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# EURO-CORDEX regional climate model simulation of precipitation on Scottish islands (1971-2000): Model performance and implications for decision-making in topographically complex regions

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**Abstract**

Due to their scale and complex topography, islands such as the Hebrides and Shetland Islands are not fully resolved by global climate models, which may impact the quality of data that can be provided about future climate in such locations. In principle, dynamical downscaling may provide helpful additional detail about future local climate. However, there is also the potential for error and uncertainty to cascade through to the regional simulation. Here, we evaluate the simulative skill of the EURO-CORDEX regional climate model ensemble on regional and local scales in the Hebrides and Shetland Islands, and consider the potential for such models to aid decision-making in island settings, and other locations characterised by complex topography. Several precipitation indices (accumulated precipitation amount, mean daily precipitation amount, max 1-day and 5-day precipitation amounts, simple daily intensity, number of heavy and very heavy precipitation days) are used to assess model performance and identify bias relative to observations. Models are compared regionally, and at specific locations, namely Stornoway in the Hebrides and Lerwick in Shetland, for the period 1971-2000. Regional evaluation utilises the UKCP09 gridded observational dataset and local evaluation at Stornoway Airport and Lerwick utilises observed mean precipitation and extreme indices from the European Climate Assessment & Dataset project. While no models perform skilfully across all the metrics studied, some models capture aspects of the precipitation climate at each location particularly well. Differences in model performance between the two case study sites highlight the value of evaluating models on multiple spatial scales. The implications of model uncertainty for decision-making are also discussed.


## 1. Introduction

Coastal communities in northern Europe are at risk from a wide range of climate change impacts, relating to sea-level rise and changing weather patterns, including extreme weather events (Muir *et al.*, 2014). For island communities, risks associated with climate change may be further compounded by their geographical characteristics. Geographical remoteness gives rise to specific challenges. For instance, Coll *et al.* (2012) highlights the vulnerability of ferry services of the Western Isles of Scotland to extreme weather, noting their vital role in local trade and communication networks. In recent years, the storm of 11-12 January, 2005, highlighted the impacts of extreme weather in the Outer Hebrides, causing five fatalities and extensive damage to properties and infrastructure (Angus and Rennie, 2014). There may also be geographical constraints on adaptation options within island communities. For example, consultation with the community of Kilpheder in the Outer Hebrides has highlighted local opposition to withdrawing from the coast as it erodes (Young *et al.*, 2014). The Uists in the Outer Hebrides also contain numerous sites of special scientific interest, most of which are low-lying and vulnerable to storm damage (Angus and Rennie, 2014).

Given this challenging range of potential climate impacts, it is critical to anticipate and prepare for future risks through appropriate adaptation measures. Whether approaches to adaptation planning are top-down (Wilby and Dessai, 2010) or bottom-up (Brown, 2004; Prudhomme *et al.*, 2010), climate model data may play a role, providing scenarios of climate change but also aiding in critical thinking around decision-making (Weaver *et al.*, 2013). For example, Tompkins *et al.* (2008) used stakeholder analysis, climate change management scenarios and deliberative techniques to assess long-term coastal management options on the south coast of England and the Orkney Islands off Scotland.

However, global climate models (GCMs), such as those used in the Coupled Model Intercomparison Project Phase 5 (CMIP5; e.g. Arora *et al.*, 2013) are still too coarse to represent complex local topography. While this may not be a limitation when developing adaptation priorities and plans at the national level, it may become more relevant as we move across spatial scales. For instance, Trivedi *et al.* (2008) note how the outcome of model projections of climate change impacts on Scottish plants is influenced by the choice of spatial scale, leading to different results for adaptation decisions.

This limitation can be partially overcome by using downscaling approaches to generate localised impacts scenarios. The importance of utilising high resolution modelling approaches, either in the form of regional climate models or statistical downscaling, in the context of certain island communities has been highlighted by (Cantet *et al.*, 2014), who noted that in their study, the islands of Lesser Antilles are considered as land by a regional climate model (RCM), but are not resolved at all by the driving GCM. As the RCM is highly dependent on the driving conditions received from the GCM (Foley *et al.*, 2013a), such a discrepancy has the potential to significantly impact the simulative skill of the RCM.

Robust decision-making techniques demand critical reflection on the skilfulness of models and data being deliberated upon, particularly in topographically complex regions where models and datasets may lack the resolution to capture local features. Identifying model strengths and deficiencies can assist in developing bias-corrected RCM projections to inform climate adaptation decision-making (Dosio, 2016; Dosio and Paruolo, 2011), and can aid more generally in communicating with decision-makers about the uses and limitations of model data. As Patt *et al.* (2007) describe, Climate Outlook Forums in Africa led to loss of trust when forecasts (at a much coarser scale than would be relevant for island communities) were taken as predictions, but the forecasts then did not come to fruition, highlighting the importance of insuring that decision-makers' assumptions around the credibility of models is in line with the expectations of the modelling community.

Yet, while there is a wealth of scholarship on climate model evaluation (E.g. Foley *et al.*, 2013b; Kotlarski *et al.*, 2014; Sillmann *et al.*, 2013) and on decision-support mechanisms separately, it is rarer for these two strands of research to come together. Indeed, Goddard *et al.*, (2010) highlights the need for "chains of experts and communications", to ensure that climate information is appropriately disseminated and effectively applied in risk management and decision-making settings.

Therefore, in this study, we examine the simulative skill of the RCM ensemble generated by the CORDEX project on regional and local scales in the Hebrides and Shetland Islands and, informed by these results, discuss the potential for such data to aid in adaptation planning, drawing on examples of decision-making practice in other locations characterised by topographical complexity, such as small island developing states (SIDS; e.g. Kelman and West, 2009; Pelling and Uitto, 2001; Turvey, 2007).

## 2. Methodology

### *2.1 Regional climate models*

The average grid resolution of CMIP5 models is ~2°in latitude/longitude (European Network for Earth System Modelling, n.d.), far coarser than would be required to resolve the complex topography of the Hebrides and Shetland Islands.

Therefore, this study uses the CORDEX RCM simulations for the European domain (EURO-CORDEX) at the 0.11 degree (EUR-11, ~12.5km) scale (Jacob *et al.*, 2013). The simulations use a rotated pole grid, with the North Pole at 39.25N, 162W. The region of interest for this study is a sub-section of the EUR-11 domain, but no additional modelling takes place using this sub-section. As such, we refer to it as 'analysis region' in Fig. 1 rather than 'domain'.

The ensemble has previously been evaluated against observational data at the European scale with the findings that, while the RCMs are capable of capturing key features of the European climate, they also exhibit nontrivial biases; for example, most simulations studied exhibited excessive precipitation in summer over northern Europe (Kotlarski *et al.*, 2014).

Differences in how the models are configured (e.g. different calendar conventions) mean that the modelled data cannot be compared as a daily time series with observations. Instead, the modelled and observed data are summarised using aggregate metrics. Data are extracted for a 30-year hindcast period (1971-2000). The 30 year 1971-2000 period is used as in a future phase of this work, results will be used to compute changes in the future 2071-2100 period relative to the baseline. RCM and driving model combinations are detailed in Table 1. There are 15 simulations in total.

### 2.2 *Observed meteorological data*

Firstly, the modelled data is compared with UKCP09 5 km gridded observational data (Perry and Hollis, 2005). The finer-resolution observed data is interpolated to this coarser grid of the models to enable comparison.

Secondly, the modelled data is compared to individual station records within the analysis region. This local evaluation is crucial, given that gridded observational data sets can exhibit deficiencies stemming from sparseness of meteorological stations (Zhang *et al.*, 2011).

For this second evaluation phase, Stornoway in the Hebrides and Lerwick in the Shetland Islands, both major population centres and key ports, are selected for study. The Hebrides and Shetland islands are both characterised by a temperate maritime climate, moderated by the North Atlantic current. Proximity to North Atlantic storm tracks result in a strong westerly regime. However, despite these similarities, the two locations differ in terms of latitude and the size of the landmass (Fig. 1).

Observed precipitation extreme indices were available through the European Climate Assessment & Dataset (ECAD) project website. Mean daily precipitation amounts were also obtained. Data was accessed for Stornoway Airport and Lerwick meteorological stations. While raw station data is available from other sources for other sites in the region, the ECAD data are preferred as they have undergone quality control and homogeneity procedures. The raw modelled data is interpolated to the coordinates of these individual meteorological stations for direct comparison with station data.

### *2.2 Precipitation metrics*

Quantile-quantile (q-q) plots illustrate the similarity of observed and modelled distributions of daily precipitation amounts. Mean monthly precipitation totals are also calculated and compared with observations.

Additionally, metrics are selected to capture the extreme statistics of precipitation, including the intensity, frequency and duration of extreme precipitation events. These metrics are summarised in Table 2. Similar approaches have been used by the World Meteorological Organization Expert Team on Climate Change Detection and Indices (ETCCDI, http://etccdi.pacificclimate.org/), and in other model evaluation studies (e.g. Casanueva *et al.*, 2016; Sillmann *et al.*, 2013). Metrics are calculated for each year. Annual values are averaged over the hindcast period to yield a single value, and compared to observed metrics using a percentage error method.

As these annual average metrics could be skewed by the presence of trends in the data, the $R^2$ value associated with a linear fit to the annual metric values was calculated. $R^2$ values ranged from 0 to 0.3, indicating an absence of major temporal trends.

## 3. Results

Fig. 2 presents the spatial distribution of bias in the annual accumulated precipitation, $R_{sum}$, for 1971-2000. Observed precipitation totals are highly variable across the region, with the highest totals found in the western highlands, and the east coast tending towards much drier conditions. Several models have biases that effectively smooth this distribution, with a dry bias in the wettest regions and a wet bias in the driest regions. As the dry regions are in the rain shadow of the Scottish mountains, this may indicate that the issue stems from the representation of orography. Fig. 1 illustrates that many models underestimate elevation in the Highlands, which may shift where orographic precipitation occurs in the models.

Biases do not appear to be linked to the choice of driving GCM, given the diversity of spatial error patterns across RCMs that share a driving GCM (e.g. Fig. 2, (m), (n), (o)). However, is still inadvisable to consider RCMs driven by the same GCM as independent simulations, as to do so could lead to misconceptions about the relationship between model spread and uncertainty in the future climate projection (Abramowitz and Gupta, 2008).

Evaluating performance at the two case study sites, the models largely capture the observed distribution of daily precipitation, as evidenced by the close agreement between plotted quantiles and the 1:1 reference line (Fig. 3). However, the modelled and observed data tends to diverge at the upper extremes of the distribution. In most cases, the models underestimate the magnitude of precipitation extremes, but there is not a systematic pattern to this divergence, with certain models overestimating precipitation values in the upper tail at one location, and underestimating in the other location. As such, it could be challenging to correct for these biases when using the data to simulate future climate.

Fig. 4 presents mean monthly modelled and observed precipitation totals over the period studied. Some models, e.g. panel (a), represent the distribution of precipitation across the year at each site with skill, while others model a more uniform precipitation climate than observed, e.g. panel (d). As before, model performance is in some cases variable between sites, e.g. panel (o), with the lack of consistency in bias posing a potential problem for end-users of the data. Several models underestimate winter precipitation at one or both locations, which, if left uncorrected in future projections, could lead to an inaccurate perception of risks. Model (d) exhibits an especially flat distribution of precipitation at Stornoway Airport; this model had a strong dry bias in the Highlands (north-west, Fig. 2), where it underestimates elevation. Corresponding errors in orographic precipitation would be more prominent in the winter months, when precipitation tends to be associated with Atlantic depressions, than in spring and summer, when precipitation may take the form of convective showers, leading to a flatter annual distribution. These results highlight how regional climate modelling and the development of local climate projections rely on chains of inferences, which must be evaluated within the local geographical context if they are to add value to decision-making.

Lastly, Table 3 presents a range of precipitation metrics, calculated for each model and compared with observations. Shading indicates the magnitude and direction of percentage error when comparing modelled and observed metrics, with red indicating overestimation of the observed metric, and blue indicating underestimation.

## 4. Discussion

This research has demonstrated that RCMs may be limited in their ability to capture the extreme precipitation of Scottish island climates. Models in this study tend to perform well for a selection of metrics, but not all metrics and all case study sites. For instance, CCLM4-8-17 driven by EC-EARTH overestimates $R_{sum}$ for Stornoway Airport, but captures values of $R_{10}$ and $R_{20}$ with remarkable accuracy (Table 3). Overestimation at this location occurs mainly in the summer months in this model (Fig. 4), and therefore this error has less impact on the calculation of wet extremes. However, deficiencies in the representation of summer precipitation may lead to misunderstanding of levels of risk in that season.

Differences in model performance between the two case study sites highlight the value of evaluating models on multiple spatial scales. Results highlight the pitfalls of examining climate means only in model assessments. Some models (e.g. RACMO22E driven by HadGEM2-ES: Table 3) that capture the observed values of $R_{sum}$ and $R_{mean}$ with skill demonstrate a more limited capacity to capture metrics of extremeness, such as $R_{10}$ and $R_{20}$.

While further developments in climate modelling and computing techniques should reduce some of the uncertainty associated with model projections, it cannot remove all error. Thus, uncertainty needs to be seen and conveyed as the norm, within which decision-making can and should take place, rather than as a barrier to decision-making. Such normalisation, rather than problematisation of it, shifts decision-making away from a computation strategy, and towards approaches that will increasingly require stakeholder and community engagement (de Boer *et al.*, 2010). Climate models can still add value in these contexts, by providing benchmarks against which to evaluate different adaptation and risk management proposals, e.g. within the context of a robust decision-making framework (Hall *et al.*, 2012).

However, Weaver *et al.* (2013) note that climate models are currently underutilised as decision-support tools, due in part to the misconception that climate models are 'prediction machines' rather than 'scenario generators'. The difference between 'prediction' and 'projection' needs to be emphasised to overcome this view. Projections are much more about suggesting scenarios under given circumstances, including certain and uncertain components, rather than providing probabilities of specific circumstances occurring.

Scenarios have long been an important component of development- and disaster-related planning, which may encompass climate change adaptation, using methods such as "Future Search" (Weisbord and Janoff, 2009) and participatory action research (Maskrey, 2011). Daly *et al.* (2010) used participatory processes to produce coastal maps for Samoa, indicating contemporary and possible future hazards and vulnerabilities, combining external and local knowledge. Gaillard and Maceda (2009) describe Participatory 3-Dimensional Maps (P3M), developed and piloted in the Philippines, in which external scientists and local community members use local materials to construct a scale model of the community and then identify current and future risks. Island settings especially benefit from such approaches as the small spatial scale makes localisation essential, and achievable only with local input, due to the coarseness of external datasets.

Similar approaches have also been analysed for Himalayan countries, indicating that the smaller, more isolated communities are likely to be more affected by climate change but that using only models in a top-down fashion does not and cannot meet those communities' needs (Lamadrid and Kelman, 2012). Much more localisation was needed, with uncertainty *per se* not being a concern, because as long as the uncertainties were indicated clearly, they could be incorporated into decision-making. By modellers working with various sectors within communities and providing model results, projections, and products which users request, top-down bottom-up adaptation is implemented and becomes much more effective and suited to local contexts.

Given the modelling uncertainties identified in this study, questions worth exploring though scenario-based methods may include what sort of safety margins should be considered in planning to account for this uncertainty. What if designs are completed to allow for plenty of contingency, but then the actual extreme precipitation events are substantially less than the models project? Working through such scenarios and mapping out the positive and negative consequences can assist decision-makers in deciding the costs and benefits which they might face depending on decisions made under uncertainty. Importantly, approaches must incorporate the knowledge of modellers into planning and decision-making, without letting this scientific knowledge dominate, or be dominated by, local needs and knowledge.

## 5. Conclusions

This paper provides a first-order examination of CORDEX RCMs' ability to capture the characteristics of precipitation, including extremes, for two locations in the Scottish isles, Stornoway Airport and Lerwick. We find significant inter-model variability, with no model emerging as skilful across all metrics and case study sites when compared with contemporary climate observations. While further analyses, such as circulation type classification (Davies *et al.*, 1990; Foley *et al.*, 2013a), could be applied to attempt to determine the causes of biases, such information is likely to be more helpful for model developers than model end-users. Instead, this paper has sought to examine the potential for regional climate model data to add value to decision-making on local scales, accepting that it is likely not feasible to seek to address all model errors.

Future work will utilise these results to generate bias-corrected future scenarios of regional climate change. However, in light of the inherent uncertainty, it is particularly important to consider how the skill of models, and skill variations within different contexts, are effectively conveyed to users, in addition to model results. For example, the Pacific ENSO (El Niño Southern Oscillation) Applications Center (PEAC) uses climate forecasting and projections to inform longer-term and wider climate-related capacity building and vulnerability reduction efforts for the American-affiliated Pacific islands, providing both model results and interpretation of those results (Schroeder *et al.*, 2012). As with the Climate Outlook Forums—which have been held for islands in the Caribbean (Glantz, 2000), but never evaluated to the extent of Patt *et al.*'s (2007) work in Africa—it is an important example of top-down bottom-up adaptation, through working with communities to make climate science useable. Their work and methods could be emulated for the Scottish islands to provide users with understandable and useable information about climate models, including their limitations, and how to use them.

If climate models are conceptualised as 'prediction machines', then the value to decision-making of this data may be perceived as limited. However, if models are considered as 'scenario generators', the data could be used effectively alongside other forms of knowledge, such as contemporary and historical climate data, and stakeholder inputs. Further research is needed to explore how to exchange with users regarding the workings and results of climate models, and their applications. This could include determining the level of detailed information required by different users, how the presentation of scenarios can be tailored to users, and optimal visualisation approaches for different contexts (see also Tufte and Graves-Morris, 1983). Visualising uncertainties would be an important component, to assist in conveying the importance of considering uncertainties without allowing them to hamstring decision-making.

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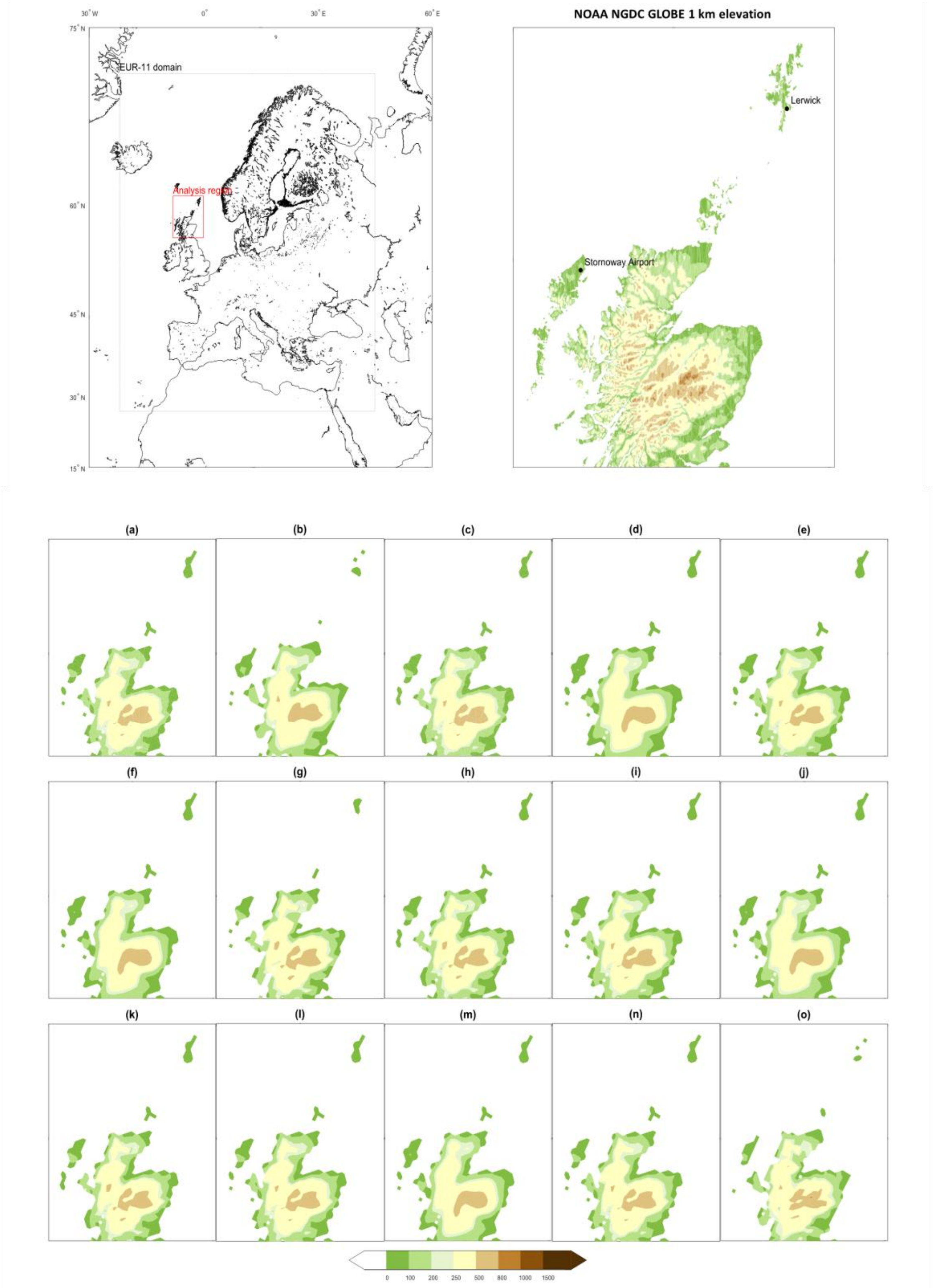


Fig. 1 Top panels: Analysis region (red) in context of EUR-11 domain (dotted line) (left) , and actual orography in metres at 1 km (right), generated using NOAA NGDC Global Land One-kilometer Base Elevation project (GLOBE) data. Bottom panels: Modelled orography and coastlines.

| | | Regional climate model | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | ALADIN53 | CCLM 4-8-17 | HIRHAM5 | RACMO 22E | RCA4 | REMO 2009 | WRF331F |
| **Driving model** | CM5A-MR | | | | | a | | b |
| | CNRM-CM5 | c | d | | | e | | |
| | EC-EARTH | | f | g | h | i | | |
| | HadGEM2-ES | | j | | k | l | | |
| | MPI-ESM-LR | | m | | | n | o | |

Table 1 EURO-CORDEX RCM and driving GCM combinations and letter references for figures.

| **ID** | **Indicator** | **Unit** |
|---|---|---|
| $R_{sum}$ | Accumulated precipitation amount | mm |
| $R_{mean}$ | Mean daily precipitation amount | mm |
| $R_{X1day}$ | Max 1-day precipitation amount | mm |
| $R_{X5day}$ | Max 5-day precipitation amount | mm |
| SDII | Simple daily intensity<br>(Ratio of total precipitation to number of wet days) | mm/day |
| $R_{10}$ | Number of heavy precipitation days (≥ 10 mm) | days |
| $R_{20}$ | Number of very heavy precipitation days (≥ 20 mm) | days |

Table 2 Description of precipitation met

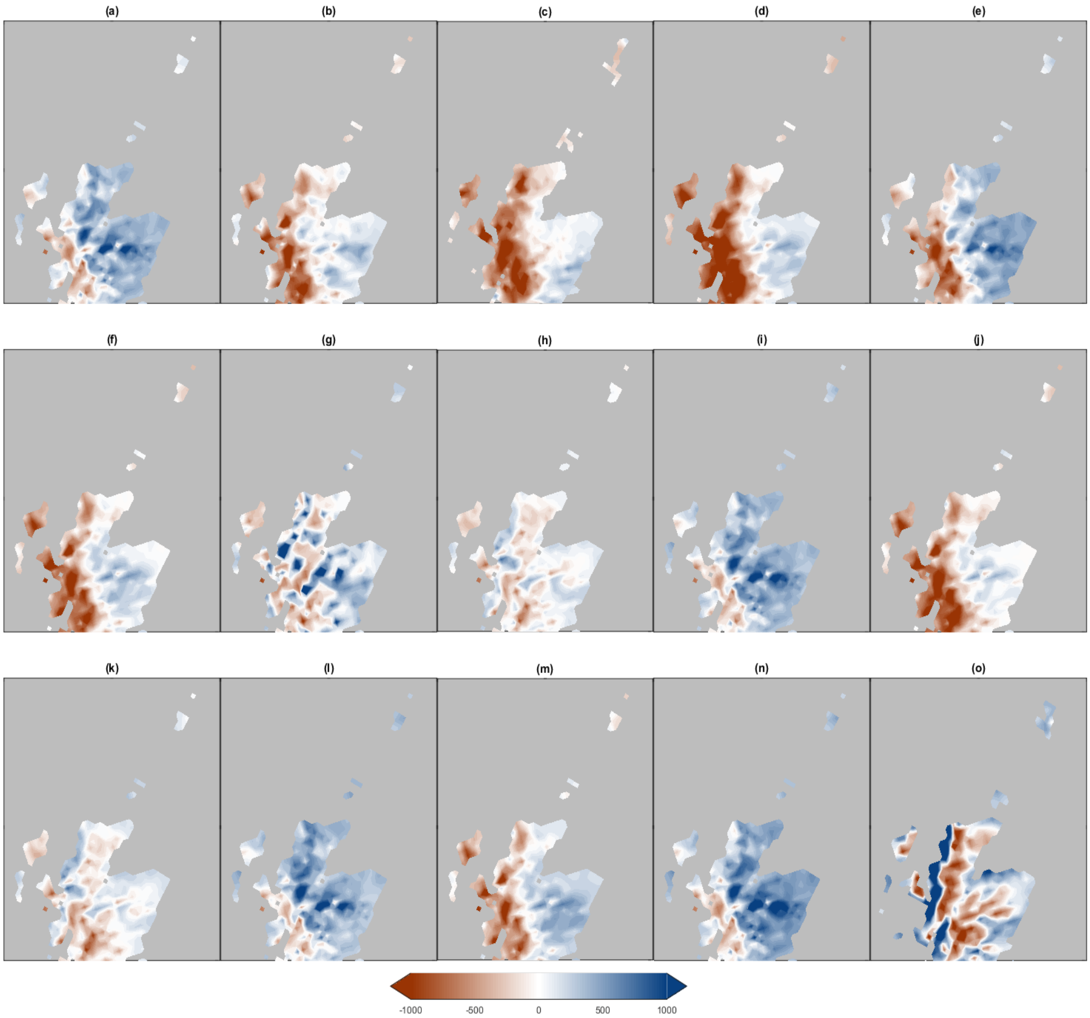


Fig. 2 Modelled mean annual Rsum bias relative to UKCP09 observations (mm).

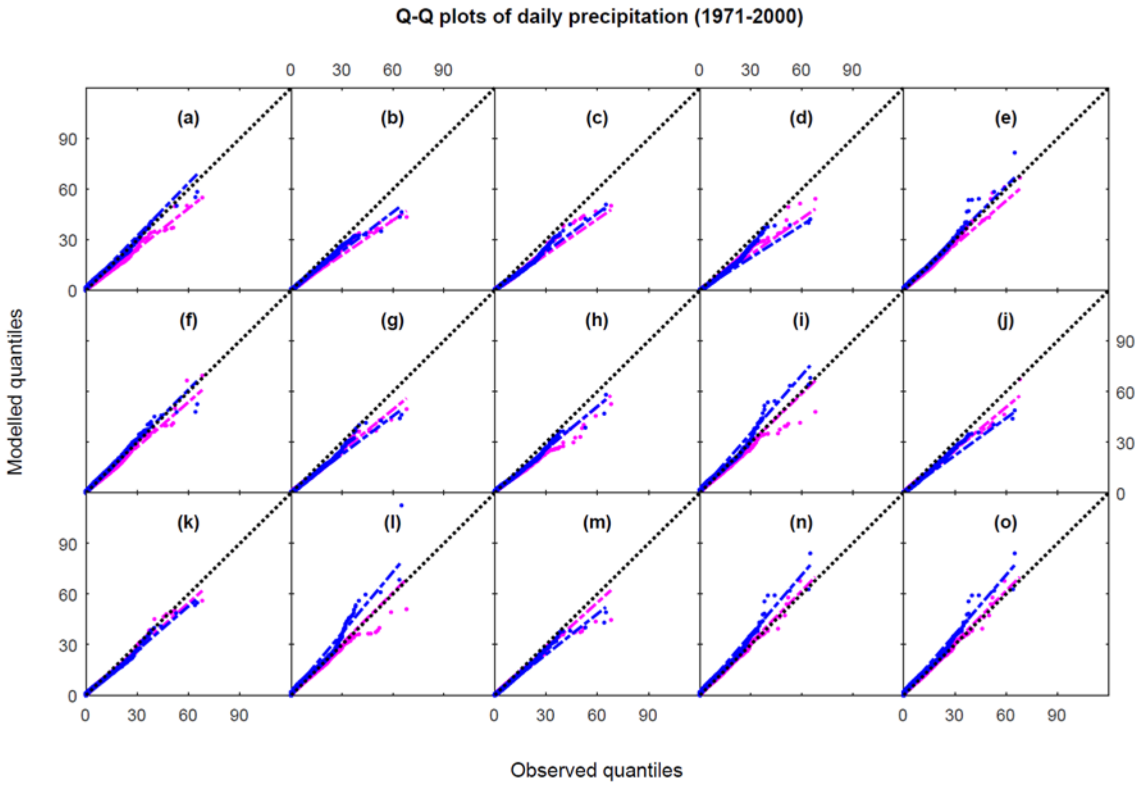


Fig. 3 Q-Q plots of observed versus modelled daily precipitation (1971-2000), with best-fit lines, for Stornoway Airport (blue) and Lerwick (magenta). The 1:1 reference line is indicated (black).

| | Stornoway Airport | | | | | | | Lerwick | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $R_{sum}$ | $R_{mean}$ | $R_{X1day}$ | $R_{X5day}$ | SDII | $R_{10}$ | $R_{20}$ | $R_{sum}$ | $R_{mean}$ | $R_{X1day}$ | $R_{X5day}$ | SDII | $R_{10}$ | $R_{20}$ |
| **Obs.** | **1294.9** | **3.5** | **34.7** | **83.3** | **6.8** | **39.8** | **7.3** | **1231.9** | **3.4** | **37.5** | **88.6** | **6.9** | **40.2** | **6.3** |
| (a) | 1610.7 | 4.4 | 31.8 | 78.6 | 5.8 | 40.2 | 5.2 | 1211.3 | 3.3 | 31.0 | 63.2 | 5.0 | 24.8 | 2.4 |
| (b) | 1091.0 | 3.0 | 27.5 | 65.3 | 5.1 | 24.6 | 3.2 | 1014.2 | 2.8 | 28.6 | 61.2 | 4.8 | 20.2 | 2.6 |
| (c) | 983.7 | 2.7 | 28.3 | 64.1 | 4.7 | 16.8 | 2.0 | 1003.1 | 2.7 | 30.0 | 61.8 | 4.7 | 17.9 | 2.2 |
| (d) | 905.5 | 2.5 | 30.4 | 57.8 | 4.7 | 17.7 | 2.4 | 938.2 | 2.6 | 27.9 | 56.2 | 4.9 | 19.4 | 2.2 |
| (e) | 1499.6 | 4.1 | 36.3 | 85.0 | 5.8 | 37.0 | 5.6 | 1259.2 | 3.4 | 35.8 | 68.1 | 5.3 | 27.5 | 3.8 |
| (f) | 1449.8 | 4.0 | 35.9 | 86.9 | 5.9 | 39.2 | 7.0 | 1281.5 | 3.5 | 33.6 | 68.3 | 5.3 | 28.8 | 3.3 |
| (g) | 1013.2 | 2.8 | 30.8 | 62.5 | 5.1 | 21.9 | 3.0 | 1068.5 | 2.9 | 31.8 | 62.6 | 5.2 | 22.4 | 2.7 |
| (h) | 1217.4 | 3.3 | 28.7 | 63.2 | 4.9 | 23.8 | 2.7 | 1138.7 | 3.1 | 24.1 | 57.7 | 4.9 | 21.1 | 1.7 |
| (i) | 1682.0 | 4.6 | 41.2 | 89.4 | 6.2 | 44.7 | 5.9 | 1347.4 | 3.7 | 29.4 | 68.5 | 5.5 | 32.3 | 3.6 |
| (j) | 1009.9 | 2.8 | 29.2 | 63.3 | 5.3 | 23.6 | 3.6 | 1085.6 | 3.0 | 30.6 | 67.3 | 5.5 | 25.4 | 2.8 |
| (k) | 1356.1 | 3.8 | 36.2 | 77.9 | 5.6 | 30.6 | 5.5 | 1240.8 | 3.4 | 40.2 | 75.2 | 5.5 | 29.1 | 5.0 |
| (l) | 1700.4 | 4.7 | 41.9 | 93.7 | 6.4 | 47.5 | 6.3 | 1445.9 | 4.0 | 30.3 | 73.7 | 5.8 | 37.5 | 4.9 |
| (m) | 1106.5 | 3.0 | 30.9 | 62.3 | 5.3 | 26.6 | 3.9 | 1194.8 | 3.3 | 31.5 | 65.7 | 5.7 | 31.7 | 3.4 |
| (n) | 1735.1 | 4.8 | 38.0 | 92.6 | 6.4 | 48.2 | 7.1 | 1472.9 | 4.0 | 39.1 | 79.7 | 5.9 | 38.3 | 5.2 |
| (o) | 1141.0 | 3.1 | 31.1 | 67.0 | 4.9 | 22.0 | 2.9 | 1580.7 | 4.3 | 33.0 | 83.1 | 6.4 | 46.1 | 7.0 |


Table 3 Observed and modelled precipitation metrics, calculated per year and averaged over 1971-2000. Shading indicates magnitude and direction of percentage error when comparing modelled and observed metrics.