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"**Engaging approaches and services for meaningful climate actions**"

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D4.1 Preliminary assessment and comparison of state-of-the-art methods for forecasts and projections of hourly extremes	
Work package:	**4**
Task:	**4.1. A review of existing forecasting technologies to identify their limitations and opportunities for improvement**

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PP	Restricted to other programme participants (including the EC Services)	
RE	Restricted to a group specified by the consortium (including the EC Services)	
CO	Confidential, only for members of the consortium (including the EC)	

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SUMMARY

The frequency and severity of extreme weather events are escalating globally, yet high-quality, sub-daily weather data remain scarce across the Balkans, particularly in Serbia. This limits the ability to design and adapt critical infrastructure for improved climate resilience.

This Deliverable presents the first global systematic review of temporal downscaling methods used to derive sub-daily weather data from daily or monthly records. It identifies seven main categories of temporal scaling techniques, with stochastic weather generators, numerical weather prediction models, and scale invariance methods among the most common. Key sectors covered include flood risk management, urban infrastructure, and renewable energy – all of which require sub-daily data.

The five-step protocol screened 296 relevant studies, revealing that nearly half employ hybrid approaches, and that scale invariance methods are particularly effective for single-site, sub-hourly rainfall extremes. A case study for Novi Sad, Serbia, demonstrated that sub-daily extreme rainfall intensities can be estimated from daily data with less than 15% error.

The Deliverable recommends applying and validating scale invariance techniques across other sites in Serbia, then exploring their utility for heatwave metrics, and conducting side-by-side comparisons of methods – including AI-based techniques – for other regions in Europe. There is also scope for advancing temporal scaling techniques for ungauged areas. These developments could enhance regional climate resilience in infrastructure planning, even when there are limited data.

1. INTRODUCTION

Floods, heatwaves, and droughts are increasing globally in terms of their frequency, severity, and duration (European Environment Agency, 2024). Climate variability and change also contributes to the occurrence of new, unprecedented weather events with significant impacts on society and the natural environment (Kelder et al., 2015). For example, the catastrophic autumn 2024 floods in Valencia, Spain (Figure 1) was triggered by intense rainfall with one weather station in Chiva recording 491 mm in just 8 hours – the equivalent to a whole year of rainfall[1]. According to World Weather Attribution such an event is now about twice as likely and 12% heavier due to global warming since preindustrial times[2].

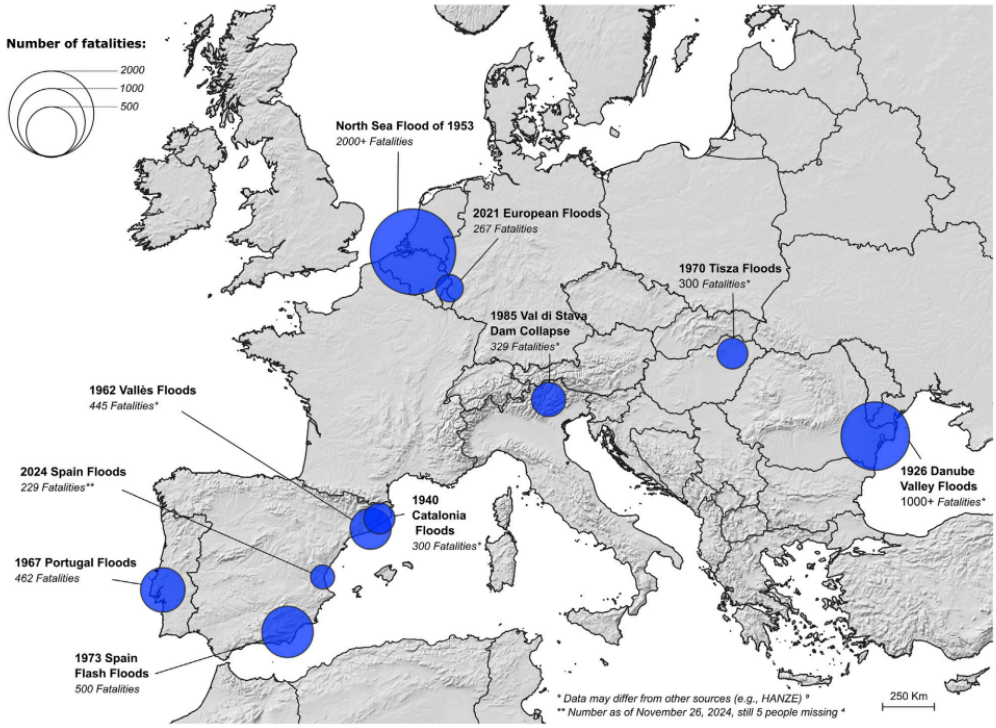

Figure 1. *Top-10 deadliest flood events in Europe, 1900–2024, based on data from the Emergency Events Database (EM-DAT; Charalampous et al., 2025)*

Flash floods, storm surges and windstorms – may occur over durations of minutes to hours; other hazards – such as droughts – may develop over weeks to months, or even years. Unfortunately, hydrometeorological information on sub-hourly to daily timescales is much less abundant than data spanning days to months. Globally there are an estimated 29,000 active weather stations of which about 6000 are automated and gathering data at 1, 3, or 6 hour intervals[3]. Moreover, the distribution of observations is highly uneven with the vast majority of weather data gathered in Australia, Northwest Europe, North America, and parts of South Asia (Jaffrés, 2019). Nonetheless, high-resolution weather information is urgently needed for the safe design of buildings, urban drainage systems, and energy infrastructure *everywhere*. Sub-daily data on extreme air temperatures (highs

[1] World Meteorological Organisation
[2] World Weather Attribution
[3] Weather Underground

and lows) and wind gusts are also required to improve building design and performance, plus protect human health.

Considerable progress been made in compiling sub-daily weather records from historic sources. For example, the Global Sub-Daily Precipitation Indices (GSDR-I) are based on 18,591 gauges with at least one effective year of hourly data (Pritchard et al., 2023). Unfortunately, these data are also concentrated in a few regions (Figure 2a) and the number of gauges with less than 20% missing data has declined dramatically since the mid-2000s (Figure 2b). The Balkans in general and Serbia in particular stand out as data sparse areas.

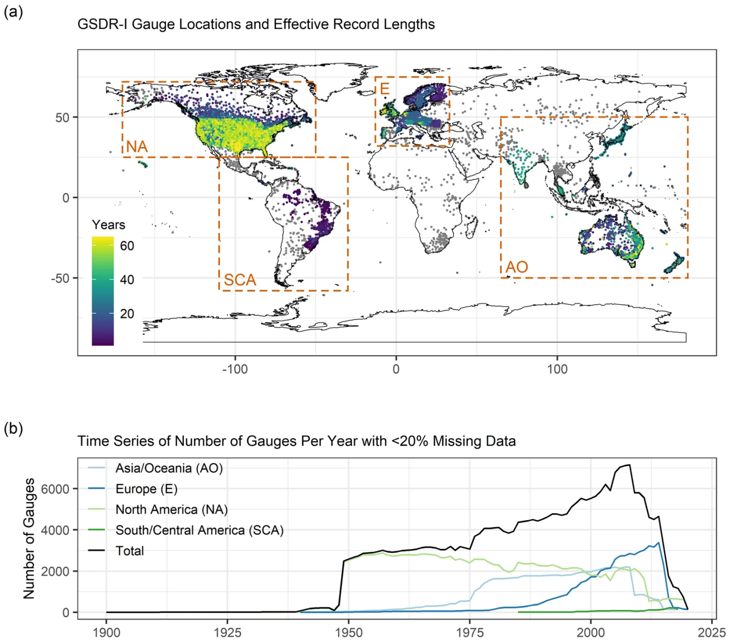

Figure 2. *Hourly precipitation gauge data in (a) space and (b) time (Pritchard et al., 2023)*

Fortunately, there are many techniques for bridging the gap between more readily available daily/ monthly weather data, and less plentiful sub-daily data. These include (1) data rescue and digitization initiatives (e.g. Hawkins et al., 2023); (2) dynamical downscaling, including numerical weather prediction, re-analysis products, and Regional Climate Models (RCMs) (e.g. Lo et al., 2008); and (3) statistical methods for temporal disaggregation (e.g. Kourtis and Tsihrintzis, 2022). The focus of this Deliverable is on evaluating methods (2) and (3) plus other techniques using a systematic literature review and demonstration study for a data sparse region.

2. AIMS AND OBJECTIVES

The overall aim of Deliverable D4.1 is to carry out a *preliminary assessment and comparison of state-of-the-art methods for forecasts and projections of hourly extremes*. This will be achieved by:

1. Undertaking a global systematic review of methods for spatial and temporal downscaling of sub-daily weather series under present and future climate conditions.
2. Demonstrating a parsimonious temporal downscaling method for estimating local intensity-frequency-duration (IDF) curves for extreme rainfall statistics for Serbia.

The next section describes the workflow of the meta-analysis, including initial identification then screening of peer-reviewed articles. The bulk of this Deliverable is then devoted to a synopsis and critique of the major themes emerging from these sources. The information is used to summarize the strengths and weaknesses of several main groups of methods for disaggregating coarse-resolution (monthly or daily) data into finer (hourly or sub-hourly) time scales. In each case, selected studies are used to show good practice. A pilot study of extreme sub-hourly rainfall estimation is presented for Serbia to demonstrate what can be achieved despite very limited data. The final section sums up the key findings and offers recommendations for next steps.

3. META-ANALYSIS

3.1. Methodology

A five-step, workflow was used to sift literature to draw out key themes and evidence (Figure 3). This follows best-practice guidance on systematic review protocols, including full transparency about the meta-analysis protocol (Page et al., 2021). The five steps were:

1. Define the research question.
2. Specify inclusion criteria for literature.
3. Develop the review protocol and search terms.
4. Remove duplicates and check eligibility.
5. Codify screened articles by year, author country, source, key words, and time-scaling method.

The research question specified in Step 1 was: What are the preferred techniques used for temporal downscaling from daily or monthly meteorological information to local sub-daily extreme weather variables and statistics?

Step 2 involved searching peer-reviewed literature on the topic of sub-daily downscaling and disaggregation of weather variables (such as rainfall, temperature, wind speed, sunshine hours, humidity) and related quantities (such as wave heights, and air quality). In each case the article title, abstract, or keywords had to refer to downscaling at sub-daily or so sub-hourly time-scales under present climate conditions. Articles that also referred to sub-daily weather extremes under climate change were included but this was not a prerequisite.

Step 3 of the workflow defines the data base, search fields, and search period. The Web of Science archive was searched for research articles (including data sets and early view papers) and conference proceedings, but the latter had to be full papers not just abstracts (to enable scrutiny of technical details). All fields were searched within the period January 1997 to March 2025. The initial search string was: *(empirical OR statistical OR temporal) downscal* climate (hour* OR sub-daily OR IDF*[4]*)*. However, it was immediately apparent that this yielded irrelevant sources, for example, on image processing or extra-terrestrial bodies. Hence, "NOT" terms were added to sift out such material. After this preliminary screening, there were 356 articles remaining for individual inspection.

Step 4 further reduced the list of candidate articles based on topic relevance or lack of technical detail (48 exclusions), article type (10 abstracts only or review papers), or language (2 exclusions). For example, case studies of individual extreme weather events, or trends in sub-daily precipitation indices would not qualify on the grounds that the data were not time-scaled. In several cases, the

[4] Intensity-Duration-Frequency (IDF) curves are widely applied in hydrologic and hydraulic engineering to describe the relationship between rainfall intensity, duration, and frequency (or return period). There are essential tools for designing infrastructure to be resilient to extreme rainfall events.

word “hour” is used in passing rather than in direct reference to a modelling technique. Following this stage, 296 articles remained.

Finally, Step 5 codifies the included articles according to the primary source of data and/or methods used to disaggregate daily (or monthly) weather information. A quasi-objective and iterative approach was taken to identify recurrent terms then classify articles by temporal downscaling method. This search for groups of alike methods was initially assisted by ChatGPT using article abstracts (Annex 1).

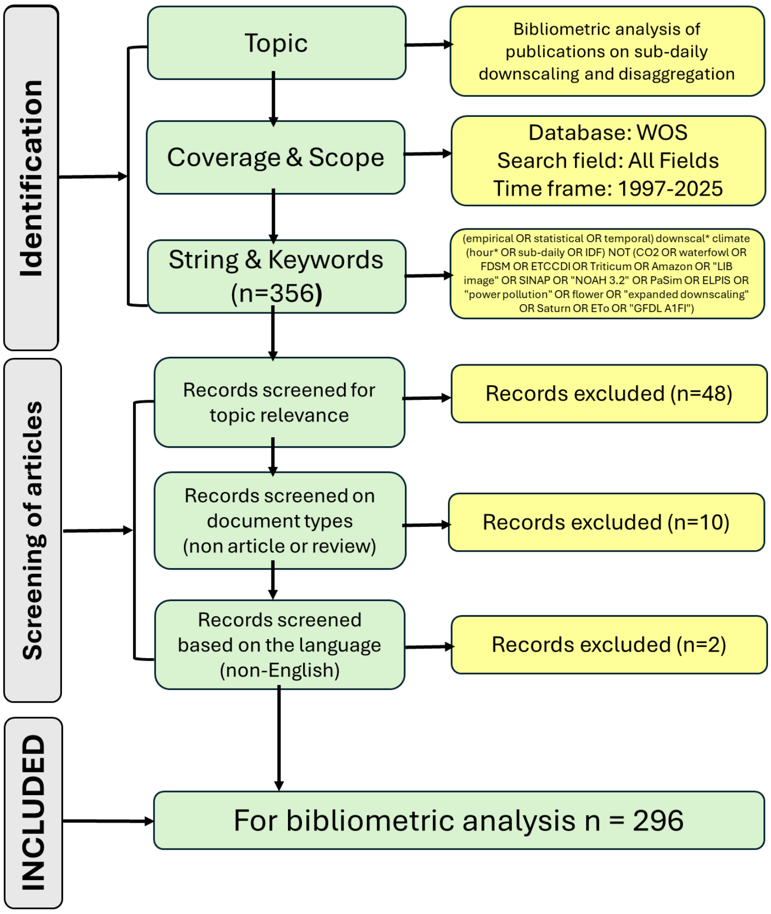

Figure 3 *Meta-analysis workflow.*

In some cases, multiple terms may be used for the same method. For instance, “change factor”, “delta change” and “morphing” are all used to describe the adjustment of present-day climate variables by projected amounts of climate change. Moreover, many articles implement multi-stage or hybrid downscaling methodologies – such as, quantile-quantile mapping of climate model rainfall to a historical rainfall series, to fit an extreme value distribution, and then project changes in the local IDF curve (e.g. Willems, 2013). In such cases, all relevant methods were tagged. This allows differentiation between single- and mixed-method approaches.

The next section describes the main themes and techniques that emerged from the included articles.

3.2. Major themes

3.2.1. Overview

Following topic identification and screening of articles, 296 articles were identified for analysis. There are few papers on the topic prior to 2010 – about 90% of included output has occurred since then. The number of articles trebled over the decade before the pandemic (2020/21) during which the volume peaked (Figure 4, left). Since then, the annual number of articles has returned to pre-2020 levels of about 25 outputs per year.

Analysis of coauthor affiliations reveals that the USA and China account for 23% and 8% of the output, respectively (Figure 4, right). Moreover, more than two thirds of the articles were attributed to coauthors affiliated to just 10 countries (USA, China, Canada, Germany, UK, South Korea, Spain, Italy, Switzerland, and Australia). The Czech Republic and Serbia are the only two countries in Eastern Europe with contributing authors (respectively Hirschi et al., 2012; Shrestha et al., 2017), but neither study referred to the Balkans.

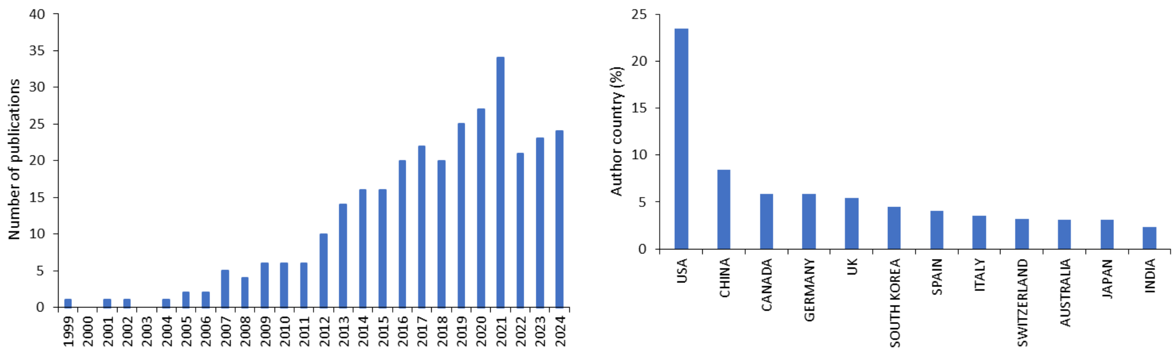

Figure 4 *Output volume by year (left panel) and as a proportion by author country (right panel).*

The top six most frequently occurring terms in paper titles were "model" (*n* = 95), "precipitation" (*n* = 72), "temperature" (*n* = 55), "rainfall" (*n* = 53), "variability" (*n* = 38), and "climate change" (*n* = 31) (Figure 5). Some of the most common multi-word phrases in the titles were "climate change" (*n* = 89), "downscaling of" (*n* = 34), "intensity duration frequency" (*n* = 38), "statistical downscaling" (*n* = 24), "high resolution" (*n* = 19), and "sub daily" (*n* = 14). This is consistent with a strong emphasis on climate change, downscaling methods, IDF curves, high-resolution modelling, and future climate projections.

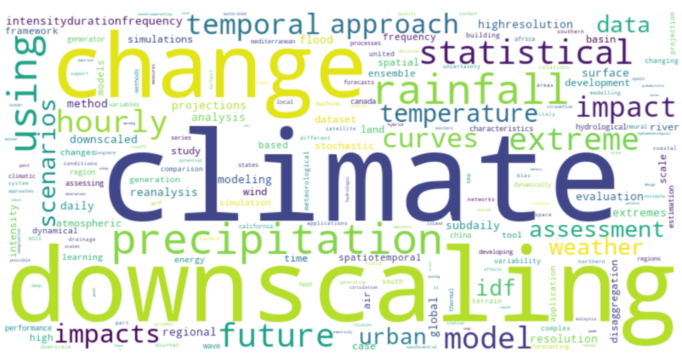

Figure 5 *Word cloud drawn from the most common words in article titles*

The top six most favoured sources were the *Journal of Hydrology* (*n* = 19), *International Journal of Climatology* (*n* = 16), *Hydrology and Earth System Sciences* (*n* = 10), *Journal of Geophysical Research-*

Atmospheres (*n* = 10), and *Theoretical and Applied Climatology* (*n* = 10). Overall, the topic appeared in 127 different journals, with the top 20 periodicals accounting for more than 50% of the total output. Amongst these 20 journals, 8 are hydrological, 5 are climate and/or meteorological, 3 are geophysical, 3 are cross-disciplinary, and 1 is energy/ building focused. Hence, there is a strong preference for the topic to be published in hydro-climate orientated journals.

The five main sectors identified from article abstracts are water and flood risk management; urban infrastructure and drainage; renewable energy and power systems; agriculture and land management; and human health (Annex A2). These require sub-daily weather information for many practical applications including: flash flood prediction and estimation of Intensity-Duration-Frequency (IDF) curves; stormwater drainage system design and infrastructure planning; energy yield and demand forecasting; soil moisture and irrigation needs; and for evaluating urban heat stress and bioclimatic indices for vulnerable populations. There are also cross-cutting uses of spatially and temporally disaggregated hydromet information by climate and weather service providers.

Downscaling and weather generator techniques have been reviewed extensively before (Wilby and Wigley, 1997; Wilks and Wilby, 1999; Fowler et al., 2007; 2025; Benestad et al., 2008; Hertig et al., 2018; Maraun and Widmann, 2018). There have also been comprehensive reviews of tools that make use of sub-daily weather information and are integral to engineering practices – such as IDF curves (e.g. Kourtis and Tsihrintzis, 2022). However, the emphasis of this Deliverable is on the specific techniques for *temporal scaling* that emerge from the included literature. The main groups of methods are (i) dynamical downscaling; (ii) statistical downscaling; (iii) stochastic; (iv) machine learning; and (v) multi-temporal models. Additionally, there are (vi) other techniques that do not fall into the previous categories or (vii) cross-cutting methods. Each set of techniques is discussed and illustrated below.

3.2.2. Dynamical downscaling

Three sub-types of dynamical downscaling are evident in the screened literature. These are based on outputs from high-resolution reanalyses, numerical weather prediction (NWP)/ forecasting models, and Regional Climate Models (RCMs).

Climate reanalyses are produced by blending climate models with observations to create gridded weather variables for the whole of the Earth's surface and for multiple levels in the atmosphere. These archives of quasi-observations can cover many decades and are typically updated in near real-time. For instance, the ECMWF Reanalysis v5 (ERA5) provides hourly estimates of numerous atmospheric, land and ocean variables since January 1940, on a 31 km grid[5]. Daily and monthly aggregates of these hourly fields are also available. Some now claim that such products have rendered obsolete traditional gridded observation data (Kusch and Davy, 2022) which gives some authors confidence in applying re-analyses products directly to land surface modelling (Muñoz-Sabater et al., 2021). However, further post-processing of reanalysis fields is normally required – such as via high-resolution forecasting (e.g. Sridhar et al., 2019), regional climate (e.g. Reder et al., 2022), or statistical downscaling models (e.g. Mahmud et al., 2008). High-resolution re-analyses may also be used to estimate temporal downscaling parameters, enabling production of IDF curves for any location globally (e.g. Courty et al., 2019; Wang et al., 2025).

[5] https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5

Numerical Weather Prediction and forecasting models are also widely used to produce information about extremes at sub-daily scales at resolutions down to just a few hundreds of metres. One potential advantage is that NWP ensembles of 10 to 50 runs are typically archived and can be post-processed to enable more thorough evaluation of forecast and downscaling uncertainties (Lee and Barker, 2023). Models such as WRF and the convection-permitting SPHERA have been used to investigate weather extremes including heavy rainfall (Giordani et al., 2023), maximum daily temperatures (Wang et al., 2016), and hourly surface ozone concentrations (Yahya et al., 2016). Some experiments have applied further scaling to NWP model output to then downscale rainfall intensities to 10 min resolution at individual weather stations (e.g. Vu et al., 2018). Alternatively, bias correction techniques (see Statistical Downscaling below) may be applied to improve the match between NWP output and extreme weather variables at the local scale (e.g. Yuan-Fong et al., 2016). Recent advances in machine learning techniques are also enabling the rapid emulation of more computationally demanding NWP models for nowcasting weather in emergency situations (e.g. Ayoub et al., 2024).

Regional Climate Models (RCMs), like NWP models, take coarse resolution information about atmospheric boundary conditions (from re-analyses and/or Global Climate Models [GCMs]) to better represent land surface feedbacks and atmospheric processes at higher resolutions over a limited area. This lateral information about wind speeds, water vapour, temperature, and pressure is generally updated every few hours. RCMs typically simulate weather at spatial resolutions of 10-50 km for several decades, although convection-permitting models may operate at 2-4 km but only for 10-20 years due to their high computational cost (Estermann et al., 2025). Results from RCMs are known to depend on the source(s) of the boundary conditions, their structure, parameterisation and resolution of rainfall processes, initial conditions, spatial and temporal resolution (Fowler et al., 2025). However, RCM experiments can be used to investigate the sensitivity of sub-daily weather extremes to land-surface changes urbanisation (e.g. Langendijk et al., 2021), as well as improve representation of topographic effects (Jang et al., 2017) and important phenomena such as atmospheric rivers (Schaller et al., 2020). Output from RCMs can also be used to assess the impact of climate change on IDF curves (e.g. Hosseinzadehtalaei et al., 2018) as well as in hybrid approaches involving statistical downscaling, weather generators, and machine learning methods (e.g. Kajbaf et al., 2023).

3.2.3. Statistical downscaling

There are literally thousands of statistical downscaling studies worldwide, but relatively few apply <u>both</u> spatial and temporal downscaling to site-level, hourly resolutions. The two main sub-types of spatial-temporal downscaling are quantile-quantile mapping (QQM) and other bias correction methods. These establish empirical relationships between variable(s) at a coarser space- (and time-) scale and variable(s) of interest at the local area/ point (sub-daily) scale.

Quantile-quantile mapping (also known as Perfect Prognosis) involves matching values in a cumulative distribution from a climate (or NWP) model with equivalent quantiles in an observed cumulative distribution (Figure 6). This is undertaken to reduce biases and/or improve resolution. For instance, percentiles of airflows from a GCM grid might be empirically related to the percentiles of observed local wind speeds (e.g. Kulkarni et al., 2018). This assumes, for example, that the 99th percentile daily mean airflow is skilful at the grid scale and is representative of the 99th percentile wind gust at the site scale. The QQM technique can be used to adjust IDF curves by matching observed daily and sub-daily rainfall quantiles within a baseline period (e.g. Crévolin et al., 2023). This involves first extracting annual maximum series and fitting them to a distribution such as GEV. The established QQM relationship is then assumed to remain valid under future climate conditions. This enables estimation of future local, sub-daily extreme rainfall from future grid-scale, daily GCM output. The QQM is highly versatile as it can be applied to reanalysis, NWP and RCM output. However, results will vary according to the expected underlying distribution and method of interpolation between distributions. The outcomes from extrapolating unobserved quantiles and/or propagation of climate change signals from GCMs are also method dependent (Pierce et al., 2015).

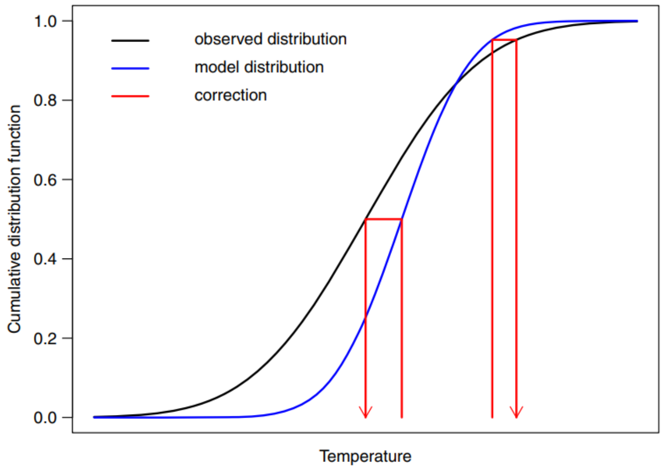

Figure 6. *Quantile mapping showing how the simulated quantile (value) from a model distribution can be replaced (downscaled) by the same quantile in an observed distribution (here temperature; Maraun, 2016)*

Most bias correction methods focus on adjusting the mean and/or variance of the target variable. However, other disaggregation techniques are needed to address frequency-dependent climate model issues. For instance, GCMs and RCMs have long been known to manifest the "drizzle" effect whereby frequencies of low-magnitude precipitation events are typically over-estimated (Dai, 2006). Various methods are available to temporally downscale bias corrected daily climate data to sub-daily precipitation values, including resampling hourly observations from meteorologically similar days (e.g. Zabel and Poschlod, 2023); applying a method based on scale-invariance (e.g. Requena et al., 2021); or disaggregating reanalysis wet-day frequencies using sub-daily remotely sensed rainfall products (Sheffield et al., 2006). Other techniques involve first bias correcting via methods akin to Model Output Statistics (MOS) – which use multiple, coarse-resolution predictor variables to estimate site-scale precipitation (and other predictands) – then secondly, scaling the *parameters* of rainfall amount distributions across different time-scales (e.g. Wilby et al., 2023). Alternatively, hourly (heat stress) metrics may be downscaled directly from bias corrected daily predictors (temperature, humidity, solar radiation, wind speed, and air pressure) from GCMs (e.g. Takakura et al., 2019).

3.2.4. Stochastic methods

Three sub-types of stochastic time-scaling methods may be used. These are weather generators (WGs), Poisson process models, and non-parametric, analogue resampling methods. Unlike dynamical downscaling and (the majority of) statistical downscaling techniques, stochastic methods are not intended to reproduce observed sub-daily *time-series*. Instead, they are meant to simulate the *distribution* of sub-daily quantities.

Stochastic weather generators – such as CLIGEN and LARS-WG – typically represent day-to-day (or multi-day) transitions between two or more weather pattern (or wet/dry day) states using Markov chains. In turn, these states condition secondary variables such as daily rainfall amounts, maximum and minimum temperatures, and solar radiation (e.g. Halder and Saha, 2024). To obtain sub-daily weather information, further statistical modelling or resampling of observed sub-daily quantities is required (Park and Chung, 2020). For example, weather types can be used to estimate daily maximum wave heights that are then used to predict distributions of hourly wave heights from which values are randomly drawn (e.g. Lucio et al., 2020). Alternatively, the hourly behaviour of variables like solar radiation, temperature and humidity can be represented via predictable diurnal cycles, specified bythe daily mean and maximum-minimum range (e.g. Aurambout et al., 2024; Saad et al., 2025). Other weather generators estimate local parameters of sub-daily behaviour (such as the monthly maximum 30-minute rainfall intensity in CLIGEN) from statistical relationships with more readily available daily to monthly aggregations of wet-day amounts, wet-to-wet day transitions, temperature, and other indices (Fullhart et al., 2023). Wet- and dry-spell durations may also be generated using an hourly (rather than daily) renewal process by sampling from mutually independent probability distributions (e.g. Peleg et al., 2019).

Poisson process algorithms such as the Bartlett-Lewis Rectangular Pulse, HYETOS, Neyman-Scott Rectangular Pulses (NSRP), and RainSim envisage sub-daily rainfall associated with clusters of rain cells within a storm (Figure 7). Storm origins occur as a Poisson process with simulated arrival rate (Figure 7a), and exponentially distributed cell number (Figure 7b), time interval, duration, and rainfall intensities (Figure 7c). The total rainfall intensity is then equal to the sum of the intensities of all the active cells at that time (Figure 7d). This approach has several advantages: (1) extreme rainfall intensity and other features of interest (such as pulse duration) can be produced over timescales of minutes to days; (2) extreme values can be stochastically generated that are outside the range of the training data; and (3) model parameters can be recalibrated using GCM or RCM rainfall series to produce IDF curves consistent with future climate conditions (Khazaei, 2021). Moreover, the basic NSRP model can be extended to multi-site applications with parameters representing the spatial density and mean radius of rain cells, and spatial autocorrelation of precipitation (Sørup et al., 2016). However, hybrid Poisson rainfall/weather generator configurations are needed to generate synthetic hourly rainfall series alongside other synthetic variables needed for hydrological modelling (e.g. Zhang et al., 2019).

Non-parametric resampling methods drawn from libraries of days with sub-daily meteorological information that can be recalled based on the similarity of their daily state with a randomly generated analogue (e.g. Keller et al., 2017). For instance, large-scale reanalysis data sets may be used to define daily weather types and associated patterns of multi-site rainfall. Hourly rainfall series from the *k* nearest neighbour candidate days are then be chosen with or without further adjustments to the sequence of amounts (as in Lin et al., 2017). Such weather pattern techniques do not require any assumptions about the distribution(s) of underlying data. They are also highly versatile as evidenced by applications to extreme hourly precipitation (Rau et al., 2020), heat and air pollution (Cheng et al., 2008), solar radiation (Jiménez-Valero et al., 2022), wind (O'Neill et al., 2017) and wave conditions (Camus et al., 2017). However, the following major assumptions are made when resampling from weather patterns under future climate conditions: (1) there is a strong relationship between the patterns and the target variable(s); (2) the weather patterns and their changed frequencies are well-represented by the GCM or RCM; and (3) the relationship between the weather patterns and target variables are stationary over decadal time-scales (Haberlandt et al., 2015).

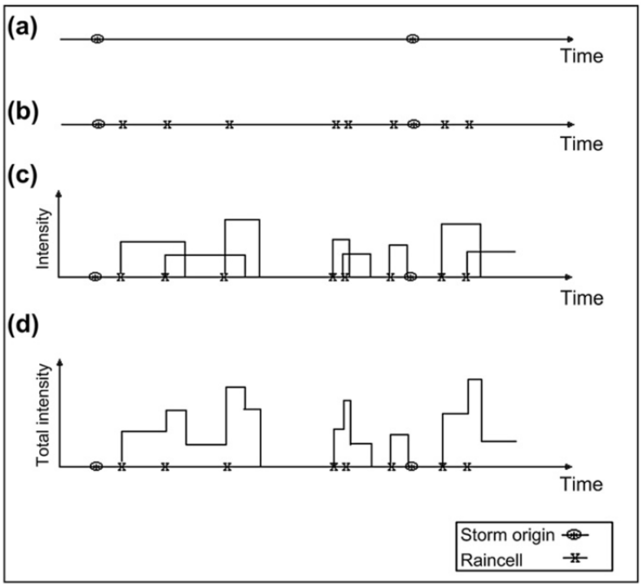

Figure 7. *A schematic of the NSRP model (Kilbsy et al., 2007)*

3.2.5. Machine learning

Two sub-types of machine learning were identified. These are Artificial Neural Networks (ANNs) and adaptive optimization techniques (such as Random Forests [RFs], Gradient Boosting [GB], and Genetic Algorithms [GA]).

Artificial Neural Networks have been used in downscaling for a long time (Hewitson and Crane, 1996) but there are relatively few examples of their application to temporal downscaling or disaggregation. ANNs are essentially black box models that relate inputs and outputs via mathematical networks of nodes, weights and linkages. This means that sub-daily data are always needed to train ANNs. Such information may be obtained from various sources, including observations/ re-analysis products (e.g. Kumar et al., 2012), weather forecasting models (Afshari et al., 2023), or GCM-RCM combinations (e.g. Mirhosseini et al., 2014). For instance, one early study used time series of pre-, concurrent, and post hourly rainfall as input, and four 15 min rainfall totals for the middle hour as output (Zhang et al., 2008). In another case, an ANN was trained on the relationship between hourly ground-level nitrogen dioxide (NO_2) observations and daily tropospheric NO_2 column density from the TROPOMI satellite and other atmospheric variables to downscale the daily NO_2 to hourly surface concentrations (Yu and Liu. 2021). Other diverse applications include downscaling daily GCM output to hourly wind, solar and temperature variables at 4 km resolution for the energy sector (Buster et al., 2024); hourly WRF output to 1 km resolution near surface urban temperatures (Afshari et al., 2023); 30 km ERA5 reanalysis to 0.1 km resolution evaporation estimates for a high-altitude saline lake ecosystem (Lobos-Roco et al., 2022); and 3 h RCM precipitation fields to 2-h, 1-h, 30- and 15-min durations to generate present and future IDF curves (Kajbaf et al., 2022).

Random Forests (RFs) and Genetic Algorithms (GAs) are machine learning techniques that support data classification and regression modelling. They have been used as an adaptive approach to optimising and calibrating temporal downscaling models. For example, RFs and GAs were able to emulate 15-min streamflow in ungauged situations given hydrological model parameter sets and daily streamflows (Budamala et al., 2022). Others have used RFs to regress monthly atmospheric predictors and daily rainfall against sub-daily rainfall statistics at hundreds of sites to estimate the parameters needed to run a Poisson cluster model (Diez-Sierra and del Jesus, 2019). Similarly, RFs can take information about site coordinates (latitude, longitude), elevation, distance from coast and climate regime to estimate a local scaling parameter for sub-daily extreme rainfall estimation (Wang et al., 2025). Regression-based estimates of IDF parameters may also be enhanced by Gradient Boosting trees (e.g. Hu and Ayyub, 2019). Likewise, non-parametric resampling algorithms for sub-daily rainfall may be optimized using Genetic Algorithms (e.g. Lee and Jeong, 2014).

3.2.6. Multi-temporal methods

Two sub-types of multi-temporal downscaling methods were identified. These are scale-invariant (fractal-based) methods and multiplicative cascade models.

Scale-invariance of annual maximum rainfall has been recognised for a long time (Menabde et al., 1999). This means that rainfall intensities of given return period and duration are scalable from intensities observed over other longer or shorter durations. Hence, intensities (mm/h) measured over durations of 1- to 24-h can be used to estimate a scaling parameter from which sub-hourly intensities can be extrapolated (Figure 8). Moreover, a very appealing aspect of scaling is that the technique can be applied to daily rainfall records to estimate sub-daily intensities (e.g. Benestad et al., 2021). In practice, there may be regionally dependent breakpoints in the scaling which relate to changes in the underlying atmospheric dynamics that are generating the extreme rainfall. In this case, multi-scaling is required (Courty et al., 2018). For example, an observed breakpoint between 30-min and 1-h in rainfall data for the Pacific island of Guam island was attributed to a transition from local storm systems to that of large-scale tropical depressions (Yeo et al., 2022). Scaling parameters for ungauged sites can be estimated from homogeneous rainfall regions and physiographic variable such as site elevation and distance from coast (e.g. Wang et al., 2024). When applied to bias corrected GCM or RCM output, scaling can be used to investigate the effect of climate change on present and future IDF curves (e.g. Herath et al., 2016; Requena et al., 2021; Tabari et al., 2021). Daily to sub-daily scaling techniques are also applicable to extreme hourly wind speeds (e.g. Shin et al., 2018).

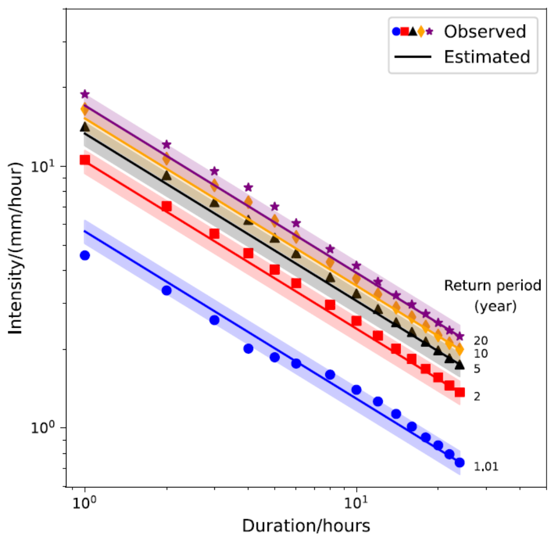

Figure 8. *Estimated (lines with 10% error zones) and observed (solid dots) IDF curves for rainfall intensities (mm/h) at a site in Oxfordshire over durations of 1–24 h (Wang et al., 2024)*

Single site cascade models disaggregate daily rainfall totals into successively finer time-steps depending on the branching number which maybe varied or held constant throughout the sequence (as in Figure 9). Rainfall amounts from the previous step are sub-divided stochastically on each bifurcation using splitting weights (based on either empirical or theoretical density functions) (Olsson, 1998). This means that the aggregate of split rainfall amounts always sums to the initial total. Temperature dependence can be introduced by stratifying the rainfall and hence model parameters by temperature bin (Bürger et al., 2019). This allows adjustment of simulations for climate change. However, the autocorrelation of cascade series typically underestimates observed but can be improved by conditioning model parameters on circulation patterns (Lisniak et al., 2013). Other (resampling) methods are needed to extend to multi-site applications (e.g. Müller and Haberlandt, 2018) and simpler methods may produce annual maximum series that are closer to observations (Alzahrani et al., 2023). Moreover, splitting weights have been shown to vary with time of day, month, decade, rainfall volume, event structure and ENSO anomaly (McIntyre et al., 2016).

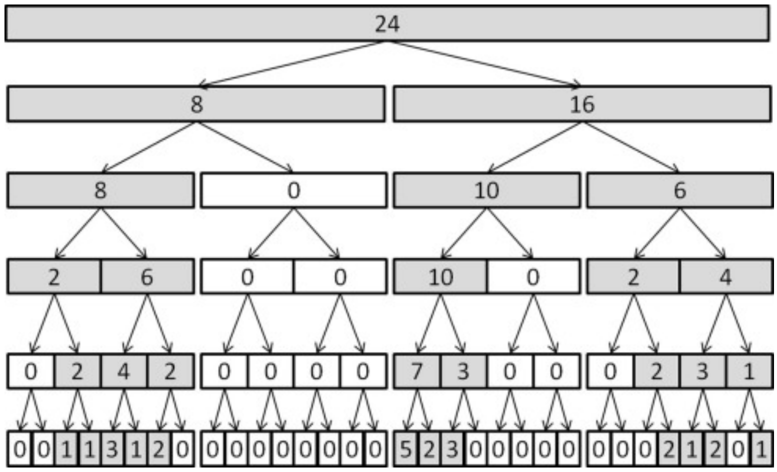

Figure 9. *Multiplicative cascade model scheme, beginning with a rainfall amount of 24 mm. In this case the branching number is 2 throughout the cascade (Müller and Haberlandt, 2018).*

3.2.7. Other approaches

Other approaches emerge from the literature. These mainly involve downscaling coarse-resolution satellite products to higher-resolution surface variables. This is particularly helpful for regions where there are sparse surface observations. Most studies are concerned with improving spatial resolution, but a few involve time-scaling. For instance, four-per-day remotely sensed Land Surface Temperature (LST) images were downscaled using regression-based methods to hourly in situ measurements of LSTs (Sara et al., 2024); LANDSAT (higher spatial resolution) and MODIS (higher temporal resolution) data have been blended by machine learning (ANN, RF, GB) to predict sub-daily LST at 30 m resolution for a remote area of the Antarctic (Lezama Valdes et al., 2021); and information from multiple satellite sensors have been combined to fill data gaps and temporally downscale LST via a pixel level fusion model (Desai et al., 2021).

Several satellite/model-derived products are also available at sub-daily time-scales for precipitation. These quasi-global gridded hourly data include the 0.1° resolution GSMaP-std V8 (Kubota et al., 2024); 0.1° MSWEP-ng V2.8 (Beck et al., 2019); 0.4° PERSIANN-CCS (Hong et al., 2004); and 0.4° PDIR-Now (Nguyen et al., 2020). Overall, MSWEP V2.8 (daily) demonstrated the best performance when used to simulate observed daily streamflow for 16,295 catchments (Abbas et al., 2025). However, further research is needed to evaluate sub-daily precipitation products in the same way.

3.2.8. Crossing-cutting methods

Finally, there are two widely adopted cross-cutting methods. These are intensity-duration-frequency (IDF) curves widely used in engineering design, and change factors (CFs) for adjusting sub-daily weather extremes by projected changes in climate.

Intensity-duration-frequency curves are the end point of ~50 included articles, regardless of the input data or downscaling techniques applied. For instance, IDF curves were cited as the rationale in all the following hybrid approaches: GCM weather types with scaling parameters (Bermúdez et al., 2022); North American Regional Reanalysis with analogues (Sridhar et al., 2019); RCM with quantile mapping (So et al., 2017); RCM with multi-temporal scaling (Wilby et al., 2023); and daily weather generator with multi-temporal scaling (Lu and Qin, 2020).

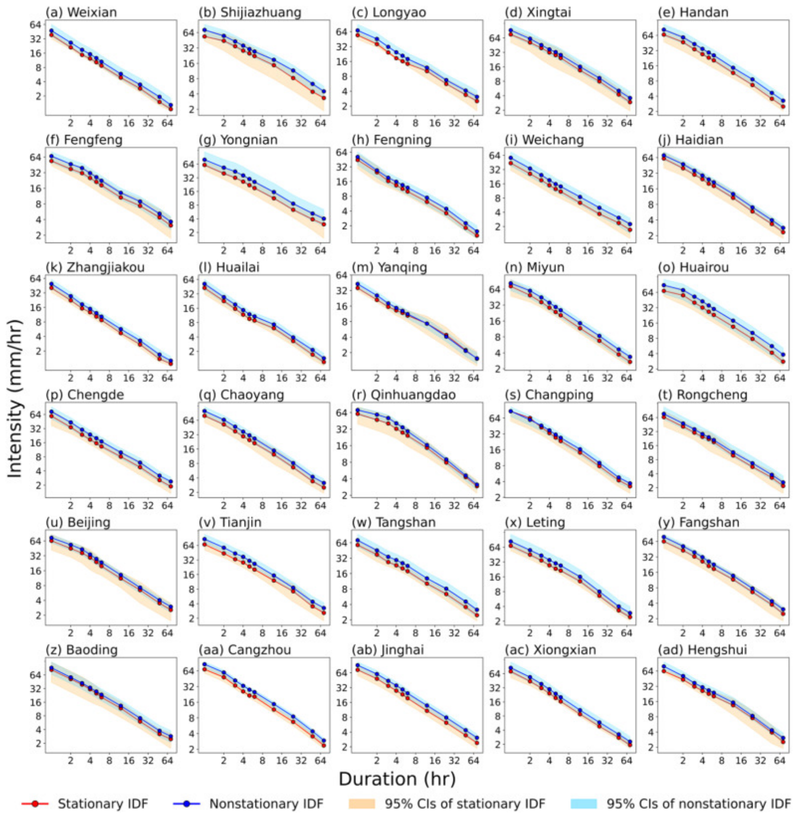

Figure 10. *Stationary and nonstationary IDF curves with 95% confidence intervals during 2050–2074 under SSP585, given a return period of 25-years. Red lines represent stationary IDF curves; blue lines are nonstationary IDF curves. Orange bands represent the 95% confidence intervals for the stationary IDF; blue bands are the same for the nonstationary IDF (Song et al., 2025).*

Some articles also incorporate procedures for adjusting IDF curves for future climate conditions (as in Figure 10). Revised curves may emerge from bias corrected and/or spatially downscaled GCM/RCM output under different greenhouse gas emissions scenarios. Climate model output can then be used in several ways to produce climate-adjusted IDF curves. First, a future IDF curve may be derived directly from spatially and temporally downscaled GCM/RCM output (e.g. Herath et al., 2016; Singh et al., 2016). Second, downscaled daily rainfall (or annual maximum) series can be modified using change factors from GCMs/RCMs then temporally scaled to sub-daily durations to create a future IDF curve (e.g. Shrestha et al., 2017). Third, changes between return-period intensities from downscaled present and future IDF curves can be used to rescale the same return-period intensities on a historical IDF curve (e.g. Cook et al., 2017; Zhao et al., 2021). Where there are ensembles of GCMs/RCMs and emissions scenarios, confidence intervals can be attached to IDF curves (e.g. Halder and Saha, 2024).

3.3. Comparison and summary of techniques

The above typology of sub-daily downscaling may give the impression that the various techniques are mutually exclusive. In practice, at least 45% of the articles are implementing more than one method so should be regarded as hybrid.

Overall, the five most preferred temporal scaling methods are: stochastic weather generators (*n* = 46 articles), numerical weather prediction and forecasting models (*n* = 40), scale invariance/power law methods (*n* = 39), RCMs (*n* = 37), and analogue/resampling techniques (*n* = 37) (Figure 11). At least 20% of the articles apply some form of bias correction to the re-analysis, NWP, GCM, or RCM inputs, prior to the temporal downscaling or disaggregation step. Quantile-quantile mapping is used in nearly 10% of the studies.

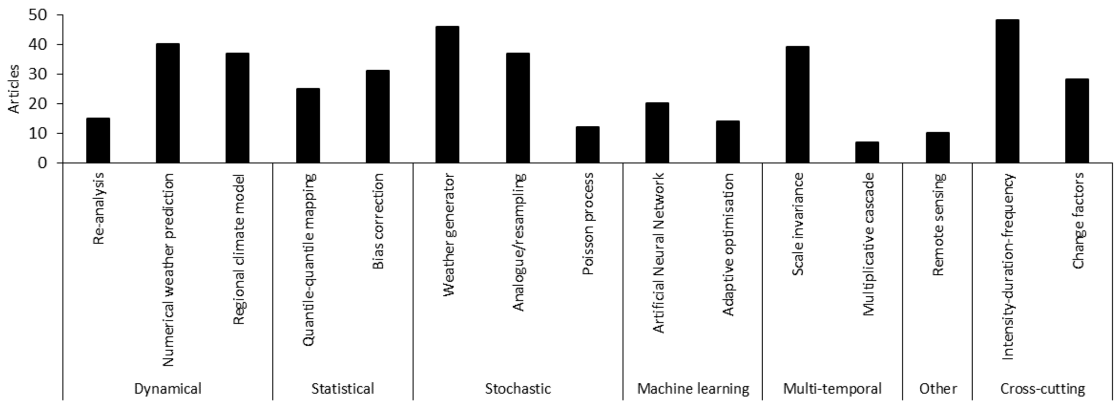

Figure 11. *Number of articles applying various time-scaling and cross-cutting methods to estimate sub-daily weather extremes. Note that counts are not mutually exclusive to reflect hybrid methods*

The three least favoured techniques (excluding remote sensing methods) are multiplicative cascade models (*n* = 7 articles), Poisson process models (*n* = 12), and machine learning adaptive optimisation methods (*n* = 14). Arguably, all of these techniques are more involved to apply.

Each temporal scaling or disaggregation method has distinctive strengths and weaknesses (Table 1). All require high-resolution (hourly or less) observational data to implement or, at very least, to verify techniques. However, varying degrees of process representation are involved. Dynamical downscaling schemes resolve physical processes, sometimes at cloud convection scales, over large domains with good representation of orographic controls. Statistical downscaling and stochastic methods have intermediate complexity and partial process representation due to the influence of circulation patterns, and other large-scale drivers of local weather extremes. Multi-temporal scaling recognises that different rainfall dynamics operate at different time- and space-scales. However, ANN methods are essentially black box models, apart from the implicit process insight conveyed by input variables.

There have been many intercomparison studies of dynamical-v-dynamical, statistical-v-statistical, and dynamical-v-statistical *spatial* downscaling methods using benchmark data sets and performance metrics (e.g. Wilby et al., 1998; Mearns et al., 1999; 2013; Haylock et al., 2006; Déqué et al., 2007; Schmidli et al., 2007; Gutmann et al., 2012; Hertig et al., 2018). The EU VALUE project also created a framework for downscaling model validation and comparison (Maraun et al. 2015). There has been no equivalent, systematic assessment of different *temporal* downscaling methods, to date.

Instead, there are a few side-by-side comparisons of some techniques. For example, Sunyer et al. (2015) assessed projected changes and uncertainties in extreme hourly precipitation over Denmark using a change factor method, weather generator, and climate analogue approach to downscale RCM output. Their results showed increases in extreme precipitation but the extent of change varied with location and RCM. Poschlod et al. (2018) compared the properties of hourly precipitation over Oslo produced by WRF and a non-parametric disaggregation technique (Method of Fragments, MoF). The stochastic model represented summary statistics well but could not replicate either the spatial or temporal coherence of precipitation. The WRF model reproduced the spatial and temporal coherence but tended to underestimate peak intensities at 1h an 3h resolutions (Figure 12). Hassanzadeh et al. (2021) found inconsistent future extreme precipitation values for Montréal when comparing the scenarios from two quantile mapping methods with a hybrid weather generator-analogue method. Arfa et al. (2021) reported that the scale invariance method outperformed the MoF for sub-daily extreme rainfall intensities in Tehran.

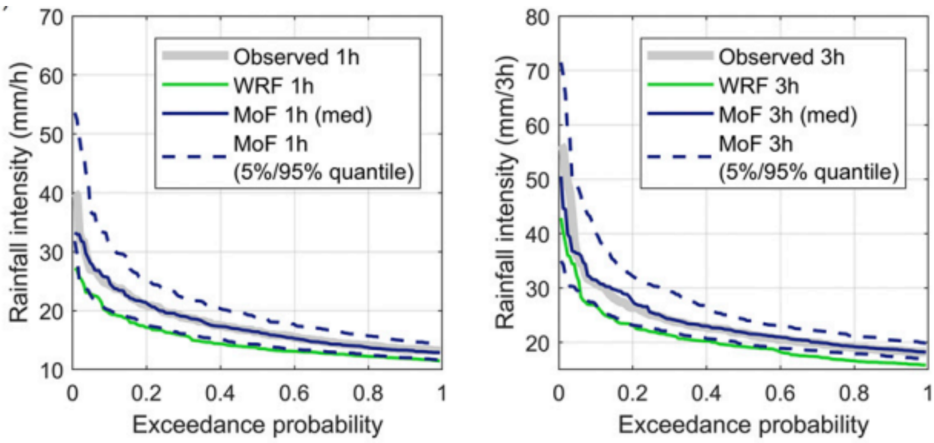

Figure 12. *Empirical annual exceedance probabilities for extreme rainfall intensities over 1h and 3h durations for observed, WRF, and the Method of Fragments (MoF; Poschlod et al., 2018).*

These pieces of evidence confirm the view – more generally from dynamical-statical downscaling intercomparisons – that different methods yield different levels of accuracy when estimating extreme rainfall in different locations. Establishing the physical basis of such variations is seldom done (Fowler et al., 2025). This leads to the conclusions that the preferred method of temporal downscaling will likely reflect practical considerations around the (1) intended use(s); (2) required spatial (single- site v multi-site) and temporal (sub-hourly v hourly) resolutions; and (3) available time, technical and (data) resources. Overall, scale invariance methods are favoured for single-site, sub-hourly extremes; hybrid weather generator-analogue methods for multi-site, hourly extremes; and hybrid NWP-QQM methods for continuous simulations of hydrology in large catchments. All these methods can be adapted for climate change projections and creation of adjusted IDF curves. However, where surface data are limited or unavailable, high temporal-spatial resolution satellite/merged precipitation products may be an option. Alternatively, IDF curves may reconstituted from global models of scaling parameters based on regional climate and physiographic variables (e.g. Wang et al., 2025).

The following case study demonstrates the construction and evaluation of hourly to sub-hourly extreme rainfall estimates for a data sparse region of eastern Europe using publicly available 6h data.

Table 1 *The main strengths and weaknesses of temporal downscaling and disaggregation methods with examples of good practice in each case.*

Group	Sub-type	Strengths	Weaknesses	Example
Dynamical downscaling	High-resolution re-analysis products (e.g. ERA5, NARR)	Globally available, gridded weather variables that are amenable for sub-daily hydrological modelling and extreme event analysis.	Highest spatial and temporal resolutions are typically ~30 km and hourly. Post-processing and/or downscaling is required for station and sub-hourly scales.	Tilloy et al. (2025)
	Numerical weather prediction and forecasting models (e.g. WRF)	High-resolution, weather simulations at 1 km hourly resolution for various extremes (heavy rain, heatwaves, wind gust). Resolves orographic effects.	Applied over limited areas due to high computational cost. Post-processing and/or further downscaling is needed for site and sub-hourly scales.	Vu et al. (2018)
	High-resolution Regional Climate Models (RCMs)	As above. Can also be run with future climate and land surface conditions. Responds in physically consistent ways to external forcings.	As above. Results are also sensitive to parameterisation, realism of the boundary model, temporal and spatial resolutions. Cloud/ convection scheme affects precipitation results.	Reder et al. (2022)
Statistical downscaling	Quantile-quantile mapping (QQM)	Relatively easy to apply and can be fit to highest resolution data available. Applicable to output from reanalyses, NWP, and RCMs.	Assumes stationary quantile-quantile relationships. Problematic when extrapolating beyond observed quantiles, including for climate change signals. Depends on assumed distribution function and interpolation method.	Song et al. (2025)
	Bias correction (BC)	As above. Typically mean and/or variance correction via first spatial downscaling then time scaling using large-scale predictor variables. Many transfer functions are available.	Extra steps are needed to address frequency-dependent biases. Future climate projections are sensitive to the bias correction method(s) applied.	Forestieri et al. (2017)
Stochastic	Weather generators (e.g. AWE-GEN, CLIGEN, LARS-WG, SDSM)	Versatile method for conditioning various sub-daily quantities. Can quickly generate very long series or distributions for impact simulations.	Typically operates on a daily time-step so further statistical disaggregation or resampling is needed to derive sub-daily series and extremes. Parameters are assumed to be valid for climate change. Can produce unanticipated effects in secondary variables when changing precipitation parameters.	Lucio et al. (2020)
	Analogue/resampling (e.g. KNN)	Versatile method for conditioning various observed sub-daily quantities such as extreme rainfall, temperatures, air pollution, wind and wave conditions. No prior assumptions are needed about the data distribution.	Typically requires bespoke or pre-existing weather patterns to stratify sub-daily data. Weather pattern to predictand relationships are assumed to be strong and stationary.	Lin et al. (2017)
	Poisson process (e.g. NSRP)	Applicable over timescales of minutes to hours and can generate previously unseen rainfall extremes. Parameters can be tuned using high-resolution RCM output for producing future IDF curves.	Poisson process models assume that storm and rain cell occurrences are independent so persistence of rainfall may be understated without incorporating autoregression. Rescaling is needed to ensure consistent rainfall totals across timescales.	Park et al. (2019)
Machine learning	Artificial Neural Networks (ANNs)	Underlying process understanding is not required. Complex, non-linear input-output relationships can be handled.	Requires well-distributed input predictor variables and data for training the network at the target time interval. Overtraining of the network can weaken predictive ability.	Noor et al. (2018)

	Adaptive optimisation (e.g. RFs, GAs, XGB, GBT)	Powerful tools for optimising regression- and *k*-nearest neighbour models for estimating stochastic rainfall model parameters or resampling sub-daily extremes.	Results are sensitive to algorithm parameters and evaluation function. Computational demands may be high for large sampling frames. Noisy data may yield unreliable predictions.	Sebbar et al. (2023)
Multi-temporal	Scale invariance methods	Relatively easy to apply and enables estimation of sub-daily extreme values from observed and climate model daily rainfall (and wind). Scaling parameters can be estimated for ungauged sites using physiographic data.	Scaling parameters are sensitive to the underlining probability distribution(s) used for extreme value estimation, the range of durations spanned, and the presence of any break-points.	Wang et al. (2024)
	Cascade models	Cascaded amounts conserve the total of the initial time-step (i.e. daily rainfall). Can achieve temporal disaggregation to a few minutes. Can be extended to multi-sites using resampling algorithms and incorporate temperature-dependent effects.	Unless the branch number can be varied from 2, the day length is required to be 1280 mins to yield 5- or 10-min values. Autocorrelation of disaggregated series is typically underestimated. Parameters vary with time of day and season.	Müller and Haberlandt (2018)
Other	Remote sensing	High temporal and spatial resolution precipitation products and Land Surface Temperatures achieved by blending information from satellites, models and surface measurements.	Relatively few examples of temporal downscaling; most studies are concerned with improving spatial resolution. Data are needed to ground-truth satellite measurements. Accuracy varies by climate regime and region.	Nguyen et al. (2020)
Cross-cutting	Intensity-duration-frequency (IDF) curves	Standard way of capturing information about extreme values in a format that is useful to engineers and planners for certain design applications.	Stationarity assumption of historic IDF curves is invalid for long-lived infrastructure. High-resolution data for creating IDF curves are not always available. Time series are needed in applications such as water resource management.	Benestad et al. (2021)
	Change factors	Straightforward technique for applying projected climate changes to baseline weather series. Uncertainty due to climate model, emissions scenario, and climate variability may be reflected in the range of factors used.	Results may vary depending on how/when the change factors are applied to baseline data, annual maximum series, extreme value distribution, or historical IDF curve. Assumes climate model biases cancel over different periods. Assumes that the climate change signal is accurate.	Cook et al. (2017)

4. CASE STUDY

The following case study demonstrates a parsimonious multi-temporal, scale invariance method using time-series of 6 h rainfall from an open access data source. Equivalent site-specific scaling parameters (Beta) for multiple locations may subsequently be related to readily accessible physiographic variables to estimate sub-6 h extreme rainfall at ungauged sites. Here, the procedure is shown using annual maximum series based on daily and 6 h rainfall records for Novi Sad in Vojvodina (Figure 13).

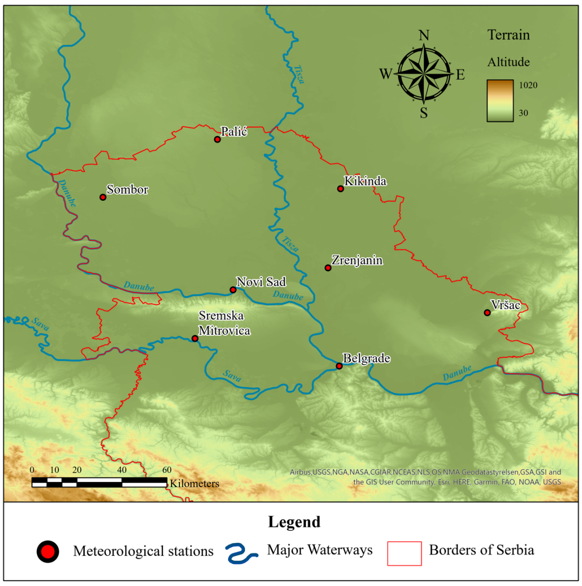

Figure 13. *Daily rainfall stations in Vojvodina, Serbia*.

4.1. Data sources

Rainfall data for Novi Sad were obtained from two sources. First, daily totals were provided by the Republički Hidrometeorološki Zavod Srbije (RHMZ) for the years 1961-2024. These data were used to calculate the 24 h and 48 h annual maximum series (AMS). Second, 6 h rainfall totals were extracted from the OGIMET Weather Information Service[6]. These raw data were post-processed to ensure consistent 6 h time steps (accounting for missing observations), disaggregation of 12 h totals into 6 h amounts, and checking the consistency of daily totals with the sum of previous four 6 h amounts. The AMS were then derived for 6 h, 12 h, 24 h and 48 h durations for the period 2001-2024. Note, that maxima were not constrained to fit within the daily reporting hours of 06:00 to 06:00. This ensures that maximum intensities for 12 h, 24 h and 48 h – that potentially span multiple reporting days – can still be detected. For consistency, all models were evaluated using a common period of 2001-2024.

4.2. Method

The workflow described by Wang et al. (2024: 288-290) is reproduced here. First, the Gumbel (EV1) distribution was used to construct IDF tables from 24 h extreme rainfall intensities because of the

[6] https://www.ogimet.com/home.phtml.en

ease of calculating parameters and performance at replicating AMS at sites globally (Rodríguez-Solà et al., 2017). Next, it was assumed that the sub-daily rainfall intensity $i_{d,T}$ for duration d (hours) and return period T (years) has the following scaling relationship with another rainfall intensity series of duration D (hours):

$$i_{\,d,T} = \lambda^{\beta} \cdot i_{D,T}$$

where λ is a scaling variable that depends on the scale ratio *d/D* and *β* is the scaling parameter. Both sides of the above equation are raised by power *q* to obtain:

$$i_{d,T}^{q} = \left(\frac{d}{D}\right)^{K(q)} \cdot i_{D,T}^{q}$$

where *K(q)* is some function of *q*. The *K(q)* function can be either linear or non-linear. When linear, the scaling process is a simple scale or mono-fractal; otherwise it is multiscale or multi-fractal. Most studies assume scaling to be linear (e.g. Angulo-Fernández et al., 2018; Menabde et al., 1999). In this case, *K(q)* is a linear function of *β* expressed below:

$$K(q) = \beta q$$

The scaling parameter *β* is derived from the slope of the *K(q)-q* plot and thus the final temporal scaling relationship is given by:

$$i_{\,d,T} = \left(\frac{d}{D}\right)^{\beta} \cdot i_{D,T}$$

Given parameter *β* and the 24 h mean intensity (mm/h) for a specified return period (assuming the EV1 distribution), it is then possible to scale sub-daily intensities for required duration(s). The accuracy of this method was assessed using (a) rainfall intensities over durations less than 2 h read from previously published IDF curves for Novi Sad (Figure 14), and (b) an IDF table of rainfall intensities with durations 6 h and 12 h based on OGIMET data.

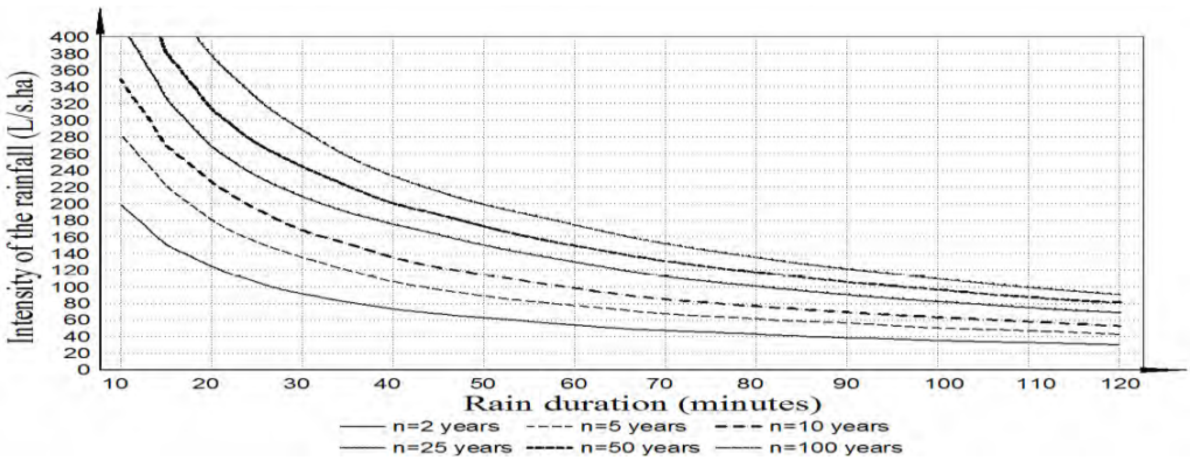

Figure 14. *IDF curves for Novi Sad. Source: Stipić et al. (2014).*

4.3. Results

Based on the 24 h and 48 h AMS derived from daily rainfall records for the period 2001-2024, the value of *β* = -0.700. If a longer calibration period 1961-2024 is used, the value of *β* = -0.715. This finding is consistent with previous analyses showing that – in the absence of major non-homogeneities, such as a weather station move – the value of *β* is generally stable between periods (Wang et al., 2024).

The first test of the temporal downscaling method was against published values for 0.25 h, 0.5 h, 1 h and 2 h rainfall intensities with 2, 5, 10 and 25 year return periods for Novi Sad (Figure 15). Return periods greater than 25 years were not considered due to the brevity of the training data. Overall, there is a tendency for the scaling model to underestimate published intensities across the assessed durations and return periods (Figure 15). However, with a Mean Absolute Error (MAE) of 13% the temporally scaled estimates are in the region of rainfall measurement error.

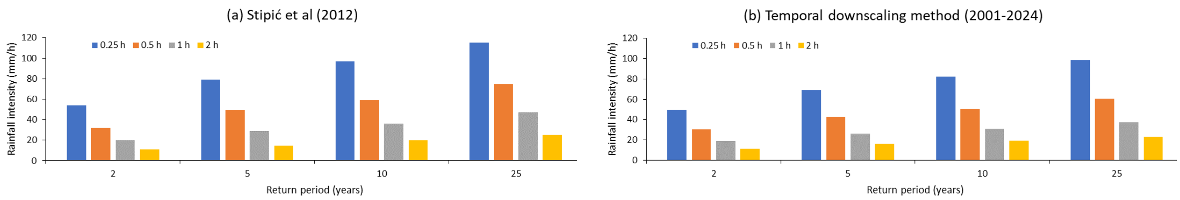

Figure 15. *Comparison of (a) published and (b) temporally downscaled IDF values for Novi Sad.*

The second test compared temporally downscaled 6 h and 12 h extreme rainfall intensities with values derived from OGIMET data (Figure 16). This enabled evaluation of longer duration, sub-daily events for return periods up to 25 years. As before, the scaling model underestimated rainfall intensities across all durations and return periods. The MAE for 6 h and 12 h durations was 18% when scaling from the RHMZ daily record. However, if the 24 h rainfall intensities from OGIMET are used instead, the MAE reduces to just 5%. This shows the benefit of relaxing the fixed 24 h period for recording.

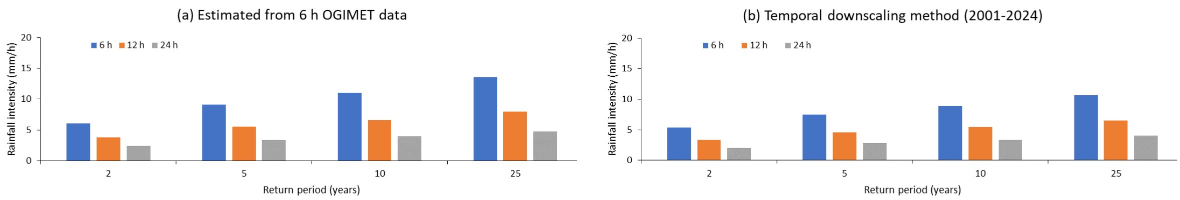

Figure 16*. Comparison of (a) OGIMET and (b) temporally downscaled IDF values for Novi Sad.*

4.4. Discussion

The above case study for Novi Sad supports the view that a single parameter (β) temporal scaling model can produce robust estimates of 0.25 h to 12 h extreme rainfall intensities when given only daily rainfall series. The next step will be to apply the same scaling model to all 26 rainfall recording stations in Serbia. This will enable testing of the generality of the findings, as well as the feasibility of predicting β from physiographic variables such as site elevation, distance from coast, latitude and longitude. Provided that such spatial-temporal scaling relationships can be established, it will then be possible to construct IDF curves for any location in Serbia – even for areas where there are currently no surface rainfall measurements. Comparable methods may also be used to scale heatwave intensity duration frequency (HIDF) curves (e.g. Ouarda and Charron, 2018; Mazdiyasni et al., 2019).

In due course, the above methods should be extended to climate change applications. This would address the likelihood that IDF curves in Serbia are non-stationary under a changing climate. Without adjusting the IDF curve, future rainfall (and heatwave) intensities could be underestimated, leading to under-design and potential failure of infrastructure during extreme weather events. Fortunately, there are several ways of incorporating future climate change into IDF curves using climate model output (e.g. Herath et al., 2016; Shrestha et al., 2017; Zhao et al., 2021). This will be a priority for future research.

5. KEY FINDINGS AND RECOMMENDATIONS

The frequency, severity, and duration of extreme weather – such as floods, heatwaves, and droughts – are increasing globally. Unfortunately, high-resolution, sub-daily weather data are not widely available in the Balkans, and especially in Serbia. This hampers efforts to upgrade the design and climate resilience of long-lived urban drainage systems, flood defences, bridges, energy systems, and other critical infrastructure.

This Deliverable provides the first global systematic review of spatial and temporal scaling methods used to bridge the gap between more readily available daily/ monthly weather data, and less plentiful sub-daily data. A parsimonious temporal downscaling method for estimating local intensity-frequency-duration (IDF) curves for extreme rainfall is also demonstrated for Serbia.

A five-step workflow was used to sift peer-reviewed, scientific literature to draw out key themes and evidence in line with best-practice guidance on systematic review protocols. After screening articles for topic relevance and output type, 296 sources were included for in depth, bibliometric analysis. The key findings were as follows:

(i) Approximately 90% of articles on temporal scaling have been published since 2010, with two thirds of these outputs attributed to coauthors affiliated to just 10 countries (USA, China, Canada, Germany, UK, South Korea, Spain, Italy, Switzerland, and Australia).

(ii) The top 20 most frequently used periodicals account for more than 50% of the articles. Amongst these journals, 8 are hydrological, 5 are climate and/or meteorological, 3 are geophysical, 3 are cross-disciplinary, and 1 is energy/ building focused.

(iii) The five main sectors identified from included article abstracts were water and flood risk management; urban infrastructure and drainage; renewable energy and power systems; agriculture and land management; and human health. These sectors all require sub-daily weather information.

(iv) Seven main groups of temporal scaling technique were identified. These are: (1) dynamical downscaling; (2) statistical downscaling; (3) stochastic methods; (4) machine learning; (5) multi-temporal models; (6) other techniques; and (7) cross-cutting methods.

(v) The five most popular methods were found to be: stochastic weather generators; Numerical Weather Prediction (NWP) and forecasting models; scale invariance/power law methods; Regional Climate Models; and analogue/resampling techniques.

(vi) Nearly half of included articles apply more than one method of sub-daily downscaling so should be regarded as hybrid in approach. Some form of bias correction and/or quantile-quantile mapping (QQM) is used in 20% and 10% of the studies, respectively.

(vii) Each temporal scaling or disaggregation method has distinctive strengths and weaknesses. However, there have been very few systematic side-by-side comparisons of different temporal scaling methods, to date.

(viii) The preferred method of temporal downscaling reflects practical considerations around the intended use(s); required spatial (single- site v multi-site) and temporal (sub-hourly v hourly) resolutions; and available time, technical and (data) resources. Overall, scale invariance methods are favoured for single-site, sub-hourly extremes; hybrid weather generator-analogue methods for multi-site, hourly extremes; and hybrid NWP-QQM methods for continuous simulations of hydrology in large catchments.

(ix) A case study of a multi-temporal, scale-invariance method for Novi Sad, Serbia showed that errors of less than 15% for 0.25 h to 2 h extreme rainfall intensities and 5% for 6 h to 12 h intensities can be achieved even when only daily data are available.

Based on the findings of the meta-analysis and case study the following recommendations are made:

(i) Apply the scale-invariance method to other weather stations across Serbia to evaluate the transferability of the technique plus any associations between extreme rainfall scaling parameters and site characteristics (such as elevation, latitude and longitude).

(ii) Test the skill of the scale-invariance method at generating heatwave intensity-frequency-duration (HIDF) curves under present and projected climate conditions.

(iii) Undertake systematic side-by-side comparisons between different temporal downscaling methods (including emerging Artificial Intelligence techniques) for extreme rainfall at test sites across Europe to establish their relative accuracy and transferability.

(iv) Extend the above techniques for climate change applications – most likely by adjusting IDF and HIDF curves – to deliver information about changing precipitation and temperature extremes in formats that are most useful for engineers and planners.

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ANNEXES

Large Language Models (LLMs) are powerful tools for initial scoping of themes from substantial amounts of textual information[7]. Accordingly, ChatGPT was given the abstracts of the screened articles and asked to identify the main (a) techniques for temporal disaggregation of coarse-resolution climate data and (b) sectors covered. The output from ChatGPT is given below and was used to shape the structure of the main body of this report.

A1. Main techniques identified by ChatGPT for temporal disaggregation

Temporal disaggregation typically refers to breaking down coarse-resolution climate data (e.g., daily or monthly) into finer time scales (e.g., hourly or sub-hourly).

Techniques for Temporal Disaggregation Identified in the Abstracts:

1. **Statistical Downscaling Approaches:**

- **Quantile-Quantile Mapping (QQM):** Adjusts distributions of observed vs. modeled data.

- **Markov Chains:** Models daily rainfall occurrence and transitions for downscaling.

- **Kernel Density Estimators (KDE):** Used for probabilistic disaggregation of rainfall data.

2. **Machine Learning-Based Approaches:**

- **Artificial Neural Networks (ANNs):** Used for sub-daily precipitation downscaling.

- **Random Forests (RF):** Applied for disaggregating daily to hourly rainfall.

- **Extreme Gradient Boosting (XGBoost):** Improves prediction accuracy for fine-scale temporal breakdowns.

3. **Stochastic Weather Generators (SWGs):**

- Simulates high-resolution weather variables based on historical data patterns.

- Used for **rainfall and temperature disaggregation** into hourly/sub-hourly scales.

4. **Multi-Fractal and Cascade Models:**

- **Multiplicative Cascade Models:** Preserve rainfall variability across multiple time scales.

- **Neyman-Scott Rectangular Pulse (NSRP) Models:** Used for synthetic disaggregation of rainfall events.

5. **Dynamical Downscaling with High-Resolution Climate Models:**

- **WRF (Weather Research and Forecasting Model):** Used to refine climate projections at sub-daily scales.

- **ICON-LAM:** A high-resolution numerical weather prediction model for hourly downscaling.

6. **Hybrid Approaches (Combination of Methods):**

[7] Wilby, R.L. and Esson, J. 2024. AI literacy in geographic education and research: Capabilities, caveats, and criticality. The Geographical Journal, 190, p.e12548.

- Combining **machine learning + statistical techniques** to improve accuracy.

- Using **bias correction + stochastic models** to improve temporal detail.

A2. Main sectors using temporal disaggregation according to ChatGPT

The **Temporal Disaggregation** papers cover multiple sectors, as identified from the abstracts. The main sectors include:

1. Hydrology & Flood Risk Management

- Disaggregating precipitation to **sub-daily scales** for **flash flood prediction**.

- Enhancing **Intensity-Duration-Frequency (IDF) curves** for better flood modeling.

- Improving **river discharge simulations** for ungauged basins.

2. Urban Infrastructure & Water Management

- **Stormwater drainage system design** under changing climate conditions.

- Assessing **urban flooding risks** using downscaled rainfall data.

- Developing **design storms** for infrastructure planning.

3. Renewable Energy & Power Systems

- Disaggregating **wind speed and solar irradiance** data for energy modeling.

- Improving **hourly electricity demand forecasting** under climate variability.

- Enhancing **power grid stability analysis** with finer time-scale data.

4. Agriculture & Land Management

- Downscaling precipitation for **soil moisture estimation**.

- Assessing **crop yield variability** using high-resolution climate projections.

- Evaluating **irrigation needs** based on sub-daily weather conditions.

5. Climate Modelling & Atmospheric Science

- Using **regional climate models (RCMs)** to generate fine-scale precipitation data.

- Applying **machine learning and stochastic models** to improve climate projections.

- Downscaling **temperature and humidity data** for climate impact studies.

6. Human Health & Thermal Stress

- Estimating **heatwave intensity at sub-daily scales**.

- Assessing **urban heat stress on vulnerable populations**.

- Improving **bioclimatic indices (e.g., UTCI) for health risk assessments**.