BINGO
a better future under
CLIMATE CHANGE

BRINGING INNOVATION TO ONGOING
WATER MANAGEMENT

Guidelines

Dynamical downscaling to 1 km scale – method, rainstorms

April 2019

www.projectbingo.eu

The BINGO project has received funding from the European Union's Horizon 2020 Research and Innovation programme, under the Grant Agreement number 641739.

Horizon 2020 Societal challenge 5:
Climate action, environment, resource
efficiency and raw materials

BINGO

Bringing INnovation to onGOing water management –

a better future under climate change

Grant Agreement n° 641739, Research and Innovation Action

Short Summary (<250 words)

High-resolution climate data are of great benefit to hydrologists and managers of hydraulic infrastructure, but are computationally very expensive to generate. BINGO has developed a transferable methodology for greatly reducing the computational expense of producing such data, focused on the study of extreme precipitation events. This methodology has been translated into specific guidelines to facilitate its implementation.

Guidelines: Dynamical downscaling to 1 km scale
– method, rainstorms

April 2019

TABLE OF CONTENT

LIST OF FIGURES

1. INTRODUCTION

High-resolution climate model data, in particular at the catchment scale, are of great value to hydrological modellers, water-managers, regional decision makers, and many more end users involved in water-related activities. Such high-resolution data (of the order of 1 km spatial resolution) can play an invaluable role in providing, for example, realistic boundary conditions for stress testing of hydrological infrastructure or process-orientated case studies of a catchment’s response to extreme events. This is particularly true for extreme precipitation events, because precipitation extremes tend to be localized in space and typically exhibit high levels of spatial and temporal variability, which cannot be captured by lower-spatial-resolution data.

Such high-resolution model data are necessary for a number of reasons. Observational data are rarely available at such high resolutions due to insufficiently dense measurement networks. As a result, the maximum intensities of extreme events are generally underestimated in observations; this is an undesirable situation when trying to estimate the maximum event intensities which hydraulic infrastructure may encounter and how the infrastructure would deal with, for example, a one in 50 year event. Lower-resolution climate model data also present problems. Climate models with lower resolution also tend to underestimate the maximum intensities of precipitation extremes, because results are averaged over a larger area and peak intensities thus get “smoothed-out” as part of this area averaging effect (Volosciuk et al., 2015). As a result, the data also have unrealistically low levels of spatial variability. In addition to that, climate models with insufficient spatial resolution are incapable of directly simulating certain key processes which are crucial to precipitation extremes, in particular convection. As a result, these models represent convective processes via parametrization schemes which often inadequately represent extreme precipitation events, particularly in the summer months. Such models tend to produce precipitation extremes which are too spatially widespread, temporally too persistent, and not locally intense enough (Kendon et al., 2012).

High-resolution, so-called “convection-permitting”, climate models have been shown to correct many of the aforementioned deficiencies and produce precipitation extremes which are far more realistic in both space and time. Convection-permitting models

(CPMs) have grid spacings of less than 4 km, allowing convective processes to be directly simulated. The added value of CPMs over models with convective parametrizations has been extensively documented (e.g. Prein et al., 2015; Kendon et al., 2017). The one downside of CPMs, however, is that they are computationally very expensive to run. For example, increasing the horizontal spatial resolution by a factor of two increases the computational expense by a factor of eight. As a result, climate simulations with CPMs are a prohibitively expensive and thus infeasible option for most users. BINGO WP2 has thus sought to develop a method to reduce the computational expense required for CPM climate simulations, while still benefiting from the added value which they offer.

The greatest added value of CPMs is found in their representation of precipitation extremes. Such events, by their nature, occur only rarely. For the study of precipitation extremes, the intervening days between the extremes are of little interest and we therefore seek to develop a methodology which eliminates the need to simulate these days as much as possible. Identifying which days will have extreme events, however, is a non-trivial task. Precipitation from the low-resolution parent model, i.e. the model that is to be dynamically downscaled to high resolution, is on its own a poor predictor of extreme precipitation in the CPM. Using a combination of characteristic large-scale circulation patterns and local-scale meteorological predictors, BINGO WP2 has developed a transferable methodology to discriminate between days with an increased likelihood of extreme precipitation – “potential extreme days” (PEDs) – and redundant days, so that dynamical downscaling to convection-permitting resolution can be performed over a catchment only when a day has been identified as a PED. With our method, we can reduce computational expense by up to 90% while still capturing the majority of the precipitation extremes, thus making high-resolution downscaling for applications related to extreme precipitation a much more feasible task.

As part of the BINGO Exploitation Strategy, guidelines to implementing our methodology are presented in this document. Separately, our method has also been published under open access in peer-reviewed scientific literature, and is citable as: **Meredith, E. P., Rust, H. W., and Ulbrich, U. (2018) “A classification algorithm for selective dynamical downscaling of precipitation extremes”, Hydrol. Earth Syst. Sci., 22, 4183-4200, https://doi.org/10.5194/hess-22-4183-2018.**

2. METHODOLOGY

The BINGO project is a H2020-funded international collaboration between academia, research scientists, hydrological modellers, social scientists and, most importantly, water-infrastructure managers and planners. Of key importance was establishing working links between researchers and practitioners, so that the state-of-the-art from research could be applied to solving the real-world problems facing practitioners.

One such problem facing BINGO's practitioners – i.e. managers of hydraulic infrastructure – was a lack of high-quality and high-resolution data with which to model the impact of precipitation extremes on their infrastructure in the present climate and in the decades ahead. Our practitioners are concerned with problems like modelling the impact of extreme precipitation events on urban sewerage networks and the related risks of sewerage overflow incidents, stress-testing their existing hydraulic infrastructure with model simulations, and designing the resilience levels of future planned infrastructure for their catchments – all for the present climate and the decades ahead. As explained in the Introduction, low-resolution climate model data are not suitable for realistically modelling such situations at the catchment scale, and provide unsatisfactory results and less robust predictions.

In cooperation with our practitioners, this lack of high-resolution data was identified as a critical issue for their operations and BINGO WP2 was tasked with finding a workable solution that could also be applied by other working groups facing similar problems. The option of continuously dynamically downscaling several decades of climate simulations with a CPM was firstly ruled out, as this would be highly computationally expensive and would not be a realistic option for other working groups, for whom BINGO was tasked with leaving a transferable legacy.

The idea of seeking to identify weather situations with an increased risk of extreme precipitation and then only dynamically downscaling to convection-permitting resolution on these days was thus arrived at. One initial concern was that this method may leave the hydrological modellers with inadequate initial conditions for their models and inadequately long high-resolution time series with which to calibrate their models. It was thus agreed that, where necessary, hydrological models would be calibrated with either observations or lower-resolution climate data. In addition to that, for the specific applications of our practitioners initial conditions in their hydrological models were either not affected by issues like soil moisture (e.g. urban sewer networks), would be prescribed based on observations, or would be varied as part of sensitivity experiments. Additionally, hydrological modellers within the BINGO project communicated with us that not just the meteorological data during the extreme event was important to them, but also the meteorological data in the period before the event, as this can have a considerable impact on the state of the hydrological system before the arrival of the event, which in turn affects the magnitude of the event's impact on the catchment. For example, if the ground had become saturated in the run-up to the most extreme precipitation, or if the ground was already covered in snow, then the magnitude of the runoff would be much higher. For this reason, it was agreed that CPM downscaling would begin at least 12 hours before the onset of the extreme event and continue until at least 12 hours after the event.

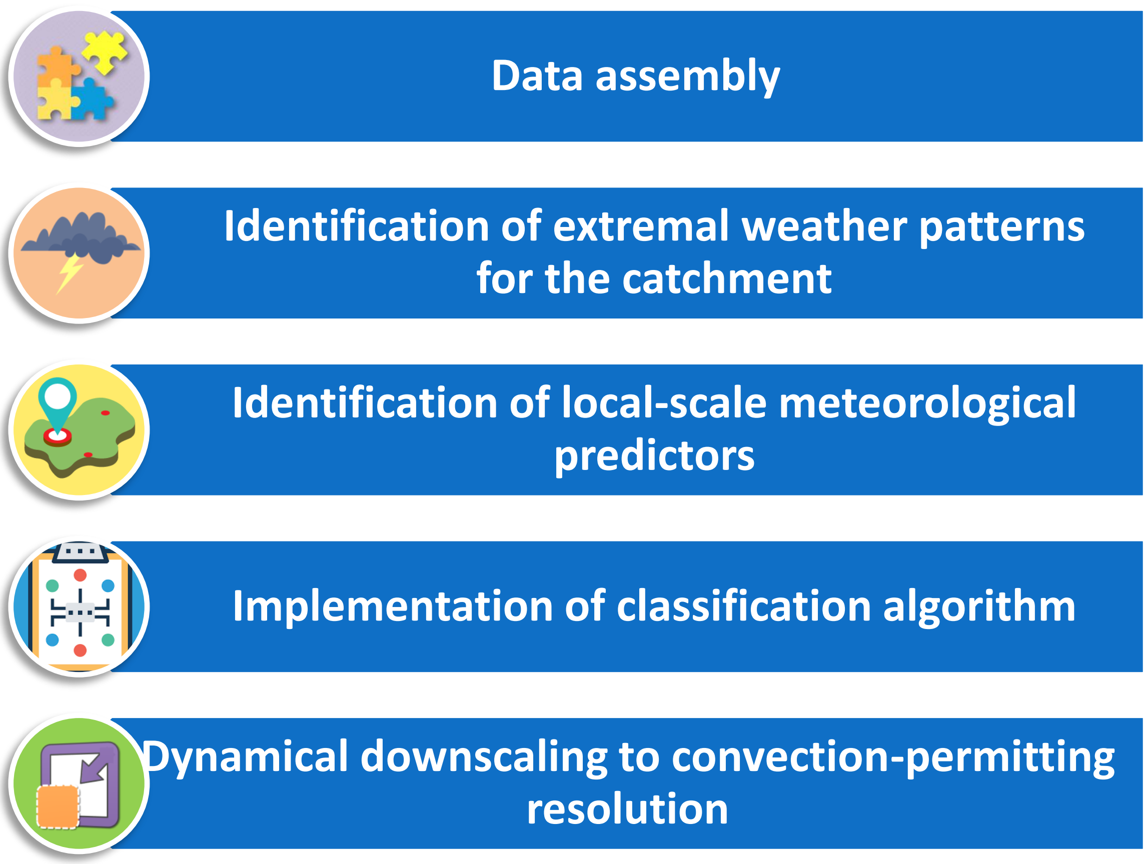
Through our methodology, we were able to reduce the computational expense of dynamically downscaling to convection-permitting resolution over the catchments by up to 90%, thus solving the problem of high-resolution simulations being computationally infeasible for many. Despite this reduction in computational expense, moderate computational resources are still required to implement our methodology. It is not something that could be easily accomplished with, for example, a single laptop computer. Apart from computational resources, the other resources which are needed to implement our method are high-quality observational data of precipitation from the catchment: the longer the time series and the higher the density of the measurement network, the better. In addition to this, access to reanalysis data and standard tools for manipulating climate data are also necessary.

Our method is primarily aimed at managers and modellers of hydraulic infrastructure and catchments who are looking to study the impacts of extreme precipitation events – from the present, past or future – on their catchments and/or infrastructure. In addition to that, our methodology may also be used for a targeted selection of climate models which to downscale, thus reducing the overall computational burden. This is discussed in the aforementioned publication in Hydrology and Earth System Sciences (Meredith et al., 2018) and will not be a focus of the remainder of this document.

While our method can greatly reduce the computational expense associated with simulating extremes at high resolutions, users should nonetheless be cognisant of certain limitations, for which applications our methodology is not suitable, and how to interpret the results of experiments based on our method. Our method cannot guarantee the capture of all extremes. If a future climate contains new weather patterns which in the past did not cause extremes, then these will not be captured. As such, the catalogue of downscaled extremes produced from our method should not be confused with traditional climate projections. Traditional projections can only be made with continuous, multi-decadal downscaling, and not with the discontinuous time series that are produced in our method.

3. GUIDELINES

This methodology has been organised into five specific steps which guide the user through the key phases of its implementation. The Guidelines are the following:



Data assembly

All precipitation observations from the catchment should be assembled, preferably with long time series of at least 30 years. In addition to this, reanalysis data should also be gathered for the region in which the catchment is located, i.e. including up to several hundred kilometres away from the catchment.

In BINGO, ERA-Interim reanalysis (Dee at al., 2011) was used, as well as any observational data which was available from the catchments. If no observational data were available from the catchments, then BINGO used the E-OBS dataset (Haylock et al., 2008) as an alternative.

Identification of extremal weather patterns for the catchment

Using standard methods like empirical percentiles, the dates on which extremes of a desired intensity (i.e. an intensity which is interesting for the study of the users) occurred in the catchment should be determined. The large-scale circulation patterns from these days should then be extracted from the reanalysis data, over an area which is large enough to encompass all of the circulation features which contribute to the event. BINGO used the 500 hPa geopotential height anomaly as a large-scale circulation variable, but other variables such as sea-level pressure could be used instead. Once these days have been selected, their circulation patterns should be fed into a clustering algorithm in order to be grouped into clusters based on their similarity to each other (Figure 1). BINGO used the SANDRA method for this step (Philip et al., 2007), which is a k-means based approach, though other clustering methods could also be used.

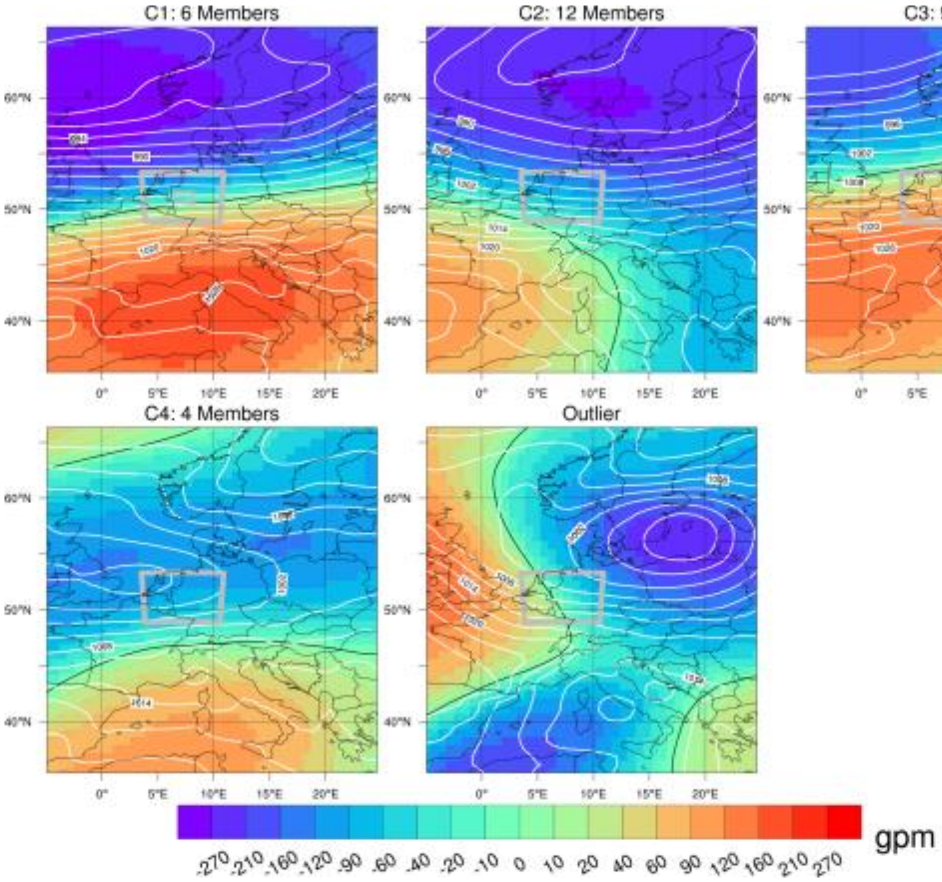


Figure 1

Extremal Circulation patterns identified for the Wupper catchment (western Germany) in winter. The Wupper catchment is one of the 6 key research sites of the BINGO project. 500 hPa geopotential height anomalies (shading) are used to represent the extremal circulation patterns, identified via a clustering algorithm, and one outlier. The zero line is marked in black. White contours represent the accompanying sea level pressure patterns. The grey box centred over western Germany is the 2-km resolution simulation domain which was used in BINGO for dynamical downscaling.

Identification of local-scale meteorological predictors

In this step, reliable meteorological predictors of extreme precipitation for the catchment must be identified. This step is particularly amenable to the active involvement of end users, as users can integrate their empirical knowledge of the catchment towards the identification of the most suitable predictors for their catchment. Apart from this, standard meteorological variables representative of atmospheric moisture content (e.g. humidity), vertical motions (e.g. vertical winds or horizontal divergence) and instability (e.g. convective available potential energy), as well as precipitation from the low-resolution model, are recommended. These are discussed in more technical detail in Meredith et al. (2018).

Steps 2 and 3 should be implemented separately for each season of interest, because the circulation patterns and predictors which cause extremes can vary between seasons.

Implementation of classification algorithm

Once the extremal patterns and local-scale predictors have been identified, they can be combined into a single classification algorithm (Figure 2).

for j in $(1, ..., K)$ **do** # Extremal patterns 1 to K
    if $(\rho_{i,j} \geq \rho_{jt})$ **then** # Synoptic-scale tests
        if $(RH700_i \geq RH700_{thresh})$ **then** # Local-scale tests
            if $(DIV500_i \geq DIV500_{thresh}$ **.OR.** $CAPE_i \geq CAPE_{thresh})$ **then**
                if $(P_i \geq P_{95})$ **then**
                    DAY_i classified as PED
                end if
            end if
        end if
    end if
end do

Figure 2

Schematic of the classification algorithm for identifying potential extreme days in summer for the Wupper catchment. Here, the schematic is for a single day ***i***.

$\boldsymbol{\rho_{i,j}}$ is the Pearson pattern correlation between day ***i*** and extremal pattern ***j***, RH700 is relative humidity at 700 hPa, DIV500 is horizontal divergence at 500 hPa, CAPE is convective available potential energy, P is accumulated daily precipitation from the low-resolution model. $\boldsymbol{\rho_{jt}}$ are thresholds for determining if the test-day is similar to an extremal pattern. **if** tests of local-scale meteorological variables are performed using the identified thresholds in Step 4. If any of the cells in the vicinity of the catchment pass the test, then the next test is applied. For winter, a similar algorithm was used for the Wupper catchment, except that CAPE was excluded and relative humidity was at 300 hPa.

In the algorithm, the circulation for a given day is first compared for similarity with the identified extremal weather patterns for the catchment; pattern correlation was used for this purpose in BINGO. If the circulation on the test day is similar, then the local-scale predictors are assessed to see if they are indicative of a potential for extreme precipitation. Crucial to the algorithm is the selection of appropriate thresholds for each variable and/or circulation pattern, beyond which each day may be identified as "potentially extreme". The algorithm can be tested using reanalysis data, to see how many days (extreme and non-extreme) are classified as potentially extreme from the reanalysis, and the thresholds can then be optimized to reduce the number of classified days as much as possible, while still retaining the dates with extreme precipitation. The choice of threshold here is flexible, and can be adjusted based on the available computational resources of the users, with the caveat that excessively high thresholds will result in an increased number of falsely rejected days.

Dynamical downscaling to convection-permitting resolution

Once the classification algorithm has been optimized for the study catchment and the needs of the end users, it can be applied to any set of climate simulations or reanalyses. Days identified as "potentially extreme" can then be dynamically downscaled from the forcing data and all other days excluded, greatly reducing the computational burden. In BINGO, the CPM simulations were begun 12 hours before the PED. To further save computational resources, BINGO simulated consecutive or near-consecutive PEDs continuously, rather than re-starting the simulations for each day with a new spinup period. A detailed evaluation of the method is available in Meredith et al. (2018).

Apart from that, users should be aware that the final catalogue of dynamically downscaled extremes will include many days which do not include intense precipitation in the catchment. This is unavoidable. In many cases, particularly in summer, chaotic small-scale processes may lead to intense precipitation occurring in the region, though outside the bounds of the study catchment. In other cases, the potential for extreme precipitation may not translate into actual extreme precipitation in the model, as such events are best viewed as probabilistic rather than deterministic phenomena (Figure 3).

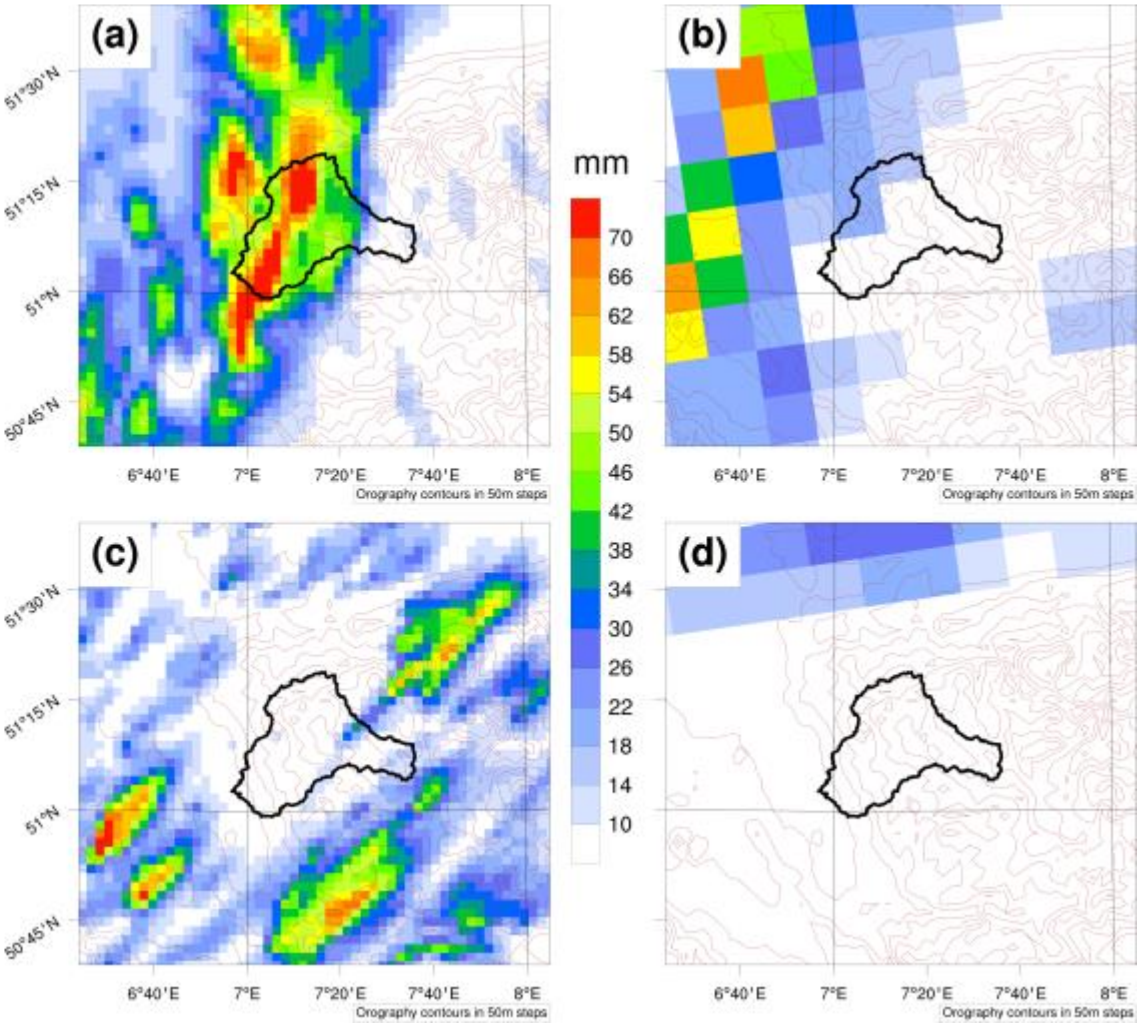


Figure 3

Illustrative modelled potential extreme days (PEDs). (a) Example summer PED downscaled to 0.02° resolution and (b) the same day in the 0.11° parent model. In this example, the strongest precipitation directly strikes the catchment in the 0.02° model despite missing the catchment in the parent 0.11° model. (c) Example summer PED with highly localized intense precipitation that falls outside the catchment in the 0.02° model. (d) The corresponding day in the 0.11° model.

4. CONCLUSION

Preconditioning the dynamical downscaling of potential extreme days on known extremal circulation patterns does not just reduce the total number of days to dynamically downscale. Importantly, it also allows conclusions to be drawn about changes in catchment-relevant precipitation between two periods, e.g. present and future climates, for these specific circulation patterns. For example, for a known extremal circulation pattern, will the likelihood that the accompanying precipitation exceeds some catchment-relevant threshold be higher or lower in the future? This could be particularly useful for catchments vulnerable to specific compound extremes, for example intense precipitation in an estuarine catchment compounded by a shoreward moving low-pressure system with strong onshore winds. As mentioned above, users should however be aware that beyond the extremal patterns identified from the training period, there remains the possibility that a future climate may also contain new extremal circulation patterns that were previously either not associated with extreme precipitation or simply not present at all. Such systematic effects can only be explored with computationally expensive continuous dynamical downscaling.

In these Guidelines, we have set out a method through which high-resolution climate model data can be generated for a catchment at greatly-reduced computational expense. The method is targeted at the study of extreme precipitation events and, for the purposes of the BINGO project, has been shown to reduce computational expense by close to 90%. While the preceding analyses required to successfully implement the method do take some time, the required methods are relatively straightforward and thus accessible to most users. More detailed technical considerations for implementing the method are discussed in Meredith et al. (2018). The method has additionally been shown to perform consistently across past and future climates (Meredith et al., 2018). The explicit simulation of important meteorological processes which can be achieved with high-resolution models gives greater confidence in the results and predictions which they produce. Through the method outlined in this document, such model simulations can be made less computationally expensive and thus accessible to a much wider range of practitioners.

5. REFERENCES

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Hólm, E. V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A. P., Monge-Sanz, B. M., Morcrette, J.-J., Park, B.-K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J.-N., and Vitart, F.: The ERA-Interim reanalysis: configuration and performance of the data assimilation system, Q. J. Roy. Meteorol. Soc., 137, 553–597, https://doi.org/10.1002/qj.828, 2011.

Haylock, M. R., N. Hofstra, A. M. G. Klein Tank, E. J. Klok, P. D. Jones, and M. New (2008), A European daily high-resolution gridded data set of surface temperature and precipitation for 1950 – 2006, J. Geophys. Res., 113, D20119, doi:10.1029/2008JD010201.

Kendon, E. J., Roberts, N. M., Senior, C. A., and Roberts, M. J.: Realism of rainfall in a very high-resolution regional climate model, J. Climate, 25, 5791–5806, 2012.

Kendon, E. J., Ban, N., Roberts, N. M., Fowler, H. J., Roberts, M. J., Chan, S. C., Evans, J. P., Fosser, G., and Wilkinson, J. M.: Do convection-permitting regional climate models improve projections of future precipitation change?, B. Am. Meteorol. Soc., 98, 79–93, 2017.

Meredith, E. P., Rust, H. W., and Ulbrich, U.: A classification algorithm for selective dynamical downscaling of precipitation extremes, Hydrol. Earth Syst. Sci., 22, 4183-4200, https://doi.org/10.5194/hess-22-4183-2018.

Philipp, A., Della-Marta, P.-M., Jacobeit, J., Fereday, D. R., Jones, P. D., Moberg, A., and Wanner, H.: Long-term variability of daily North Atlantic–European pressure patterns since 1850 classified by simulated annealing clustering, J. Climate, 20, 4065–4095, 2007.

Prein, A. F., Langhans, W., Fosser, G., Ferrone, A., Ban, N., Goergen, K., Keller, M., Tölle, M., Gutjahr, O., Feser, F., Brisson, E., Kollet, S., Schmidli, J., van Lipzig, N. P., and Leung, R.: A review on regional convection-permitting climate modeling: Demonstrations, prospects, and challenges, Rev. Geophys., 53, 323–361, 2015.

Volosciuk, C., Maraun, D., Semenov, V. A., and Park, W.: Extreme precipitation in an atmosphere general circulation model: impact of horizontal and vertical model resolutions, J. Climate, 28, 1184–1205, 2015.