and maximum air temperatures (TN and TX), specific humidity (Q), precipitation rate (RR), wind speed (FF) and direction (DD) computed from the zonal and meridional wind components (U and V). The meteorological data required for the LWTs attribution were taken from a reanalysis produced with the French numerical weather prediction model AROME (Seity et al. 2011) with a 2.5-km resolution over the 10-year period 2000–2009 (Pouponneau et al. 2017). This classification method was evaluated for Toulouse (Hidalgo and Jougla 2018), and Orléans, Paris, and Tours (Jougla et al. 2019). For each city, the meteorological variables used for the LWTs classification were taken from the AROME reanalysis for a reference rural grid point located near the city to represent the local climate but far enough to avoid urban influences.

The LWTs classification for Paris consists of 12 LWTs. Figure 2 presents the seasonal occurrence frequencies of the LWTs for the 2000–2008 period. Every LWT can be found in every season with the exception of LWT09 and 12 for winter (DJF). Seasonal predominances are found: LWT01, 02, 03, 04 and 06 in DJF, and LWT05, 07, 08, 09, 10, 11 and 12 in summer (JJA). Except for LWT08, no LWT is specific to the transition seasons, i.e. spring (MAM) or autumn (SON). These two seasons are represented by a combination

of all possible LWTs. The different steps of the classification are presented in “Appendix 1” and more details on the Paris LWTs classification are given by Jougla et al (2019).

2.2 Short-term high-resolution urban climate simulations

2.2.1 Model configuration

Mesoscale atmospheric models incorporating an UCM can simulate the urban climate at horizontal resolutions as fine as 100 m × 100 m. These models not only have higher resolution than RCMs but also better represent mesoscale meteorological phenomena (e.g. an urban breeze) and near-surface processes (i.e. in the urban canopy layer). They make use of finer land cover databases with more details regarding the geometry (e.g. building height, plan area building density, aspect ratio of the street canyons) and the physical parameters (e.g. albedo, emissivity, thermal conductivity and capacity) of the city.

Schoetter et al. (2020) and Gardes et al. (2020) conducted high-resolution urban climate simulations for 42 French cities including Paris based on the LWTs approach. They used the non-hydrostatic limited-area research atmospheric model Meso-NH (Lac et al. 2018) driven by lateral boundary conditions provided by the European Centre for Medium-Range Weather Forecast (ECMWF) Integrated Forecasting System (IFS) high-resolution operational forecast analysis (ECMWF 2019). Two intermediary domains centred over the city of Paris were used to downscale the ECMWF-IFS analysis up to a horizontal resolution of 1 km (Table 1). Surface-atmosphere exchanges in Meso-NH are calculated using the SURFEX platform (Masson et al. 2013), which includes the UCM TEB (Masson 2000; Lemonsu et al. 2012; Bueno et al.

Fig. 2 The occurrence frequency of Local Weather Types (LWTs) in the Paris region for the period 2000–2008 and different seasons. The numbers besides each bar denote the seasonal frequency of LWTs

Table 1 Characteristics of the Meso-NH model setup and physical parameterization used by Schoetter et al. (2020), Gardes et al. (2020) and in the present study for Paris

Domain	Extent (km)	Horizontal resolution (km)	Time step (s)	Parametrisation of deep convection	Parametrisation of shallow convection and dry thermals	Mixing length calculation
D1	1600×1600	8	20	Kain and Fritsch (1990)	Pergaud et al. (2009)	Bougeault and Lacarrère (1989)
D2	400×400	2	20	None	Pergaud et al. (2009)	Bougeault and Lacarrère (1989)
D3	200×200	1	20	None	Pergaud et al. (2009)	Bougeault and Lacarrère (1989)

2012; Pigeon et al. 2014). TEB is a state-of-the-art UCM which represents the complex urban geometry as an urban street canyon of infinite length (Oke 1981). More details regarding the physical parameterisations are given in Kwok et al. (2019). The present study uses the exact same model configuration as in Gardes et al. (2020) for the city of Paris over the Meso-NH model domain at 1-km horizontal resolution (Fig. 3).

Schoetter et al. (2020) simulated an ensemble of past meteorological situations representative of each LWT for each season. They found that for each combination of LWT and season, ideally 6 days should be simulated to obtain a robust average UHI pattern during these specific meteorological conditions. With 12 LWTs and 4 seasons, this would result in 288 days to be simulated. However, not all LWTs occur in each season and some LWTs occur for less than 6 days in the 10-year LWTs attribution period, which reduces the number of days to be simulated slightly. For

LWTs which occur less than 6 days in one season during the 10-year attribution period, all days belonging to this combination of LWT and season are simulated. For LWTs which occur for more than 6 days during one season, the days are selected to prioritize more stationary meteorological situations (e.g. 3 consecutive days with the same LWT), since we assume that the UHI pattern for these more stationary situations is better representative of the specific influence of this LWT on the local meteorological conditions. As a result, a total of 255 days were simulated (not counting two days of spinup before each simulation).

For each day, two simulations were conducted: (1) SIM_{URB} for which the city of Paris was represented using a detailed urban database for French cities (Schoetter et al. 2019) containing information on urban morphology (Bocher et al. 2018), building construction materials (Tornay et al. 2017), and human behaviour related to building energy consumption (Schoetter et al. 2017); and

Fig. 3 Map of the city of Paris and the area studied for the SDD methodology (a). EURO-CORDEX domain (b). Comparison of the EURO-CORDEX domain resolution and the Meso-NH resolution (c)

(2) SIM_{RUR} for which the urban land cover was replaced with the predominant natural land cover in the surroundings of Paris from the ECOsystem CLimate MAP (ECOCLIMAP)-I database (Masson et al. 2003; Champaux et al. 2005), which is “warm temperate crops”. The two simulations being otherwise identical, the difference in the meteorological fields allows to isolate the effect of the city of Paris on the local climate.

2.2.2 Computation of the urban influence on daily air temperature

The Meso-NH urban climate simulations are used here to derive the urban influence on air temperature, hereafter called the urban increment (Bohnenstengel 2011). While the UHI denotes the difference in air temperature between an urban and a rural location, and can be calculated based on observations or numerical model results; the urban increment is the air temperature difference between two numerical simulations at the same location, one with urbanisation and one without. The local effect of the city is calculated in the same way as what Duchêne et al. (2020) called the “urban signature”, according to:

$$\Delta T_{URB}(x, y, z, t) = T_{URB}(x, y, z, t) - T_{RUR}(x, y, z, t) \quad (1)$$

with T_{URB} and T_{RUR} the air temperature simulated with SIM_{URB} and SIM_{RUR} , respectively, x, y, z the longitude, latitude, vertical height above ground level of the Meso-NH grid point, and t the time.

The high-resolution simulations not only provide information about the city’s effect on the local climate but can also be used to refine the regional and topographic effects, which are not included in ΔT_{URB} . Such regional gradients are obtained by subtracting the average background temperature from the 2D air temperature fields of SIM_{RUR} :

$$\Delta T_{REG}(x, y, z, t) = \overline{T_{RUR}}(x, y, z, t) - \overline{T_{RUR}}(z, t) \quad (2)$$

with $\overline{T_{RUR}}$ the spatial average of the horizontal temperature field (i.e. the spatial average of all grid points in SIM_{RUR} at height z and time t). The combination of the urban effect (ΔT_{URB}) and the regional refinement (ΔT_{REG}) yields the temperature correction (ΔT_{COR}) that will be added to the coarse resolution RCM air temperature time series:

$$\Delta T_{COR}(x, y, z, t) = \Delta T_{URB}(x, y, z, t) + \Delta T_{REG}(x, y, z, t) \quad (3)$$

This correction (thereafter referred to as urban increment for simplicity) can be computed for any height above ground z or model output frequency available in the high-resolution urban climate simulations. Model results from SIM_{URB} are evaluated in Sect. 3.1.

2.3 Regional climate model ensemble

2.3.1 EURO-CORDEX

The Coordinated Regional Downscaling Experiment (CORDEX; Giorgi et al. 2009) is an internationally coordinated framework initiated by the World Climate Research Program to define a common guideline regarding regional climate modelling. RCMs are either forced by General Circulation Models (GCMs) from the CMIP5 global climate projections (Taylor et al. 2012) or by the European Centre for Medium-Range Weather Forecasts Reanalysis (ECMWF ERA-Interim; Dee et al. 2011) for the RCMs evaluation.

To produce LWT time series from RCM data following the Hidalgo and Jougla (2018) method, the average climatic conditions representative for the rural areas surrounding Paris need to be calculated. To do so, the daily variables (TN, TX, RR, Q, U, V) are extracted for grid points surrounding the city, by considering that urban areas extend on a domain of 3×3 RCM grid points (Fig. 3c). The meteorological variables are then averaged over those grid points to obtain daily time series. These are used to perform a day-to-day LWT attribution (“Appendix 1”) to build a time series of LWTs for the 12 RCM evaluation experiments available (Table 2) over the EUR-11 domain (Fig. 3). RCMs cover different time periods of more than 20 years and are evaluated against a reanalysis with the AROME model for the common time period 2000–2008 (Sect. 3.2).

2.3.2 Correction of RCM temperature with the urban influence on air temperature

RCM LWT time series are used to determine the urban increment to be combined with the daily temperature time series simulated by each RCM. The Meso-NH simulation results provide around six days (i.e. six dates) for every LWT and season which allows to obtain robust UHI patterns free of small-scale meteorological variability (Schoetter et al. 2020) and offers the opportunity to describe the intra-cluster variability for each LWT. For each successive day of the LWTs time series constructed from the RCM data, a Meso-NH day (date) is randomly selected from the associated LWT/season pool. The random selection is done equiprobably such as to not bias the mean for each LWT and season while providing the desired day-to-day variability. By concatenating the selected days from the Meso-NH simulations, time series of 2D 1-km temperature fields are constructed and combined with the RCM daily time series:

$$T_{SDD}(x, y, z, t) = T_{RCM}(z, t) + \Delta T_{COR}(x, y, z, t) \quad (4)$$

Table 2 The EURO-CORDEX EUR-11 RCM evaluation ensemble used for the present study

Institute	RCM	Start	End	References
CNRM	ALADIN53	1979-01-01	2008-12-31	Colin et al. (2010)
CNRM	ALADIN63	1979-01-01	2018-12-31	Daniel et al. (2019)
CLMcom	CCLM4-8-17	1989-01-01	2008-12-31	Doms and Baldauf (2011); Doms et al. (2011)
CLMcom-ETH	COSMO-crCLIM-v1-1	1979-01-01	2010-12-31	Leutwyler et al. (2017)
MOHC	HadREM3-GA7-05	1982-12-01	2012-12-01	In preparation, see Walters et al. (2019) for HadGEM3-GC3.1
DMI	HIRHAM5	1989-01-01	2011-12-31	Christensen et al. (2007)
KNMI	RACMO22E	1979-01-01	2012-12-31	van Meijgaard et al. (2008; 2012)
SMHI	RCA4	1980-01-01	2010-12-31	Samuelsson et al. (2015)
MPI-CSC	REMO2009	1989-01-01	2008-12-31	Jacob et al. (2012)
GERICS	REMO2015	1979-01-02	2012-12-31	
ICTP	RegCM4-6	1979-01-01	2016-11-30	Giorgi et al. (2012)
IPSL	WRF381P	1989-01-01	2008-12-31	Skamarock et al. (2005)

Fig. 4 Simulated time series of TN and TX by ALADIN63 for the month of August 2003 (black line) and corrected with the SDD methodology for urban (red line) and rural (green line) areas. LWTs attributed for each day are noted at the bottom of the graph and represented

by different colours while the associated Meso-NH day is represented by different symbols. For each Meso-NH day, UHIs are computed by comparing the mean TN and TX of the model points located near urban stations to model points located near rural stations

with T_{SDD} the downscaled temperature field combining the horizontally homogeneous rural climate simulated by the RCM (T_{RCM}) and the high-resolution urban increment (ΔT_{COR}). Figure 4 illustrates the method for an example of TN/TX RCM time series. Based on RCM daily meteorological variables, a LWT is assigned to each day (and indicated at the bottom in Fig. 4). In accordance with the LWT and the season, a Meso-NH day is randomly selected from the pool of up to 6 days available for each season and LWT; the

successive dates are listed on the right side of Fig. 4. Finally, urban increments of TN and TX corresponding to this day are added to the RCM TN and TX. The figure highlights that these 2D fields of urban increment result in different air temperature corrections for urban ($\Delta T_{COR,URB}$) and rural ($\Delta T_{COR,RUR}$) grid points. In addition, the methodology, here focused on daily temperatures, can also be extended to produce sub-daily atmospheric temperature fields, which can then be used to drive impact models (such as energy building

models) at the city or neighbourhood scale. This step is presented in “Appendix 2”.

3 Evaluation

3.1 Evaluation of high-resolution urban climate simulations

The quality of the reconstructed temperature fields is directly related to the ability of the high-resolution UCM to correctly simulate UHIs in term of intensity, spatial pattern and seasonal evolution. A systematic evaluation of the 1-km horizontal resolution Meso-NH simulations (coupled to the TEB model) is done for the 255 days by comparison to 124 meteorological station observations available from the Météo-France observation network (Fig. 3). Observed TN and TX are compared station by station to the model output using the closest Meso-NH grid point. The five stations located in a 10 km × 10 km sub-domain centred on Paris are classified as urban, whereas the 119 stations located further from the centre of Paris than a box of 50 km × 50 km and in non-urban areas (according to the ECOCLIMAP-II land cover map; Faroux et al. 2013) are considered as rural. The average TN and TX are computed from urban and rural stations separately, and the corresponding UHIs (referred to as UHI_N and UHI_X, respectively) are computed from their difference. Quantitative evaluation is made using the mean seasonal bias (Δ), root mean squared error (RMSE), and hit-rate (HR in %) defined as:

$$HR = \frac{1}{N} \times \sum_{d=1}^N n_d \times 100 \text{ with } n_d = \begin{cases} 1, & \text{if } |T_{M,d} - T_{O,d}| \leq \Delta T \\ 0, & \text{else} \end{cases} \quad (4)$$

with d the index for the days and N the total number of days, T_M the modelled air temperature, T_O the observed air temperature, and ΔT the desired accuracy threshold. It is here prescribed to 2 K for TN and TX and 1 K for the UHI. HR values range between 0 and 100%, with 0% (100%) meaning that no (every) day is in the desired accuracy range. Table 3 lists the average seasonal scores weighted according to the 2000–2009 AROME LWT frequencies (Jougla et al 2019) for urban and rural TN and TX, and associated UHIs. Meso-NH slightly overestimates TN, with a systematic positive bias whatever the season and the urban or rural environment. The positive bias is maximal during the winter season ($\Delta TN_{URB} = 1.5$ K and $\Delta TN_{RUR} = 1.4$ K in DJF) in accordance with higher rmse, lower hit-rates, and minimal in the spring season (0.5 and 0.6 K for the urban and rural environment, respectively). Due to the comparable and small ΔTN in urban and rural areas, UHI_N is well simulated. Absolute bias (rmse) does not exceed 0.2 K (1.0 K). Hit-rates vary between 68 and 92% depending on the season, with lowest values in JJA and SON because the LWTs associated with the highest UHI_N intensities are the most frequent in these seasons. Opposite results are found for TX. The biases are systematically negative and their absolute values are larger than for TN ($\Delta TX_{URB,ALL} = -1.6$ K and $\Delta TX_{RUR,ALL} = -2.3$ K). The scores vary with the season, poorer model performance is found in JJA than in DJF. Model performance also differs between urban and rural

Table 3 Evaluation measures calculated based on daily values for every station and the corresponding Meso-NH grid point. URB (RUR) represents the mean of the evaluation measures for stations/points categorised as urban (rural) and UHI represents their difference. The desired accuracy for the calculation of the hit-rate is 2 K

for URB and RUR and 1 K for the UHI. All averages of each evaluation measure are first computed inside the LWT/season pool, and then weighted by the LWTs seasonal frequencies (following frequencies presented in Jougla et al 2019). Numbers in parentheses represent the number of stations used

		TN					TX				
		ALL	DJF	MAM	JJA	SON	ALL	DJF	MAM	JJA	SON
<i>URB (5)</i>											
Bias	(K)	0.9	1.5	0.5	0.7	0.9	− 1.6	− 0.2	− 2.0	− 2.4	− 1.5
RMSE	(K)	1.3	1.8	1.0	1.1	1.3	2.2	1.8	2.4	2.6	1.9
Hit-rate	(%)	88	74	94	90	90	58	72	52	35	69
<i>RUR (119)</i>											
Bias	(K)	0.8	1.4	0.6	0.8	0.8	− 2.3	− 0.8	− 2.5	− 3.4	− 2.1
RMSE	(K)	1.4	1.7	1.1	1.4	1.4	2.7	1.6	2.7	3.5	2.5
Hit-rate	(%)	83	70	92	78	83	40	80	35	6	49
<i>UHI</i>											
Bias	(K)	0.0	0.2	0.0	− 0.1	0.1	0.7	0.6	0.5	1.1	0.7
RMSE	(K)	0.9	0.7	0.8	1.0	1.0	1.0	1.0	0.8	1.2	0.9
Hit-rate	(%)	74	92	74	68	69	67	74	80	43	66

areas. On average, TX_{RUR} is less well simulated than TX_{URB} with a bias (hit-rate) of -2.3 K (40%), compared with -1.6 K (58%) for TX_{URB} . These urban/rural discrepancies of the bias might be due to a shortcoming in soil moisture initialisation, as well as an insufficient number of spin-up days (2) used. This could explain why the worst simulated season is JJA. The combination of too humid soil, strong solar radiation, and developed vegetation leads to an overestimation of evapotranspiration thus leading to an underestimation of daytime air temperature especially in the rural areas. From these biases in TX results an overestimation of UHI_X ($\Delta UHI_X = 0.7$ K).

In summary, the Meso-NH model coupled with TEB at 1 km horizontal resolution is able to simulate realistic UHIs in the nighttime. It slightly overestimates UHIs in the daytime, especially in JJA, but the biases remain acceptable.

3.2 Evaluation of EURO-CORDEX RCMs

Intrinsic errors in RCM simulations can impact the time series of downscaled temperature fields through the frequencies of LWTs that can be biased and that determine the corresponding UHI patterns. To understand the possible

LWTs attribution differences between RCMs and reanalysis, the EURO-CORDEX daily variables are first compared to the corresponding AROME reanalysis variables rather than to the meteorological station observations. While Pouponneau et al. (2017) and Hidalgo and Jougla (2018) highlighted the high quality of the AROME reanalysis both in terms of the individual meteorological variable's biases and the LWTs attribution, it is not expected to perfectly match station observations. Therefore, the RCMs evaluation presented below focuses more on the agreement between RCMs and AROME than on a general assessment of the quality of the RCMs.

3.2.1 Seasonal evaluation of air temperature and precipitation

The results of the EURO-CORDEX RCMs, providing the rural background climatic conditions, are compared to the AROME reanalysis. TN, TX, the resulting daily temperature range dT, and RR are evaluated for the 2000–2008 period.

Figure 5 compares the RCM quantile distributions against those of AROME for DJF and JJA. In DJF, TN is mostly overestimated by the RCMs, except for ALADIN53 and

Fig. 5 QQ plots of the 12 EURO-CORDEX RCMs against the AROME reanalysis for TN, TX, dT and RR in DJF and JJA. The grey area represents an accuracy range of 2 K for TN and TX and 1 K for dT

RACMO22E. Almost all quantiles simulated by the RCMs are within a 2 K accuracy range (grey area in Fig. 5), with the exception of the lowest quantiles. Biases are accentuated for negative temperatures, resulting in an even larger spread between RCMs. For TX, an overestimation is found for mid to high quantiles, with the exception of CCLM4-8-17 and HIRHAM5. Again, a greater ensemble spread is observed for the lowest quantiles. This time, it does not result from the exacerbation of biases but rather from the fact that some RCMs underestimate and others overestimate low values of TX_{DJF} . Larger biases and/or larger ensemble spread for the lower quantiles of DJF temperature can be due to the large sensitivity of DJF temperatures on differences in the regional temperature field since there is a strong west–east air temperature gradient in DJF in Europe and might also be due to the snow-albedo feedback. The biases of dT are very variable because they can be the result of a compensation or an accumulation of bias in TN_{DJF} and TX_{DJF} . Eight RCMs mostly underestimate it, two slightly overestimate it, and two strongly (outside of the 1 K range). The largest deviations are not found for the first quantiles, where the greatest spread and biases of TN_{DJF} and TX_{DJF} are found, but rather for the medium to high dT_{DJF} . The four RCMs aforementioned, for which important biases for TN and TX are found are outliers for dT : ALADIN53 and RACMO22E on the upper part with high dT_{DJF} strongly overestimated mainly because of their underestimation of TN_{DJF} and to a lesser extent CCLM4-8-17 and HIRHAM5 with lowest values of dT .

In JJA, TN are systematically overestimated, with the exception of ALADIN53(RCA4) lowest(highest) quantiles. The overall ensemble spread is larger than for TN_{DJF} and relatively constant across the entire distribution except for the highest quantiles. Conversely to TN_{DJF} where RCM biases are accentuated towards the distribution tails, for TN_{JJA} , some RCMs show a relatively constant bias throughout their distribution and better results for high quantiles (e.g. REMO2009 and REMO2015). For TX_{JJA} , a lot of variability is noted between RCMs (i.e. some overestimate the whole distribution like RegCM4-6, some others only the tails like REMO2015). Nevertheless, TX_{JJA} are on average mostly overestimated, with the exception of HIRHAM5, RACMO22E, RCA4 that underestimate it on their whole distribution. The largest deviations are observed for the largest TX_{JJA} values with half of the models underestimating and the other half overestimating up to 4 K (ALADIN63). The large ensemble spread for TX_{JJA} might be due to the differences in the soil moisture availability simulated by the different RCMs. As for dT_{DJF} , dT_{JJA} is almost systematically underestimated (except for ALADIN53 on the whole distribution, and ALADIN63 and WRF381P for the largest and lowest quantiles, respectively) and these deviations are more important for larger dT . This might be due to the fact that the 2.5-km resolution of the reanalysis is able to capture

more extreme TN and TX than the 12-km resolution RCMs. The RCMs with the worst performance in terms of dT_{JJA} relative to the AROME reanalysis are not the ones with the worst performances in terms of TN and TX (e.g. RCA4 and RegCM4-6) but rather those with large differences between their TN and TX biases (e.g. HIRHAM5).

For precipitation, RR_{DJF} lower quantiles are systematically overestimated. This might be due to an overestimation of drizzle in RCMs (Piani et al. 2010; Maraun 2013). While the drizzle bias is also present in the AROME reanalysis (not shown here), the biases are smaller, which might be due to the finer resolution of the reanalysis. RCMs systematically underestimate the number of dry days (i.e. $RR < 0.1 \text{ mm d}^{-1}$; with the exception of CCLM4-8-17 and COSMO-crCLIM-v1-1 and HadREM3-GA7-05). Every RCM overestimates rainy days ($1 < RR \leq 10 \text{ mm d}^{-1}$) up to 12% for RCA4. In JJA, RCMs show a similar overestimation of lower quantiles, but with smaller biases. This is both due to an almost systematic overestimation of lower quantiles in RCMs with the exception of ALADIN63, CCLM4-8-17, COSMO-crCLIM-v1-1 and HIRHAM5) and an underestimation in AROME. The frequencies of days with more than 10 mm precipitation are underestimated in every RCM (between 4 and 7% against AROME's 8%), which can be explained by the fact that most of the high daily precipitation amount is due to convective storms that cannot be represented in the RCMs because their resolution is too coarse compared to the reanalysis.

3.2.2 Evaluation of the seasonal local weather type frequencies

In addition to their influence on the simulated climate conditions representative for the rural areas, RCM biases can also influence the frequency of the LWTs, which in turn would affect the Meso-NH days selected to represent the urban influence on air temperature. Even if the RCM climatologies matched the AROME reanalysis perfectly, differences in LWTs attribution on a day-to-day basis would still be expected due to the local scale meteorological variability (e.g. different wind directions or precipitating events), but on a seasonal average, the RCM LWT frequencies should be very similar to those obtained for the AROME reanalysis. These differences are objectively quantified using the Perkins et al. (2013) skill score (SSC, in %):

$$SSC = \sum_{LWT=1}^{12} \min(f_{M,LWT}, f_{R,LWT}) \quad (5)$$

with f the frequency of the LWT in the model M or the reference R . The SSC's theoretical range lies between 0 and 100%, with 0% meaning that the RCM only simulates LWTs that do not occur in the AROME reanalysis, and 100%

Fig. 6 Frequencies of the Local Weather Types (LWTs) attributed based on the results of 12 EURO-CORDEX RCMs compared to those obtained from the AROME reanalysis for DJF over 2000–2008, and associated skill scores (SSC, middle-right panel). The table (top-right

panel) summarises the LWTs' mean meteorological parameters based on the AROME reference classification, and associated average UHI_N and UHI_X simulated by Meso-NH. LWTs with a seasonal frequency larger than 2% in the AROME reanalysis are highlighted in grey

meaning a perfect match between RCM and AROME reanalysis LWT frequencies.

Figure 6 illustrates the frequencies of every LWT for DJF and each EURO-CORDEX RCM as well as the associated SSCs. As discussed in Sect. 2.1, the only LWTs typically observed in DJF are LWT01, 02, 03, 04 and 06. This is found for all RCMs except for ALADIN53 (and RACMO22E to a lesser extent) which simulates some

meteorological situations classified as LWT05, 07, 08. These LWTs are characterised by high dT, which are strongly overestimated by ALADIN53. Consequently, it has the lowest SSC (79%) while all other RCMs present an SSC of at least 85%. For LWT01 and LWT02, two groups of RCMs stand out: ALADIN63, RACMO22E, RCA4, RegCM4-6 and WRF381P simulate LWT01(02) frequencies well with a slight under(over) estimation whereas other RCMs show the

opposite with larger deviations. However, these two LWTs mainly differ in wind speed (FF) and RR, and exhibit a quite similar UHI_N , therefore no large bias of the downscaled UHI_N can be expected due to this shortcoming. LWT04 that results in the strongest UHI_N ($UHI_{N,DJF,LWT4} = 3$ K), is the only LWT with winds coming from the North-East and its frequency is underestimated in every RCM and especially in ALADIN53 and WRF381P. The frequency of LWT03 is, with the exception of ALADIN53 for which it is underestimated, either well simulated (in ALADIN63, CCLM4-8-17, COSMO-crCLIM-v1-1, HADREM3-GA7-05 and

RACMO22E), or strongly overestimated. The frequency of LWT06 is overestimated in every RCM and especially in CCLM4-8-17 and COSMO-crCLIM-v1-1. This is explained by the overestimation of days with winds coming from the South-East which are always associated with either LWT06 or LWT10.

In JJA, the LWTs occurring are LWT05, 07, 08, 09, 10, 11 and 12 (Fig. 7). There are more frequency differences between RCMs for a given LWT than in DJF [i.e. there is no general trend besides LWT05(07) whose frequency is systematically under(over)estimated]. This might be due to the

Fig. 7 Same as Fig. 6, but for JJA

fact that during JJA the synoptic scale circulation regimes are less relevant for the local scale meteorological conditions than for DJF, it is therefore more likely that the different RCMs simulate different meteorological conditions in the Paris region for the same lateral forcing at continental scale. As a result, the majority of RCMs has lower (or equal) values for SSC_{JJA} than SSC_{DJF} , with the exception of ALADIN53 and REMO2015. The overall attribution is still satisfactory with an average SCC_{JJA} of 85%. The LWTs in JJA discriminate the UHI_N more than in DJF, therefore LWT attribution errors could impact more significantly the quality of the UHI_N reconstruction. Nonetheless, RCMs all yield slightly overestimated but quite realistic frequencies for LWT10, which is associated with the strongest UHI_N (average $UHI_{N,JJA,LWT10} = 4.3$ K). The positive bias found in dT_{JJA} for ALADIN53 might explain its overestimation of the LWT09 frequency (+7 points) and underestimation of the LWT07 frequency (−6 points), which are relatively similar LWTs mainly differing in dT . HIRHAM5 which strongly underestimates dT_{JJA} overestimates the LWT03 frequency, which is low in JJA and high in DJF, at the expense of the frequency of LWT09. For every RCM except ALADIN53, LWTs typically more specific to other seasons and associated to small UHI_N intensities are more frequent than in the AROME reanalysis.

In summary, the EURO-CORDEX RCMs tend to well reproduce the LWT frequencies found in the AROME reanalysis for DJF and JJA. Specific exceptions for some RCMs/LWTs are found; they are related to the biases of the simulated meteorological predictors of the LWT. For some RCMs, these deviations are related to LWTs with distinct UHI_N , and thus might impact the statistically–dynamically downscaled UHIs.

3.3 Evaluation of the statistically–dynamically downscaled UHIs

To evaluate the ability of the methodology to reconstruct robust UHI patterns, seasonal maps of downscaled TN and TX are produced for DJF and JJA. Meso-NH days are randomly selected from the appropriate pool of LWT and season for each RCM and the corresponding masks of correction ΔT_{COR} (Eq. 3 in Sect. 2.2.2) are temporally averaged. These masks are not combined with the TN and TX time series of the RCM and directly analysed in order to assess the impact of errors in LWT frequencies (while leaving aside the RCM biases). Hereafter, the seasonal averages of ΔTN_{COR} and ΔTX_{COR} are called ΔTN and ΔTX , respectively. The same approach is also applied to AROME's TN and TX time series to reconstruct reference ΔTN and ΔTX seasonal maps.

Fig. 8 Seasonal maps (DJF, JJA) of ΔTN_{COR} obtained using the LWTs attributed for the AROME reanalysis and spatial bias (compared to AROME) when using the LWTs attributed from the EURO-CORDEX RCM ensemble

Figure 8 presents the RCMs ΔTN difference maps for DJF (top) and JJA (bottom) compared to AROME's. All RCMs are close to the AROME reference with differences never exceeding 0.4 K for an UHI of around 2–3 K, depending on the season. For DJF, the bias maps mostly highlight regional patterns with low bias over the city. The most important regional biases are noted in the north-west of the domain for ALADIN53, RACMO22E, and WRF381P. These RCMs have in common that they either overestimate the frequency of LWTs associated with above-average DJF temperature in this area (e.g. LWT05 and 07 for ALADIN53 and RACMO22E) or they underestimate the frequency of LWTs with lower than average DJF temperature (e.g. LWT04 for ALADIN53 and WRF381P). The overestimation of LWT05 and 07 frequencies in ALADIN53 (and to a lesser extent RACMO22E) also results in a small positive bias over the city. Other regional patterns are found, such as the positive bias in the North-East of the domain shared by multiple RCMs (HIRHAM5, REMO2009, and REMO2015), which might be due to an overestimation (underestimation) of the LWT01 (LWT02) frequency associated to higher (lower) temperature in this area.

In JJA, more variability is found between the statistically–dynamically downscaled ΔTN for the different RCMs. Regional patterns similar to those found in DJF are also present for some RCMs (e.g. the positive bias in the North-West

of the domain for CCLM4-8-17 and HIRHAM5), but the results for JJA are characterised by larger biases in the urban area. This can be explained by the overall larger deviations found in the LWT frequencies in JJA, especially since the Meso-NH UHI_N cover a larger range of intensities in JJA than in DJF. Nonetheless, a comparable maximal absolute bias of 0.4 K is found for both seasons, that means the relative bias is lower in JJA than in DJF. With the exception of COSMO-crCLIM-v1 and HIRHAM5, most RCMs lead to a positive bias over the city. Especially, the UHI_N statistically–dynamically downscaled with ALADIN63 and WRF381P (and to a lesser extent ALADIN53) are too strong and have a too high spatial extent. Each one of those three RCMs overestimate the frequency of one of the four LWTs in JJA associated with strong UHI_N (LWT07 for WRF381P, LWT08 for ALADIN63 and LWT09 for ALADIN53) at the expense of LWTs with low UHI_N (e.g. LWT11).

For ΔTX , no bias is observed over the city (Fig. 9). Instead, a regional gradient of the bias common to most RCMs is noted in the main wind direction (south-west to north-east). As a result, we hypothesise that differences in ΔTX are more driven by the air circulation rather than the surface, which is consistent with daytime UHI characteristics. In JJA, as for ΔTN , more variability is found between RCMs, but this time without urban bias.

Fig. 9 Same as Fig. 8, but for ΔTX_{COR}

In summary, some differences of the statistically–dynamically downscaled Δ TN and Δ TX are found between RCMs and the AROME reanalysis. Biases are more important in JJA for Δ TN both in rural areas in relation with topographic and climatological gradients, and over the city for some RCMs. We hypothesise that the strongest observed biases are linked to an overestimation of the frequency of the LWTs with large UHI intensities in the mesoscale simulations. Nevertheless, biases remain small (absolute values below 0.4 K) compared to UHI intensities, and the results for the RCMs agree well with those of the AROME reanalysis.

4 Discussion

The SDD methodology developed in the present study to produce high-resolution climatological average UHI fields assumes that the RCM's horizontal resolution is not sufficient to adequately represent the urban climate (e.g. an urban breeze). Furthermore, with resolutions in the order

of ten kilometres, RCMs can not simulate cities with a specific urban parameterisation. Based on a community survey, Langendijk et al. (2019) have gathered different information about the surface parameters used in several EURO-CORDEX RCMs and especially regarding the urban representation. While sometimes available, UCMs are not activated for EURO-CORDEX simulations, therefore urban land cover is either treated as rock surfaces, with adjusted parameters (e.g. roughness length for RACMO22E, as well as roughness length and albedo for REMO2009 and WRF381P, Langendijk et al. 2019), or disregarded. To our knowledge, only CCLM4-8-17 and COSMO-crCLIM-v1-1 replaced Paris' city by natural land covers to completely eliminate the UHI effect in their simulation. RCMs also use different land cover databases, different land surface schemes, and different methodologies to deal with subgrid heterogeneity of land covers (e.g. REMO2009 uses a fractional approach, RACMO22E a dominant tile approach and COSMO-CLM a tiling approach, i.e. treats each sub-grid land cover type separately). All these disparities can impact simulation results,

Fig. 10 Average TN and TX simulated by the EURO-CORDEX RCM ensemble for DJF and JJA during 2000–2008. Below and above season-average temperatures are represented in blue and red, respectively

e.g. the near-surface air temperature simulated in the urban environment; Jänicke et al. (2017).

An in-depth analysis of these different approaches could help to understand the differences observed between RCMs but is beyond the scope of the present study. Figure 10 presents the average maps of TN and TX using results of all EURO-CORDEX RCMs for DJF and JJA. Even without explicit urban representations, an influence of the city on local air temperature is found, especially for TN_{JJA} . UHIs directly simulated by the RCMs can be compared to the ones reconstructed by the SDD methodology.

Table 4 lists the mean UHI intensities for TN and TX in DJF and JJA computed in the same way as for the Meso-NH evaluation in Sect. 3.1. UHI intensities are also computed directly in each EURO-CORDEX RCM (UHI_{RCM}) as well as in the statistically–dynamically downscaled maps of ΔTN and ΔTX (UHI_{SDD}), and the observation (UHI_{OBS}). Night-time UHIs directly simulated by RCMs ($UHI_{N,RCM}$) are almost all positive but systematically underestimated. The small positive UHI_N found in the RCMs for which the urban land cover has been replaced by rural land covers might be only due to topographic and regional temperature gradients (e.g. for CCLM4-8-17 and COSMO-crCLIM-v1-1 $UHI_{N,RCM,JJA}=0.2$ and 0.4 K, respectively). $UHI_{N,RCM}$ is only overestimated by WRF381P in JJA. The underestimation of UHI_N intensities is more important in DJF than in JJA. This could be explained by not taking into account the anthropogenic heat fluxes that are the main driver of the UHI phenomenon in DJF, since heating of buildings is a large contribution to anthropogenic heat flux in DJF,

whereas air conditioning of buildings during JJA is not commonly applied in Paris during the selected time period. While RCMs using rock covers are able to simulate positive $UHI_{N,RCM}$, they also systematically overestimate $UHI_{X,RCM}$. This might be due to the thermal properties as well as the lack of shading inherent to the approach of representing cities using rock covers. Because rock surfaces are subject to a high amount of incoming solar radiation, they heat up strongly during the day, resulting in an overestimation of $UHI_{X,RCM}$ that is more important in JJA than DJF because of the greater amount of incoming solar radiation. Conversely, at night, they do not have the heat storage capacity provided by the 3D geometry of the city and cool down more quickly, resulting in lower TN_{URB} and an underestimation of $UHI_{N,RCM,JJA}$.

The SDD part of Table 4 illustrates the multiple remarks made in Sect. 3.3, and also allows for a quantitative comparison against observations. Differences between UHI_{SDD} and UHI_{OBS} may result from both errors in LWT frequencies and Meso-NH biases. To focus on the LWT frequencies part alone, UHI_{SDD} is also computed for the reconstructed UHI maps using the AROME reanalysis. AROME UHI_{SDD} biases are quite similar to the ones observed for the Meso-NH evaluation which reinforces the idea that the LWTs classification is adapted to reconstruct the time series of the UHI. The small differences between AROME UHI_{SDD} and the Meso-NH UHI biases can be explained by the fact that even if the selection of Meso-NH day is done randomly and equiprobably, some days might be favoured by chance (therefore possibly giving more importance to days with greater biases).

Table 4 Average seasonal UHI_N and UHI_X for DJF and JJA during 2000–2008. UHIs are calculated in the same way as for the Meso-NH evaluation (Sect. 3.1)

Observation	UHI_N (K)				UHI_X (K)			
	DJF		JJA		DJF		JJA	
	2.1		3.0		1.2		0.6	
	RCM	SDD	RCM	SDD	RCM	SDD	RCM	SDD
AROME reanalysis	–	2.3	–	3.0	–	1.6	–	2.0
ALADIN53	0.4	2.4	2.1	3.2	0.0	1.6	0.8	2.0
ALADIN63	0.5	2.3	1.3	3.3	0.2	1.6	0.9	2.0
CCLM4-8-17	0.2	2.3	0.2	3.2	0.3	1.6	1.0	1.9
COSMO-crCLIM-v1-1	0.3	2.3	0.4	3.0	0.4	1.6	0.6	1.9
HadREM3-GA7-05	1.1	2.2	2.4	3.1	0.7	1.6	0.9	1.9
HIRHAM5	– 0.2	2.3	1.0	3.0	– 0.2	1.6	0.8	1.9
RACMO22E	0.1	2.3	1.0	3.1	0.1	1.6	0.6	1.9
RCA4	0.4	2.2	1.0	3.1	0.5	1.6	1.6	1.9
REMO2009	1.2	2.2	2.7	3.1	0.5	1.6	1.0	1.9
REMO2015	0.0	2.2	0.9	3.1	– 0.1	1.6	2.0	1.9
RegCM4-6	0.1	2.3	1.0	3.1	0.1	1.6	1.9	1.9
WRF381P	2.0	2.2	4.5	3.3	0.7	1.6	1.8	1.9
ENSEMBLE mean	0.5	2.3	1.5	3.1	0.3	1.6	1.2	1.1

UHI_{SDD} shows overall relatively small deviations from the AROME reanalysis. The largest deviation of $\text{UHI}_{\text{N,SDD,JJA}}$ is found for WRF381P, which is 0.3 K too large, but which corresponds only to an overestimation of 10% of UHI_{OBS} . Biases are even smaller during the day because UHI_{X} are quite similar between LWTs both in Meso-NH and in the station observations. Overall, the end results of the statistical–dynamical downscaling are highly satisfactory. The UHI_{N} intensities are clearly improved by the downscaling compared to the RCM results with average biases of the ensemble in the order of a tenth of a degree. For UHI_{X} , DJF intensities are also improved due to the downscaling even though they are slightly overestimated. However, because of the Meso-NH TX biases noted in JJA, $\text{UHI}_{\text{X,SDD,JJA}}$ intensities are overestimated. The dynamical uncertainties coming from the Meso-NH biases are much greater than the statistical uncertainties associated to the LWT attribution errors. Consequently, to improve the overall results of the methodology, efforts should be focused on improving the Meso-NH simulations.

5 Conclusion

A statistical–dynamical downscaling methodology has been developed to produce high-resolution climatological daily UHI fields combining the climatology of the rural areas surrounding the city of Paris (France) from regional climate projections and the urban influence on the local climate simulated with a mesoscale atmospheric model. The methodology has been applied to 12 RCMs from the EURO-CORDEX ensemble for the 2000–2008 period. The different steps of the downscaling approach are evaluated against urban and rural weather station observations. The short-term high-resolution urban climate simulations slightly underestimate TN and overestimate TX. UHIs are overall well simulated, especially in the nighttime with average errors in the order of one tenth of a degree. Important disparities between RCMs are observed on the daily variables used for the LWTs attribution. Nevertheless these differences have on average relatively small impacts on the LWT frequencies simulated by the RCMs. Consequently the reconstructed temperature fields maintain the small Meso-NH biases and allow to strongly improve the UHI intensities compared to those directly simulated by the RCMs.

Limitations common to other SDD methodologies are also present here, such as the stationarity hypothesis of LWTs in a future climate, as well as the stationarity of simulated UHI patterns. Nevertheless the satisfactory results obtained here, combined with the easy applicability of the method encourage its application to other cities where high-resolution urban climate simulations are available. In addition, most of the biases and uncertainties observed during

the evaluation are related to the dynamical part of the methodology and could be improved without calling into question the statistical assumptions made. Other steps, specific to the reconstruction of atmospheric forcings have yet to be evaluated, as well as the quantification of the improvement of such a method compared to more simplistic (i.e. other SD) or complex (DD) ones.

By taking into account the UHI signal in climate projections, the SDD method should make it possible to study the evolution of temperature in the city under climate change conditions, and to derive standard meteorological indicators related to thermal effects, e.g. summer days, hot days or tropical nights (Karl et al. 1999; Peterson et al. 2001). Besides the impact diagnostics that can be directly deduced from the method, the data produced could also be used to feed more specific and high-resolution impact models, such as building energy models to evaluate energy consumption (Schoetter et al. 2020), or the indoor conditions of exposure of inhabitants to heat. Other environmental issues linked to urban climate but not directly related to air temperature, e.g. air quality or hydrology (Gidhagen 2020), imply different methodologies for impacts studies. Especially, the impact assessment of climate change on water resources in cities, require specific downscaling methods adapted to rainfall. A reflection is underway on these questions, in order to combine the two approaches and produce complete climatic forcing datasets.

Given the available databases, the methodology could be applied to all major French cities, as well as to other regional climate simulations (e.g. the next generation of EURO-CORDEX based on CMIP6; Eyring et al. 2016). But, it will first be applied on the EURO-CORDEX climate projections to study the effects of climate change on the UHI.

Appendix 1: Local weather type classification and attribution

The Local Weather Types (LWTs) classification developed by Hidalgo and Jouglé (2018) uses the “Partition Around Medoids” clustering algorithm (PAM; Kaufman and Rousseeuw 1990) with Gower’s distance as a measure of dissimilarity (Gower 1971).

The classification uses five daily variables: the daily thermal amplitude ($dT = TX - TN$ in $^{\circ}\text{C}$), the daily mean precipitation rate (RR in mm h^{-1}), the daily mean specific humidity (Q in kg kg^{-1}), the daily mean wind speed (FF in m s^{-1}) and the daily mean wind direction (obtained from the daily average of the hourly wind components and expressed in 4 wind quadrants of 90° from the north).

The PAM algorithm uses a matrix of dissimilarity to represent the distance between each pair of days in the AROME re-analysis time series. To produce this matrix, the partial

similarity (S_V) is computed for each variable V and each pair of days (D_1, D_2) by normalising the absolute difference between the two days by the maximum amplitude of V over the complete period ($\Delta V = V_{MAX} - V_{MIN}$)

$$s_{V(D_1, D_2)} = 1 - \frac{|V_{D_1} - V_{D_2}|}{\Delta V}$$

In the case of the wind direction, which is considered here as a categorical variable (in sectors from 1 to 4), the partial similarity is expressed as:

$$s_{V(D_1, D_2)} = \begin{cases} 1, & \text{if } V_{D_1} = V_{D_2} \\ 0, & \text{else} \end{cases}$$

Gower's index of similarity (S_G) is computed for each pair of days as the average of the partial similarities of the five variables taken into account for the classification:

$$S_{G(D_1, D_2)} = \frac{1}{5} \sum_{j=1}^5 s_{V_j(D_1, D_2)}$$

And Gower's distance (D_G) which is used to produce the matrix is expressed as:

$$D_{G(D_1, D_2)} = 1 - S_{G(D_1, D_2)}$$

From the dissimilarity matrix, the PAM algorithm chooses a first set of k medoids, and assigns each day to the nearest medoid by minimising the Gower distance, thus forming k clusters. To find a satisfactory non-random first set of clusters, PAM first selects the day with the lowest sum of the distances to all others, and then selects other days (until k is reached) always minimising the total sum of the distances (Schubert and Rousseeuw 2019).

From this initial set of medoids and clusters, PAM swaps all the medoids with all the available days and keeps the day associated with the smallest sum of the distances as a new medoid. The days are then again associated with the closest medoid. These two steps (inversion then reallocation) are repeated until the sum of the distances no longer decreases (Schubert and Rousseeuw 2019).

Hidalgo and Joula (2018) conducted a sensitivity study to determine the optimal number of clusters. They applied several iterations of PAM by varying the number of prescribed clusters from 4 to 15 and then compared, for the different LWT classifications, the quality of the seasonal diurnal cycles reconstructed from the daily variables (see their temporal downscaling method in Hidalgo and Joula 2018). For the Paris region, the classification into 12 LWTs (or clusters) gave the best results.

The attribution of LWTs on a new dataset on the basis of an existing classification follows the previous steps with some modifications. A new dissimilarity matrix is

constructed for the new data, following the same principle, but retaining for normalisation the maximum amplitude ΔV of the reference classification. The PAM algorithm uses the 12 medoids of the reference classification to assign each day of the new period to one of the clusters by minimising the distance within a cluster while maximising the distance between clusters.

Appendix 2: Sub-daily atmospheric forcing computation

The downscaling methodology presented and evaluated here is restricted to daily minimum and maximum temperatures but can be extended to sub-daily time-steps.

While the LWTs attribution step remains the same, the combination of RCM sub-daily outputs with Meso-NH is more challenging. The finest sub-daily temporal resolution of the RCMs (e.g. three hours for EURO-CORDEX) is to be combined with Meso-NH. The LWTs being defined from daily variables, the simplest approach would be to combine with the three-hourly urban increment of the same Meso-NH day (from 0 to 21 UTC). However, the thermal signature of the city (i.e. the UHI) does not result from the same physical processes during the day and night. Daytime UHI depends on the current atmospheric conditions whereas the nocturnal UHI is strongly governed by the conditions during the previous day, especially the incoming solar radiation that drives the process of heat storage in the construction materials. Therefore, rather than concatenating the daily cycles of the urban increment simulated by Meso-NH at 0 UTC, the transition time between two daily cycles is shifted to 9 UTC when temperature differences between urban and rural areas are expected to be at minimum, ensuring a smoother transition between two cycles. This involves starting the Meso-NH daily cycle at 12 UTC for the selected date and then extending it to 9 UTC using the following day. This date can correspond to a different LWT but it is assumed that the urban increments between 0 and 9 UTC are influenced by the previous day's conditions. For this purpose, the next day of every simulation is also simulated (i.e. 104 days) resulting in a total of 359 simulated days. Following this approach, time series of sub-daily climate projections maps of 200×200 km taking into account the effect of the city on the atmosphere are created and can, in turn, be used to drive impact models.

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References

- Arnfield AJ (2003) Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island. *Int J Climatol J R Meteorol Soc* 23(1):1–26. <https://doi.org/10.1002/joc.859>
- Barles S (2007) Urban metabolism and river systems: an historical perspective—Paris and the Seine, 1790–1970
- Beck C, Philipp A (2010) Evaluation and comparison of circulation type classifications for the European domain. *Phys Chem Earth Parts A/B/C* 35(9–12):374–387. <https://doi.org/10.1016/j.pce.2010.01.001>
- Berne A, Delrieu G, Creutin JD, Obled C (2004) Temporal and spatial resolution of rainfall measurements required for urban hydrology. *J Hydrol* 299(3–4):166–179. <https://doi.org/10.1016/j.jhydrol.2004.08.002>
- Bocher E, Petit G, Bernard J, Palominos S (2018) A geoprocessing framework to compute urban indicators: the MAPUCE tools chain. *Urban Clim* 24:153–174. <https://doi.org/10.1016/j.uclim.2018.01.008>
- Boé J, Terray L, Habets F, Martin E (2006) A simple statistical–dynamical downscaling scheme based on weather types and conditional resampling. *J Geophys Res Atmos* 111:D23. <https://doi.org/10.1029/2005JD006889>
- Bohnenstengel SI, Evans S, Clark PA, Belcher S (2011) Simulations of the London urban heat island. *Q J R Meteorol Soc* 137(659):1625–1640. <https://doi.org/10.1002/qj.855>
- Bougeault P, Lacarrere P (1989) Parameterization of orography-induced turbulence in a mesobeta–scale model. *Mon Weather Rev* 117(8):1872–1890
- Bueno B, Pigeon G, Norford LK, Zibouche K, Marchadier C (2012) Development and evaluation of a building energy model integrated in the TEB scheme. <https://doi.org/10.5194/gmd-5-433-2012>
- Buyantuyev A, Wu J (2009) Urbanization alters spatiotemporal patterns of ecosystem primary production: a case study of the Phoenix metropolitan region, USA. *J Arid Environ* 73(4–5):512–520. <https://doi.org/10.1016/j.jaridenv.2008.12.015>
- Cassou C, Terray L, Phillips AS (2005) Tropical Atlantic influence on European heat waves. *J Clim* 18(15):2805–2811. <https://doi.org/10.1175/JCLI3506.1>
- Champeaux JL, Masson M, Chauvin F (2005) ECOCLIMAP: a global database of land surface parameters at 1 km resolution. *Meteorol Appl* 12:29–32. <https://doi.org/10.1017/S1350482705001519>
- Christensen OB, Drews M, Christensen JH, Dethloff K, Ketelsen K, Hebestadt I, Rinke A (2007) The HIRHAM regional climate model. Version 5 (beta)
- Christensen JH, Kanikicharla KK, Aldrian E, An SI, Cavalcanti IFA, de Castro M, et al. (2013) Climate phenomena and their relevance for future regional climate change. In: *Climate change 2013 the physical science basis: working group I contribution to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge University Press, pp 1217–1308. <https://doi.org/10.1017/CBO9781107415324.028>
- Colin J, Déqué M, Radu R, Somot S (2010) Sensitivity study of heavy precipitation in Limited Area Model climate simulations: influence of the size of the domain and the use of the spectral nudging technique. *Tellus A Dyn Meteorol Oceanogr* 62(5):591–604. <https://doi.org/10.1111/j.1600-0870.2010.00467.x>
- Daniel M, Lemonsu A, Déqué M, Somot S, Alias A, Masson V (2019) Benefits of explicit urban parameterization in regional climate modeling to study climate and city interactions. *Clim Dyn* 52(5–6):2745–2764. <https://doi.org/10.1007/s00382-018-4289-x>
- Dee DP, Uppala SM, Simmons AJ, Berrisford P, Poli P, Kobayashi S et al (2011) The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q J R Meteorol Soc* 137(656):553–597. <https://doi.org/10.1002/qj.828>
- Doms G, Baldauf M (2011) A description of the nonhydrostatic regional COSMO model. Part I. Dynamics and numerics. Deutscher Wetterdienst, Offenbach
- Doms G, Förstner J, Heise E, Herzog HJ, Mironov D, Raschendorfer M et al (2011) A description of the nonhydrostatic regional COSMO model. Part II. Physical parameterization. Deutscher Wetterdienst, Offenbach
- Dousset B, Gourmelon F, Laaidi K, Zeghnoun A, Giraudet E, Bretin P, Mauri E, Vandentorren S (2011) Satellite monitoring of summer heat waves in the Paris metropolitan area. *Int J Climatol* 31(2):313–323. <https://doi.org/10.1002/joc.2222>
- Duchêne F, Van Schaeybroeck B, Caluwaerts S, De Troch R, Hamdi R, Termonia P (2020) A Statistical–dynamical methodology to downscale regional climate projections to urban scale. *J Appl Meteorol Climatol* 59(6):1109–1123. <https://doi.org/10.1175/JAMC-D-19-0104.1>
- Duh JD, Shandas V, Chang H, George LA (2008) Rates of urbanisation and the resiliency of air and water quality. *Sci Total Environ* 400(1–3):238–256. <https://doi.org/10.1016/j.scitotenv.2008.05.002>
- ECMWF (2019) Changes in ECMWF model-evolution of the IFS. <https://www.ecmwf.int/en/forecasts/documentation-and-support/changes-ecmwf-model>
- Ewing R, Rong F (2008) The impact of urban form on US residential energy use. *Housing Policy Debate* 19(1):1–30. <https://doi.org/10.1080/10511482.2008.9521624>
- Eyring V, Bony S, Meehl GA, Senior CA, Stevens B, Stouffer RJ, Taylor KE (2016) Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci Model Dev* 9(5):1937–1958. <https://doi.org/10.5194/gmd-8-10539-2015>
- Faroux S, Kaptué Tchuenté AT, Roujean JL, Masson V, Martin E, Moigne PL (2013) ECOCLIMAP-II/Europe: a twofold database of ecosystems and surface parameters at 1 km resolution based on satellite information for use in land surface, meteorological and climate models. *Geosci Model Dev* 6(2):563–582. <https://doi.org/10.5194/gmd-6-563-2013>
- Fletcher TD, Andrieu H, Hamel P (2013) Understanding, management and modelling of urban hydrology and its consequences for receiving waters: a state of the art. *Adv Water Resour* 51:261–279. <https://doi.org/10.1016/j.advwatres.2012.09.001>
- Foster SSD, Morris BL, Lawrence AR (1994). Effects of urbanization on groundwater recharge. In: *Groundwater problems in urban areas: proceedings of the international conference organized by the institution of civil engineers and held in London, 2–3 June 1993*. Thomas Telford Publishing, pp 43–63. <https://doi.org/10.1680/gpiua.19744.0005>
- Frey-Buness F, Heimann D, Sausen R (1995) A statistical–dynamical downscaling procedure for global climate simulations. *Theoret Appl Climatol* 50(3–4):117–131. <https://doi.org/10.1007/BF00866111>
- Gardes T, Schoetter R, Hidalgo J, Long N, Marquès E, Masson V (2020) Statistical prediction of the nocturnal urban heat island intensity based on urban morphology and geographical factors—An investigation based on numerical model results for a

- large ensemble of French cities. *Sci Total Environ.* <https://doi.org/10.1016/j.scitotenv.2020.139253>
- Gidhagen L, Olsson J, Amorim JH, Asker C, Belusic D, Carvalho AC, Lindstedt D (2020) Towards climate services for European cities: lessons learnt from the Copernicus project Urban SIS. *Urban Clim* 31:100549
- Giorgi F, Jones C, Asrar GR (2009) Addressing climate information needs at the regional level: the CORDEX framework. *World Meteorol Organ Bull* 58(3):175
- Giorgi F, Coppola E, Solmon F, Mariotti L, Sylla MB, Bi X et al (2012) RegCM4: model description and preliminary tests over multiple CORDEX domains. *Clim Res* 52:7–29. <https://doi.org/10.3354/cr01018>
- Gosling SN, Lowe JA, McGregor GR, Pelling M, Malamud BD (2009) Associations between elevated atmospheric temperature and human mortality: a critical review of the literature. *Clim Change* 92(3–4):299–341. <https://doi.org/10.1007/s10584-008-9441-x>
- Gower JC (1971) A general coefficient of similarity and some of its properties. *Biometrics.* <https://doi.org/10.2307/2528823>
- Graham LP, Andréasson J, Carlsson B (2007) Assessing climate change impacts on hydrology from an ensemble of regional climate models, model scales and linking methods—a case study on the Lule River basin. *Clim Change* 81(1):293–307. <https://doi.org/10.1007/s10584-006-9215-2>
- Gutiérrez C, Somot S, Nabat P, Mallet M, Corre L, van Meijgaard E et al (2020) Future evolution of surface solar radiation and photovoltaic potential in Europe: investigating the role of aerosols. *Environ Res Lett* 15(3):034035. <https://doi.org/10.1088/1748-9326/ab6666>
- Hammond MJ, Chen AS, Djordjević S, Butler D, Mark O (2015) Urban flood impact assessment: a state-of-the-art review. *Urban Water J* 12(1):14–29. <https://doi.org/10.1080/1573062X.2013.857421>
- Hidalgo J, Jouglar R (2018) On the use of local weather types classification to improve climate understanding: an application on the urban climate of Toulouse. *PLoS One* 13(12):e0208138. <https://doi.org/10.1371/journal.pone.0208138>
- Hidalgo J, Masson V, Baehr C (2014) From daily climatic scenarios to hourly atmospheric forcing fields to force soil–vegetation–atmosphere transfer models. *Front Environ Sci* 2:40. <https://doi.org/10.3389/fenvs.2014.00040>
- Hoffmann P, Schoetter R, Schlünzen H (2018) Statistical–dynamical downscaling of the urban heat island in Hamburg, Germany. *Meteorol Z* 27:89–109. <https://doi.org/10.1127/metz/2016/0773>
- Hogrefe C, Lynn B, Civerolo K, Ku JY, Rosenthal J, Rosenzweig C et al (2004) Simulating changes in regional air pollution over the eastern United States due to changes in global and regional climate and emissions. *J Geophys Res Atmos* 109:D22. <https://doi.org/10.1029/2004JD004690>
- Hope D, Gries C, Zhu W, Fagan WF, Redman CL, Grimm NB et al (2008) Socioeconomics drive urban plant diversity. *Urban Ecology.* Springer, Boston, pp 339–347. https://doi.org/10.1007/978-0-387-73412-5_21
- IPCC (2018) Global Research and Action Agenda on Cities and Climate Change Science. Cities IPCC, Geneva
- Jacob D, Elizalde A, Haensler A, Hagemann S, Kumar P, Podzun R et al (2012) Assessing the transferability of the regional climate model REMO to different coordinated regional climate downscaling experiment (CORDEX) regions. *Atmosphere* 3(1):181–199. <https://doi.org/10.3390/atmos3010181>
- Jänicke B, Meier F, Fenner D, Fehrenbach U, Holtmann A, Scherer D (2017) Urban–rural differences in near-surface air temperature as resolved by the Central Europe Refined analysis (CER): sensitivity to planetary boundary layer schemes and urban canopy models. *Int J Climatol* 37(4):2063–2079. <https://doi.org/10.1002/joc.4835>
- Jouglar R, Hidalgo J, Pouponneau B (2019) Identification des situations météorologiques locales pour une cinquantaine de villes françaises. *La Météorol.* <https://doi.org/10.4267/2042/70370>
- Kain JS, Fritsch JM (1990) A one-dimensional entraining/detraining plume model and its application in convective parameterization. *J Atmos Sci* 47(23):2784–2802
- Karl TR, Nicholls N, Ghazi A (1999) Clivar/GCOS/WMO workshop on indices and indicators for climate extremes workshop summary. Weather and climate extremes. Springer, Dordrecht, pp 3–7
- Kaufman L, Rousseeuw PJ (1990) Partitioning around medoids (program pam). *Find Groups Data Introd Cluster Anal* 344:68–125
- Kolokotroni M, Ren X, Davies M, Mavrogianni A (2012) London's urban heat island: impact on current and future energy consumption in office buildings. *Energy Build* 47:302–311. <https://doi.org/10.1016/j.enbuild.2011.12.019>
- Kovats RS, Hajat S (2008) Heat stress and public health: a critical review. *Annu Rev Public Health* 29:41–55. <https://doi.org/10.1146/annurev.publhealth.29.020907.090843>
- Künzli N, Kaiser R, Medina S, Studnicka M, Chanel O, Filliger P et al (2000) Public-health impact of outdoor and traffic-related air pollution: a European assessment. *Lancet* 356(9232):795–801. [https://doi.org/10.1016/S0140-6736\(00\)02653-2](https://doi.org/10.1016/S0140-6736(00)02653-2)
- Kwok YT, Schoetter R, Lau KKL, Hidalgo J, Ren C, Pigeon G, Masson V (2019) How well does the local climate zone scheme discern the thermal environment of Toulouse (France)? An analysis using numerical simulation data. *Int J Climatol* 39(14):5292–5315. <https://doi.org/10.1002/joc.6140>
- Lac C, Chaboureaud P, Masson V, Pinty P, Tulet P, Escobar J et al (2018) Overview of the Meso-NH model version 5.4 and its applications. *Geosci Model Dev* 11:1929–1969. <https://doi.org/10.5194/gmd-11-1929-2018>
- Landrigan PJ, Fuller R, Acosta NJ, Adeyi O, Arnold R, Baldé AB et al (2018) The Lancet Commission on pollution and health. *Lancet* 391(10119):462–512. [https://doi.org/10.1016/S0140-6736\(17\)32345-0](https://doi.org/10.1016/S0140-6736(17)32345-0)
- Langendijk GS, Rechid D, Jacob D (2019) Urban areas and urban-rural contrasts under climate change: what does the EURO-CORDEX ensemble tell us?—Investigating near surface humidity in Berlin and its surroundings. *Atmosphere* 10(12):730. <https://doi.org/10.3390/atmos10120730>
- Lauwaert D, Maiheu B, De Ridder K, Boëne W, Hooyberghs H, Demuzere M, Verdonck ML (2020) A new method to assess fine-scale outdoor thermal comfort for urban agglomerations. *Climate* 8(1):6. <https://doi.org/10.3390/cli8010006>
- Lemonsu A, Masson V, Shashua-Bar L, Errell E, Pearlmutter D (2012) Inclusion of vegetation in the Town Energy Balance model for modelling urban green areas. <https://doi.org/10.5194/gmd-5-1377-2012>
- Lemonsu A, Kounkou-Arnaud R, Desplat J, Salagnac JL, Masson V (2013) Evolution of the Parisian urban climate under a global changing climate. *Clim Change* 116(3–4):679–692. <https://doi.org/10.1007/s10584-012-0521-6>
- Lemonsu A, Beaulant AL, Somot S, Masson V (2014) Evolution of heat wave occurrence over the Paris basin (France) in the 21st century. *Clim Res* 61(1):75–91. <https://doi.org/10.3354/cr01235>
- Lemonsu A, Viguie V, Daniel M, Masson V (2015) Vulnerability to heat waves: impact of urban expansion scenarios on urban heat island and heat stress in Paris (France). *Urban Clim* 14:586–605. <https://doi.org/10.1016/j.uclim.2015.10.007>
- Leung LR, Gustafson WI Jr (2005) Potential regional climate change and implications to US air quality. *Geophys Res Lett* 32:16. <https://doi.org/10.1029/2005GL022911>
- Leutwyler D, Lüthi D, Ban N, Fuhrer O, Schär C (2017) Evaluation of the convection-resolving climate modeling approach on

- continental scales. *J Geophys Res Atmos* 122(10):5237–5258. <https://doi.org/10.1002/2016JD026013>
- Maraun D (2013) Bias correction, quantile mapping, and downscaling: revisiting the inflation issue. *J Clim* 26(6):2137–2143. <https://doi.org/10.1175/JCLI-D-12-00821.1>
- Masson V (2000) A physically-based scheme for the urban energy budget in atmospheric models. *Bound Layer Meteorol* 94(3):357–397. <https://doi.org/10.1023/A:1002463829265>
- Masson V, Champeaux JL, Chauvin F, Meriguet C, Lacaze R (2003) A global database of land surface parameters at 1-km resolution in meteorological and climate models. *J Clim* 16(9):1261–1282. <https://doi.org/10.1175/1520-0442-16.9.1261>
- Masson V, Le Moigne P, Martin E, Faroux S, Alias A, Alkama R et al. (2013) The SURFEXv7. 2 land and ocean surface platform for coupled or offline simulation of earth surface variables and fluxes. <https://doi.org/10.5194/gmd-6-929-2013>
- Menut L, Tripathi OP, Colette A, Vautard R, Flaounas E, Bessagnet B (2013) Evaluation of regional climate simulations for air quality modelling purposes. *Clim Dyn* 40(9–10):2515–2533. <https://doi.org/10.1007/s00382-012-1345-9>
- Mignot E, Li X, Dewals B (2019) Experimental modelling of urban flooding: a review. *J Hydrol* 568:334–342. <https://doi.org/10.1016/j.jhydrol.2018.11.001>
- Mitchell VG, Mein RG, McMahon TA (2001) Modelling the urban water cycle. *Environ Model Softw* 16(7):615–629. [https://doi.org/10.1016/S1364-8152\(01\)00029-9](https://doi.org/10.1016/S1364-8152(01)00029-9)
- Muratet A, Machon N, Jiguet F, Moret J, Porcher E (2007) The role of urban structures in the distribution of wasteland flora in the greater Paris area, France. *Ecosystems* 10(4):661. <https://doi.org/10.1007/s10021-007-9047-6>
- Oke TR (1973) City size and the urban heat island. *Atmos Environ* (1967) 7(8):769–779. [https://doi.org/10.1016/0004-6981\(73\)90140-6](https://doi.org/10.1016/0004-6981(73)90140-6)
- Oke TR (1981) Canyon geometry and the nocturnal urban heat island: comparison of scale model and field observations. *J Climatol* 1(3):237–254. <https://doi.org/10.1002/joc.3370010304>
- Patz JA, Campbell-Lendrum D, Holloway T, Foley JA (2005) Impact of regional climate change on human health. *Nature* 438(7066):310–317. <https://doi.org/10.1038/nature04188>
- Pergaud J, Masson V, Malardel S, Couvreur F (2009) A parameterization of dry thermals and shallow cumuli for mesoscale numerical weather prediction. *Bound Layer Meteorol* 132(1):83
- Perkins SE, Pitman AJ, Sisson SA (2013) Systematic differences in future 20 year temperature extremes in AR4 model projections over Australia as a function of model skill. *Int J Climatol* 33(5):1153–1167. <https://doi.org/10.1002/joc.3500>
- Peterson T, Folland C, Gruza G, Hogg W, Mokssit A, Plummer N (2001) Report on the activities of the working group on climate change detection and related rapporteurs. World Meteorological Organization, Geneva
- Philipp A, Bartholy J, Beck C, Erpicum M, Esteban P, Fettweis X et al (2010) Cost733cat—a database of weather and circulation type classifications. *Phys Chem Earth Parts A/B/C* 35(9–12):360–373. <https://doi.org/10.1016/j.pce.2009.12.010>
- Piani C, Haerter JO, Coppola E (2010) Statistical bias correction for daily precipitation in regional climate models over Europe. *Theoret Appl Climatol* 99(1–2):187–192. <https://doi.org/10.1007/s00704-009-0134-9>
- Pigeon G, Zibouche K, Bueno B, Le Bras J, Masson V (2014) Improving the capabilities of the town energy balance model with up-to-date building energy simulation algorithms: an application to a set of representative buildings in Paris. *Energy Build* 76:1–14. <https://doi.org/10.1016/j.enbuild.2013.10.038>
- Pouponneau B, Pourret V, Faucou É, Mestre O, Sorel M, Bellini R et al (2017) Évaluation de la ressource éolienne terrestre en France. *Météorologie*. <https://doi.org/10.4267/2042/62457>
- Revi A, Satterthwaite DE, Aragón-Durand F, Corfee-Morlot J, Kiunsi RBR, Pelling M, Roberts DC, Solecki W (2014) Urban areas. In: Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds) *Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge University Press, Cambridge, pp 535–612
- Rummukainen M (2010) State-of-the-art with regional climate models. *Wiley Interd Rev Clim Change* 1(1):82–96. <https://doi.org/10.1002/wcc.8>
- Salmond J, Sabel CE, Vardoulakis S (2018) Towards the integrated study of urban climate, air pollution, and public health. <https://doi.org/10.3390/cli6010014>
- Samuelsson P, Gollvik S, Kupiainen M, Kourzeneva E, van de Berg WJ (2015) The surface processes of the Rossby Centre regional atmospheric climate model (RCA4). SMHI, Norrköping
- Santamouris M, Papanikolaou N, Livada I, Koronakis I, Georgakis C, Argiriou A, Assimakopoulos DN (2001) On the impact of urban climate on the energy consumption of buildings. *Sol Energy* 70(3):201–216. [https://doi.org/10.1016/S0038-092X\(00\)00095-5](https://doi.org/10.1016/S0038-092X(00)00095-5)
- Schoetter R, Masson V, Bourgeois A, Pellegrino M, Lévy JP (2017) Parametrisation of the variety of human behaviour related to building energy consumption in the Town Energy Balance (SURFEX-TEB v. 8.2). *Geoscientific Model Development*, 10(7), 2801. doi: <https://doi.org/10.5194/gmd-10-2801-2017>
- Schoetter R, Masson V, Amossé A, Bernard J, Bocher E, Bonhomme M et al (2019) Caractérisation du tissu urbain français pour la modélisation du climat urbain et de son interaction avec la consommation énergétique dans les bâtiments. *Météorologie*. <https://doi.org/10.4267/2042/70169>
- Schoetter R, Hidalgo J, Jougla R, Masson V, Rega M, Pergaud J (2020) A statistical-dynamical downscaling for the urban heat island and building energy consumption—analysis. *J Appl Meteorol Climatol* 59(5):859–883. <https://doi.org/10.1175/JAMC-D-19-0182.1>
- Schubert E, Rousseeuw PJ (2019) Faster k-medoids clustering: improving the PAM, CLARA, and CLARANS algorithms. In: *International conference on similarity search and applications*. Springer, Cham, pp 171–187
- Seity Y, Brousseau P, Malardel S, Hello G, Bénard P, Bouttier F et al (2011) The AROME-France convective-scale operational model. *Mon Weather Rev* 139(3):976–991. <https://doi.org/10.1175/2010MWR3425.1>
- Skamarock WC, Klemp JB, Dudhia J, Gill DO, Barker DM, Wang W, Powers JG (2005) A description of the advanced research WRF version 2 (No. NCAR/TN-468+ STR). National Center for Atmospheric Research Boulder Co Mesoscale and Microscale Meteorology Div.
- Stocker TF, Qin D, Plattner GK, Tignor M, Allen SK, Boschung J, et al. (2013) *Climate change 2013 the physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change*, p 1535
- Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design. *Bull Am Meteorol Soc* 93(4):485–498. <https://doi.org/10.1175/BAMS-D-11-00094.1>
- Tobin I, Vautard R, Balog I, Bréon FM, Jerez S, Ruti PM et al (2015) Assessing climate change impacts on European wind energy from ENSEMBLES high-resolution climate projections. *Clim Change* 128(1–2):99–112. <https://doi.org/10.1007/s10584-014-1291-0>
- Tornay N, Schoetter R, Bonhomme M, Faraut S, Masson V (2017) GENIUS: a methodology to define a detailed description of buildings for urban climate and building energy consumption

- simulations. *Urban Clim* 20:75–93. <https://doi.org/10.1016/j.uclim.2017.03.002>
- United Nations, Department of Economic and Social Affairs, Population Division (2019) *World Urbanization Prospects: the 2018 Revision (ST/ESA/SER.A/420)*. New York: United Nations
- van Meijgaard E, van Ulft LH, van de Berg WJ, Bosveld FC, van den Hurk BJJM, Lenderink G, Siebesma AP (2008) The KNMI regional atmospheric climate model RACMO, version 2.1. KNMI, De Bilt, p 43
- van Meijgaard E, van Ulft LH, Lenderink G, De Roode SR, Wipfler EL, Boers R, van Timmermans RMA (2012) Refinement and application of a regional atmospheric model for climate scenario calculations of Western Europe (No. KVR 054/12). KVR.
- Vautard R, Menut L, Beekmann M, Chazette P, Flamant PH, Gombert D et al (2003) A synthesis of the Air Pollution Over the Paris Region (ESQUIF) field campaign. *J Geophys Res Atmos* 108:D17. <https://doi.org/10.1029/2003JD003380>
- Vautard R, Gobiet A, Jacob D, Belda M, Colette A, Déqué M et al (2013) The simulation of European heat waves from an ensemble of regional climate models within the EURO-CORDEX project. *Clim Dyn* 41(9–10):2555–2575. <https://doi.org/10.1007/s00382-013-1714-z>
- Viguie V, Lemonsu A, Hallegatte S, Beuland AL, Marchadier C, Masson V et al (2020) Early adaptation to heat waves and future reduction of air-conditioning energy use in Paris. *Environ Res Lett*. <https://doi.org/10.1088/1748-9326/ab6a24>
- Walters D, Baran AJ, Boutle I, Brooks M, Earnshaw P, Edwards J et al (2019) The Met Office Unified Model global atmosphere 7.0/7.1 and JULES global land 7.0 configurations. *Geosci Model Dev* 12(5):1909–1963. <https://doi.org/10.5194/gmd-12-1909-2019>
- Wilby RL (2007) A review of climate change impacts on the built environment. *Built Environ* 33(1):31–45. <https://doi.org/10.2148/benv.33.1.31>
- Wilby RL, Wigley TM (1997) Downscaling general circulation model output: a review of methods and limitations. *Prog Phys Geogr* 21(4):530–548. <https://doi.org/10.1177/030913339702100403>
- Wu J (2014) Urban ecology and sustainability: the state-of-the-science and future directions. *Landsc Urban Plann* 125:209–221. <https://doi.org/10.1016/j.landurbplan.2014.01.018>

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