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

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11 **Running head:** RCM extreme precipitation on Scottish islands

12 **Keywords:** regional climate models, model evaluation, climate change, uncertainty

13

14 **Abstract**

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

34 **1. Introduction**

35 Coastal communities in northern Europe are at risk from a wide range of climate change impacts,  
36 relating to sea-level rise and changing weather patterns, including extreme weather events (Muir *et*  
37 *al.*, 2014). For island communities, risks associated with climate change may be further compounded  
38 by their geographical characteristics. Geographical remoteness gives rise to specific challenges. For

39 instance, Coll *et al.* (2012) highlights the vulnerability of ferry services of the Western Isles of  
40 Scotland to extreme weather, noting their vital role in local trade and communication networks. In  
41 recent years, the storm of 11-12 January, 2005, highlighted the impacts of extreme weather in the  
42 Outer Hebrides, causing five fatalities and extensive damage to properties and infrastructure (Angus  
43 and Rennie, 2014). There may also be geographical constraints on adaptation options within island  
44 communities. For example, consultation with the community of Kilpheder in the Outer Hebrides has  
45 highlighted local opposition to withdrawing from the coast as it erodes (Young *et al.*, 2014). The  
46 Uists in the Outer Hebrides also contain numerous sites of special scientific interest, most of which  
47 are low-lying and vulnerable to storm damage (Angus and Rennie, 2014).

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

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

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

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

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

87 Therefore, in this study, we examine the simulative skill of the RCM ensemble generated by the  
88 CORDEX project on regional and local scales in the Hebrides and Shetland Islands and, informed by  
89 these results, discuss the potential for such data to aid in adaptation planning, drawing on examples  
90 of decision-making practice in other locations characterised by topographical complexity, such as  
91 small island developing states (SIDS; e.g. Kelman and West, 2009; Pelling and Uitto, 2001; Turvey,  
92 2007).

## 93 **2. Methodology**

### 94 *2.1 Regional climate models*

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

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

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

107 Differences in how the models are configured (e.g. different calendar conventions) mean that the  
108 modelled data cannot be compared as a daily time series with observations. Instead, the modelled  
109 and observed data are summarised using aggregate metrics. Data are extracted for a 30-year  
110 hindcast period (1971-2000). The 30 year 1971-2000 period is used as in a future phase of this work,

111 results will be used to compute changes in the future 2071-2100 period relative to the baseline. RCM  
112 and driving model combinations are detailed in Table 1. There are 15 simulations in total.

### 113 *2.2 Observed meteorological data*

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

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

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

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

### 132 *2.2 Precipitation metrics*

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

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

143 As these annual average metrics could be skewed by the presence of trends in the data, the  $R^2$  value  
144 associated with a linear fit to the annual metric values was calculated.  $R^2$  values ranged from 0 to  
145 0.3, indicating an absence of major temporal trends.

### 146 **3. Results**

147 Fig. 2 presents the spatial distribution of bias in the annual accumulated precipitation,  $R_{sum}$ , for 1971-  
148 2000. Observed precipitation totals are highly variable across the region, with the highest totals  
149 found in the western highlands, and the east coast tending towards much drier conditions. Several  
150 models have biases that effectively smooth this distribution, with a dry bias in the wettest regions  
151 and a wet bias in the driest regions. As the dry regions are in the rain shadow of the Scottish  
152 mountains, this may indicate that the issue stems from the representation of orography. Fig. 1  
153 illustrates that many models underestimate elevation in the Highlands, which may shift where  
154 orographic precipitation occurs in the models.

155 Biases do not appear to be linked to the choice of driving GCM, given the diversity of spatial error  
156 patterns across RCMs that share a driving GCM (e.g. Fig. 2, (m), (n), (o)). However, is still inadvisable



157 to consider RCMs driven by the same GCM as independent simulations, as to do so could lead to  
158 misconceptions about the relationship between model spread and uncertainty in the future climate  
159 projection (Abramowitz and Gupta, 2008).

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

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

181 inferences, which must be evaluated within the local geographical context if they are to add value to  
182 decision-making.

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

#### 187 **4. Discussion**

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

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

201 While further developments in climate modelling and computing techniques should reduce some of  
202 the uncertainty associated with model projections, it cannot remove all error. Thus, uncertainty  
203 needs to be seen and conveyed as the norm, within which decision-making can and should take  
204 place, rather than as a barrier to decision-making. Such normalisation, rather than problematisation

205 of it, shifts decision-making away from a computation strategy, and towards approaches that will  
206 increasingly require stakeholder and community engagement (de Boer *et al.*, 2010). Climate models  
207 can still add value in these contexts, by providing benchmarks against which to evaluate different  
208 adaptation and risk management proposals, e.g. within the context of a robust decision-making  
209 framework (Hall *et al.*, 2012).

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

216 Scenarios have long been an important component of development- and disaster-related planning,  
217 which may encompass climate change adaptation, using methods such as "Future Search" (Weisbord  
218 and Janoff, 2009) and participatory action research (Maskrey, 2011). Daly *et al.* (2010) used  
219 participatory processes to produce coastal maps for Samoa, indicating contemporary and possible  
220 future hazards and vulnerabilities, combining external and local knowledge. Gaillard and Maceda  
221 (2009) describe Participatory 3-Dimensional Maps (P3M), developed and piloted in the Philippines,  
222 in which external scientists and local community members use local materials to construct a scale  
223 model of the community and then identify current and future risks. Island settings especially benefit  
224 from such approaches as the small spatial scale makes localisation essential, and achievable only  
225 with local input, due to the coarseness of external datasets.

226 Similar approaches have also been analysed for Himalayan countries, indicating that the smaller,  
227 more isolated communities are likely to be more affected by climate change but that using only  
228 models in a top-down fashion does not and cannot meet those communities' needs (Lamadrid and  
229 Kelman, 2012). Much more localisation was needed, with uncertainty *per se* not being a concern,

230 because as long as the uncertainties were indicated clearly, they could be incorporated into  
231 decision-making. By modellers working with various sectors within communities and providing  
232 model results, projections, and products which users request, top-down bottom-up adaptation is  
233 implemented and becomes much more effective and suited to local contexts.

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

## 243 **5. Conclusions**

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

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

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

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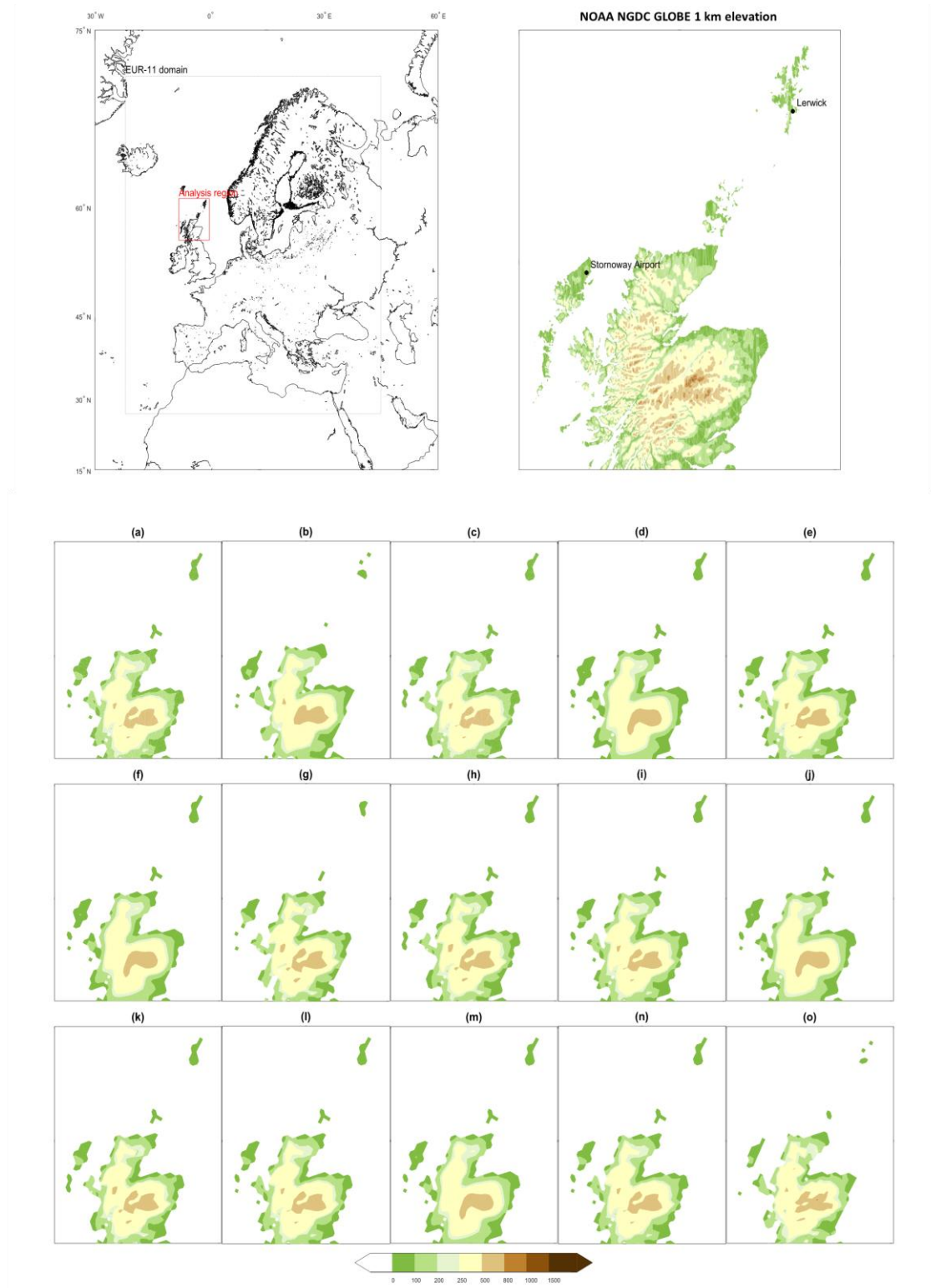
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Fig. 1 Top panels: Analysis region (red) in context of EUR-11 domain (dotted line) (left) , and actual orography in metres at 1 km (right), generated using NOAA NGDC Global Land One-kilometer Base Elevation project (GLOBE) data. Bottom panels: Modelled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

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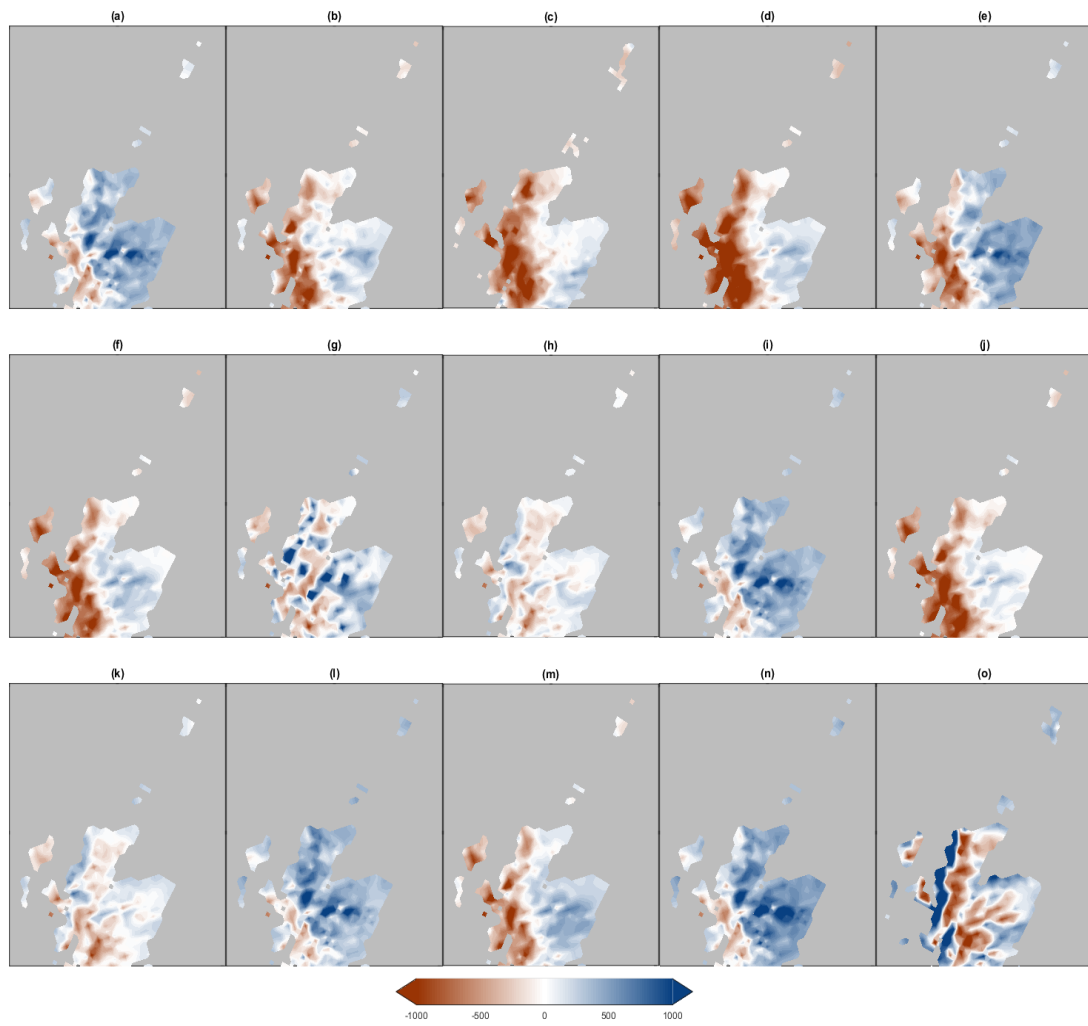
410 Table 1 EURO-CORDEX RCM and driving GCM combinations and letter references for figures.

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 (Ratio of total precipitation to number of wet days)	mm/day
$R_{10}$	Number of heavy precipitation days ( $\geq 10$ mm)	days
$R_{20}$	Number of very heavy precipitation days ( $\geq 20$ mm)	days

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412 Table 2 Description of precipitation met

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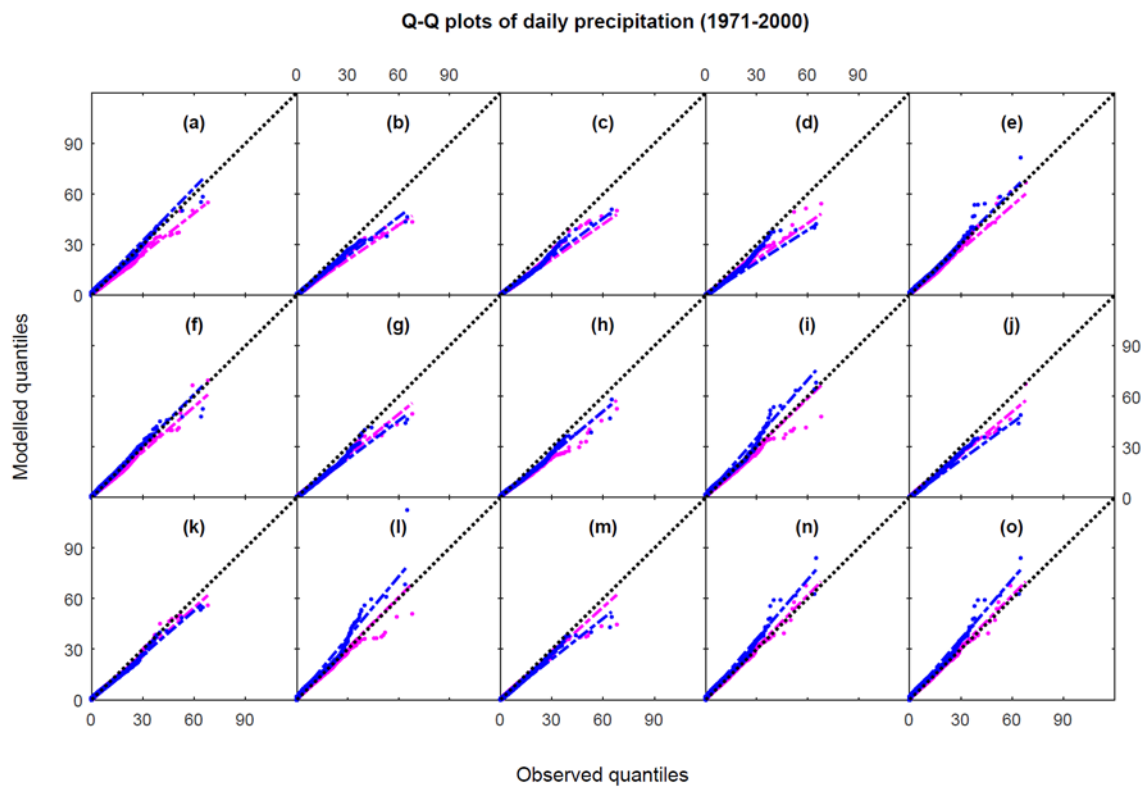


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Fig. 2 Modelled mean annual Rsum bias relative to UKCP09 observations (mm).

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

	Stornoway Airport							Lerwick						
	R <sub>sum</sub>	R <sub>mean</sub>	R <sub>X1day</sub>	R <sub>X5day</sub>	SDII	R <sub>10</sub>	R <sub>20</sub>	R <sub>sum</sub>	R <sub>mean</sub>	R <sub>X1day</sub>	R <sub>X5day</sub>	SDII	R <sub>10</sub>	R <sub>20</sub>
<b>Obs.</b>	<b>1294.9</b>	<b>3.5</b>	<b>34.7</b>	<b>83.3</b>	<b>6.8</b>	<b>39.8</b>	<b>7.3</b>	<b>1231.9</b>	<b>3.4</b>	<b>37.5</b>	<b>88.6</b>	<b>6.9</b>	<b>40.2</b>	<b>6.3</b>
(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



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421 Table 3 Observed and modelled precipitation metrics, calculated per year and averaged over 1971-

422 2000. Shading indicates magnitude and direction of percentage error when comparing modelled and

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observed metrics.