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Relevant information will appear here if provided.

Ethics

Does your article include research that required ethical approval or permits?:

This article does not present research with ethical considerations

Statement (if applicable):

CUST_IF_YES_ETHICS :No data available.

Data

It is a condition of publication that data, code and materials supporting your paper are made publicly available. Does your paper present new data?:

Yes

Statement (if applicable):

All HighResMIP model output data is available via the Earth System Grid at <https://esgf-node.llnl.gov/search/cmip6/>

CAM5.1 model data is available via the C20C data portal at <https://portal.nersc.gov/c20c/>

The NCEP-EMC observed precipitation data is available at <https://data.eol.ucar.edu/dataset/21.093>

Conflict of interest

I/We declare we have no competing interests

Statement (if applicable):

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Authors' contributions

This paper has multiple authors and our individual contributions were as below

Statement (if applicable):

Wehner conceived and wrote the paper

Lee made the Taylor diagrams

Risser reviewed and added to the discussion

Glecker reviewed and added to the discussion

Ullrich provided remapping software and commentary

Collins downloaded the HighResMIP data and added to the discussion

Evaluation of extreme subdaily precipitation in high-resolution global climate model simulations

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We examine the resolution dependence of errors in extreme subdaily precipitation in available high-resolution climate models. We find that simulated extreme precipitation increases as horizontal resolution increases but that appropriately constructed model skill metrics do not significantly change. We find little evidence that simulated extreme winter or summer storm processes significantly improve with resolution because the model performance changes identified are consistent with expectations from scale dependence arguments alone. We also discuss the implications of these scale dependent limitations on the interpretation of simulated extreme precipitation.

1) Introduction

Extreme precipitation at sub-daily scales can have significant flooding impacts in both urban and rural environments. Climate change is expected to increase the risk of such impacts as the magnitude of short term extreme precipitation will increase in many regions due to increases in available moisture and energy. Confidence in projection of these future increases as well as the attribution of current changes, if any, requires that climate models both simulate observed subdaily extreme precipitation statistics well and adequately represent the relevant physical processes causing severe storms. Climate models in recent coordinated international projects such as CMIP5 and CMIP6, the 5th and 6th generation of the Coupled Model Intercomparison Project (Eyring et al., 2016; Taylor et al., 2012) are typically configured at effective horizontal grid resolutions of 100km or coarser. For dynamical reasons alone, many properties of the severe storms responsible for extreme precipitation cannot be resolved at these grid spacings, no matter how good the subgrid scale physical parameterizations are (Reed and Jablonowski, 2012; Zarzycki et al., 2014)

Climate models at horizontal resolutions of ~20-50km have been shown to improve upon this situation (Wehner et al., 2014). In particular, the stronger gradients in moisture and temperature enabled at higher resolutions permit reasonable simulation of tropical cyclone properties (Reed et al., 2015; Shaevitz et al., 2014) and other severe storm statistics (Champion et al., 2011; Rhoades et al., 2020; Roberts et al., 2018; Walsh et al., 2015; Wehner et al., 2015). Advances in high performance computing technologies have progressed to the point where a limited number of multi-decadal simulations of climate models at these finer resolutions can now be performed. The multi-tiered HighResMIP

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3 47 subproject of the CMIP6 is the first attempt to intercompare the simulated past climate
4 48 and projected future climate change of such models (Haarsma et al., 2016). The
5 49 HighResMIP protocols specify that modeling groups perform simulations with both a
6 50 coarse and fine resolution model configuration. In practice, the coarse grid configurations
7 51 are generally the operational version of the model and the high resolution configuration
8 52 an experimental version with grid spacings of 50km or finer. Hence, the physical
9 53 parameterizations in the models are specified by the protocols to be the same across
10 54 resolutions. However, for stability reasons some groups may have had to make minor
11 55 parameter value adjustments, including time stepping controls. The HighResMIP
12 56 protocols specify both fully coupled ocean-atmosphere model configurations as well as
13 57 atmosphere only configurations forced by fixed surface ocean and sea-ice datasets.
14 58 Simulations of the recent historical period from 1950 to 2014 and a near future period
15 59 from 2015 to 2050 under the high emissions scenarios of RCP8.5 or SSP85 are called for
16 60 in both the coupled and atmospheric-only configurations.

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21 61 To the extent observations permit it, some aspects of subdaily simulated
22 62 precipitation have been evaluated including the diurnal cycle (Dai et al., 2007).
23 63 More recently, irregular subdaily fluctuations about the mean diurnal cycle or
24 64 “intermittency” have been shown to be underestimated by models, even after taking
25 65 into account the observational “error bars” implied by different space-time
26 66 resolutions (Covey et al., 2018).

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29 67 In this paper, we utilize standard practice model evaluation techniques (Gleckler et al.,
30 68 2008; Lee et al., 2019) to analyze the quality of seasonal 3 hourly precipitation extremes
31 69 produced by available HighResMIP models. Previous evaluations of simulated extreme
32 70 precipitation has focused on daily or pentadal accumulations (Akinsanola et al., 2020;
33 71 Bador et al., 2020; Sillmann et al., 2013; Srivastava et al., 2020; Wehner et al., 2020).

34 72
35 73 Model evaluation is only as good as the observational datasets used as a reference and
36 74 quality observed sub-daily precipitation accumulations are even more limited than for
37 75 daily accumulations (Trenberth et al., 2017). Furthermore, as shown by (Gervais et al.,
38 76 2014) and explored in this paper, the order of operations in calculating gridded
39 77 observational extreme subdaily precipitation metrics can affect their magnitude and the
40 78 interpretation of model quality. In this first evaluation, we thus confine our analyses to
41 79 the conterminous United States (CONUS) and the winter (DJF) and summer (JJA)
42 80 seasons.

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46 82 To date, six modeling groups have submitted both coarse and fine resolution 3 hourly
47 83 precipitation data to the historical period atmosphere only (*highresSST-present*)
48 84 experiment. Several of these groups have also submitted simulations to the fully coupled
49 85 model simulations. Errors in simulated sea surface temperature can significantly affect
50 86 the location and intensity of severe storms that would likely degrade the quality of
51 87 simulated extreme precipitation statistics. Hence in this study we focus our model
52 88 evaluation on the more complete *highresSST-present* experiment and defer analysis of the
53 89 effect of ocean-atmosphere coupling on extreme precipitation. We also add a seventh

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3 90 model that is not part of the HighResMIP but was integrated under similar boundary
4 91 conditions.

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6 93 In section 2, we describe the merged radar and station observational dataset used as an
7 94 evaluation standard and briefly describe the climate models with available fine and coarse
8 95 resolution 3 hourly precipitation datasets. We also describe the effect of the order of
9 96 gridding and extrema on the construction of a model evaluation standard in that section.
10 97 In section 3, we present the model error metrics including bias maps for each model and
11 98 summary Taylor diagrams (Taylor, 2001). In section 4, we discuss these errors and offer
12 99 some interpretation of how model resolution affects the simulation quality of extreme
13 100 sub-daily precipitation. We further discuss the limitations of simulated extreme
14 101 precipitation and provide some context supplied by the expectations provided by the
15 102 model evaluation standards. In section 5, we summarize our principal conclusions about
16 103 the effect of refined horizontal resolution on simulated sub-daily precipitation quality.
17 104

18 105 **2) Methods, observations and models.**

19 106
20 107 Recognizing that the nature and magnitude of extreme storms in the mid and high
21 108 latitudes is strongly seasonally dependent, we focus on the winter and summer seasonal
22 109 extremes rather than on annual extremes. While long period return values of seasonal
23 110 maxima would be relevant for impacts, we focus only on the average winter and summer
24 111 maxima as uncertainties from the short observational record in fitted extreme value
25 112 distributions would be large, even with non-stationary statistical models (Wehner et al
26 113 2020a). However, we note that a previous model evaluation of average annual daily
27 114 maximum precipitation and associated long period return values (Wehner et al., 2020)
28 115 found that although model performance degrades as rarity increases, the patterns of errors
29 116 are similar.
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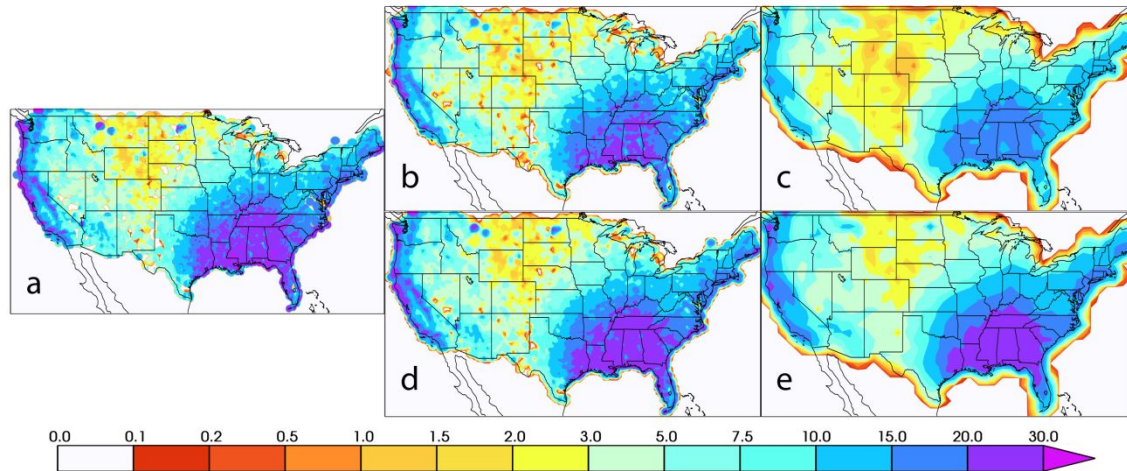
31 118 Long records of observed subdaily precipitation data are a scarce resource and is
32 119 available only over limited land regions from weather stations and/or radar. Sampling
33 120 limitations currently make satellite-based products unsuitable reference data for our
34 121 analysis. The HadISD (Dunn et al., 2016) is an available multi-variate station data set but
35 122 precipitation is not one of the variables subjected to stringent quality control. The Global
36 123 Sub-Daily Rainfall Dataset (GSDR), part of the INTENSE project (Lewis et al., 2019) is
37 124 the first real attempt to collect and quality control station based sub-daily precipitation.
38 125 Long, spatial dense records are mostly confined to the United States and some Western
39 126 European countries. However, this dataset is not yet publicly available.
40 127

41 128 Operational weather radar provides a remote sensing alternative to ground-based
42 129 observations. The National Centers for Environmental Prediction (NCEP) Environmental
43 130 Modeling Center (EMC) has provided a merged ground based and radar derived hourly
44 131 precipitation dataset from ~3000 weather stations and the 159 Doppler radars of the
45 132 Next-Generation Radar (NEXRAD) on an approximately 4km polar stereographic grid
46 133 spanning the CONUS region (Du et al. 2011) and is available at
47 134 <https://data.eol.ucar.edu/dataset/21.087>. Most HighResMIP modeling groups provide 3
48 135 hourly precipitation accumulations so these hourly observations are similarly
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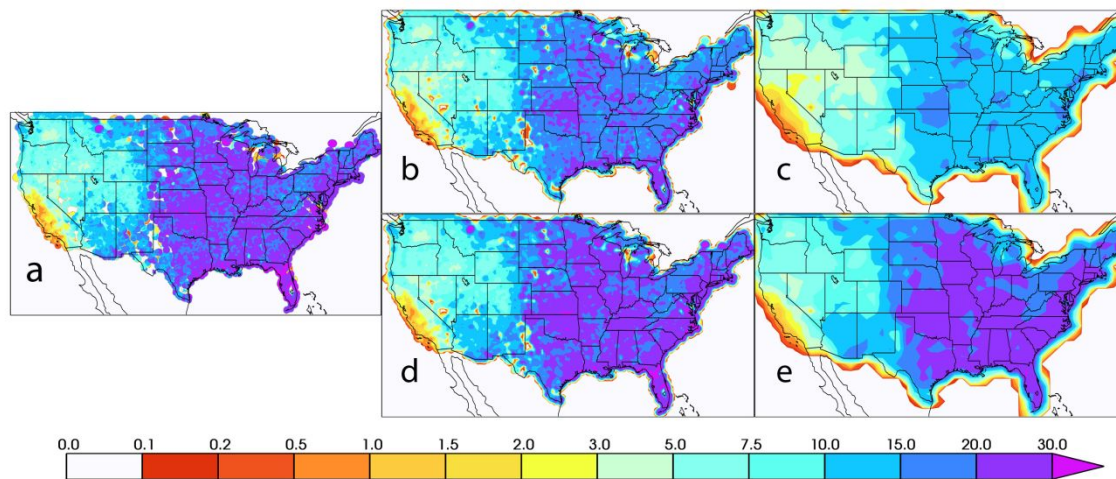
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3 136 accumulated on the original stereographic grid from the raw downloaded data as the first
4 137 step. We next used the data over the period June 1997 to February 2020 to calculate
5 138 estimates of the average seasonal maximum 3 hourly precipitation accumulation in two
6 139 ways discussed below. Note that there are substantial missing data throughout this period,
7 140 especially prior to 2002.
8 141

9 142 As mentioned above the order of operations in the construction of the reference
10 143 observations can introduce false estimation of model biases that are likely to be larger for
11 144 subdaily than for daily extreme precipitation model performance metrics (Gervais 2013 et
12 145 al). The observational extreme precipitation product most similar to model output is
13 146 obtained by first gridding the raw high frequency data to the model grid then calculating
14 147 block extrema, usually annually or seasonally. As precipitation is by definition a moisture
15 148 flux, this procedure should be made conservative. In this paper, we refer to such model
16 149 evaluation results as the “native grid” results since the observational extremes are
17 150 calculated on each models’ native grid. In this case, a different reference set must be
18 151 calculated for each model further adding to the complexity of the evaluation process.
19 152

20 153 However, this order of operation is not always practical, especially for subdaily extremes
21 154 due to the high computational cost of regridding and/or the availability of the high
22 155 frequency observational data itself. For instance, high frequency station data may not be
23 156 made available by the owners but block maxima or other extreme value indices are
24 157 provided. In fact, this is the case for the daily extrema contained in the HadEX3 global
25 158 land dataset (Dunn, 2020) where the stations’ extrema are gridded rather than the
26 159 stations’ daily values themselves. In this paper, we refer to such model evaluation results
27 160 as the “non-native grid” since the observational extremes are not calculated on the
28 161 models’ native grid but are calculated either at individual stations or on a different grid.
29 162 For precipitation, it is generally unlikely that the extrema at different locations within the
30 163 same grid cell occur at the same time. Hence, observational estimates of gridded station
31 164 extrema are generally larger than the extrema of gridded high frequency station data. This
32 165 order of operations bias also extends to the case where the observations are on a much
33 166 finer grid than the models, as is the case here with the NCEP-EMC hybrid radar station
34 167 product. Figures 1 and 2 shows the observed average winter (1a) and summer (2a)
35 168 maximum 3 hour precipitation accumulations calculated on the original 4km polar
36 169 stereographic grid but regridded to a 4km latitude/longitude for plotting purposes. Also
37 170 shown in figure 1 are “native grid” results at 25km (1b, 2b) and 100km (1c, 2c) and the
38 171 “non-native grid” results at 25km (1d, 2d) and 100km (1e, 2e). Clearly, the non-native
39 172 regridding shown in the bottom rows result in values close to the original 4km resolution.
40 173 However, as Gervais et al., (2014) point out, the smaller values produced by the native
41 174 mesh regridding shown in the top rows are what the models should be expected to
42 175 produce. Figure S1 shows the percent differences between the native and non-native
43 176 gridding results further revealing that the effect of the order of operations is larger for
44 177 lower resolutions than higher resolutions. In the next section we show the effect of this
45 178 order of regridding operations on model evaluation. Herein we use the conservative and
46 179 consistent TempestRemap package for regridding operations (Ullrich et al., 2016; Ullrich
47 180 and Taylor, 2015).
48 181



182
 183 Figure 1. Average DJF maximum 3 hour precipitation accumulation. a) Maximum values
 184 calculated on the original 4km polar stereographic mesh and regridded to a 4km latitude-
 185 longitude mesh. b) Maximum values obtained by first regridding daily precipitation to a
 186 25km mesh. c) Maximum values obtained by first regridding daily precipitation to a
 187 100km mesh. d) Maximum values obtained by regridding 4km maxima to a 25km mesh.
 188 e) Maximum values obtained by regridding 4km maxima to a 100km mesh.
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190
 191 Figure 2. Average JJA maximum 3 hour precipitation accumulation. a) Maximum values
 192 calculated on the original 4km polar stereographic mesh and regridded to a 4km latitude-
 193 longitude mesh. b) Maximum values obtained by first regridding daily precipitation to a
 194 25km mesh. c) Maximum values obtained by first regridding daily precipitation to a
 195 100km mesh. d) Maximum values obtained by regridding 4km maxima to a 25km mesh.
 196 e) Maximum values obtained by regridding 4km maxima to a 100km mesh.
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198 The CNRM-CM6-1 models were developed at the Centre National de Recherches
 199 Meteorologiques and the Centre Europeen de Recherche et de Formation Avancee en
 200 Calcul Scientifique in Toulouse, France (Voltaire et al., 2013). The EC-Earth3P models
 201 were developed by a consortium of European universities and laboratories

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3 202 (<http://www.ec-earth.org>) from Belgium, Denmark, Finland, Germany, Ireland, Italy,
4 203 The Netherlands, Norway, Portugal, Spain, Sweden and the United Kingdom (Haarsma et
5 204 al., 2016) and is based on the European Centre for Medium Range Forecasting IFS
6 205 seasonal forecasting system (C. D. Roberts et al., 2018). The HadGEM3-GC3.1 is the
7 206 current version of the United Kingdom's MetOffice Unified Model (Roberts et al., 2019)
8 207 and results were supplied at three resolutions. The IPSL-CM6A models were developed
9 208 at the Institut Pierre Simon Laplace in Paris, France (Boucher et al., 2019). The MRI-
10 209 AGCM3-2 models were developed at the Max Planck Institute for Meteorology in
11 210 Hamburg, Germany (Gutjahr et al., 2019). The NICAM16 models are based non-
12 211 hydrostatic equations and were developed at multiple institutions in Yokohama, Tokyo
13 212 and Tsukuba, Japan (Kodama et al., 2020). Additionally, we also evaluate the
14 213 Community Atmospheric Model (CAM5.1), developed at the National Center for
15 214 Atmospheric Research in Boulder, Colorado, United States (Bacmeister et al., 2014;
16 215 Wehner et al., 2014). While this model was not submitted to the HighResMIP subproject,
17 216 it was integrated under similar boundary conditions for the period evaluated. The model
18 217 names and their provided latitude and longitude dimensions are listed in table 1.
19 218 However, models' true native grids may not be based on a latitude-longitude coordinate
20 219 system and submitted data is regridded according to CMIP6 protocols in such cases.
21 220 Interested readers are directed to the cited model documentation.
22 221

23 222 The *highresSST-present* simulations nominally end in 2014 although some models end in
24 223 2015. For these simulations, we average the seasonal maxima over the 20 year period
25 224 1995 to 2014. The CAM5.1 model data is available only from 1996 to 2015, so we
26 225 average over that 20 year period instead. While these periods are not identical to the
27 226 observed period used here, the length of period is about the same when accounting for the
28 227 missing observations. While any anthropogenic trend in extreme precipitation from 2014
29 228 to 2020 is negligible, we admit that some differences due to natural modes of sea surface
30 229 temperature variability might not be. However, Risser et al. (2020) find that percentage of
31 230 variance in extreme daily precipitation over the CONUS region explained by these modes
32 231 is smaller than might be expected. Some models provide multiple realizations (table 1)
33 232 and in these cases, the seasonal maxima are further averaged over realizations.
34 233

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Model	latitude X longitude	# of realizations	DJF skill	JJA skill
CAM5-1-1degree	128x256	49	0.75	0.54
CAM5-1-2-025degree	360x720	5	0.79	0.60
CNRM-CM6-1	256x512	1	0.67	0.65
CNRM-CM6-1-HR	512x1024	1	0.76	0.68
EC-Earth3P	144x192	3	0.73	0.68
EC-Earth3P-HR	324x432	3	0.74	0.69
HadGEM3-GC31-LM	143x144	2	0.68	0.53
HadGEM3-GC31-MM	361x512	2	0.74	0.52
HadGEM3-GC31-HM	768x1024	3	0.80	0.54
IPSL-CM6A-LR	320x640	1	0.70	0.52
IPSL-CM6A-ATM-HR	960x1920	1	0.73	0.60
MRI-AGCM3-2-H	320x640	1	0.82	0.57
MRI-AGCM3-2-S	640x1280	1	0.82	0.56
NICAM16-7S	192x288	1	0.77	0.46
NICAM16-8S	768x1152	1	0.74	0.32

235 Table 1. Model resolution (column 2) and the number of realizations used in evaluation
 236 (column 3). Taylor's modified skill over the CONUS region for average maximum DJF
 237 and JJA 3 hourly precipitation using subdaily observations regridded to the models'
 238 resolutions is shown in columns 5 and 6. High resolution model versions are shown in
 239 bold font.

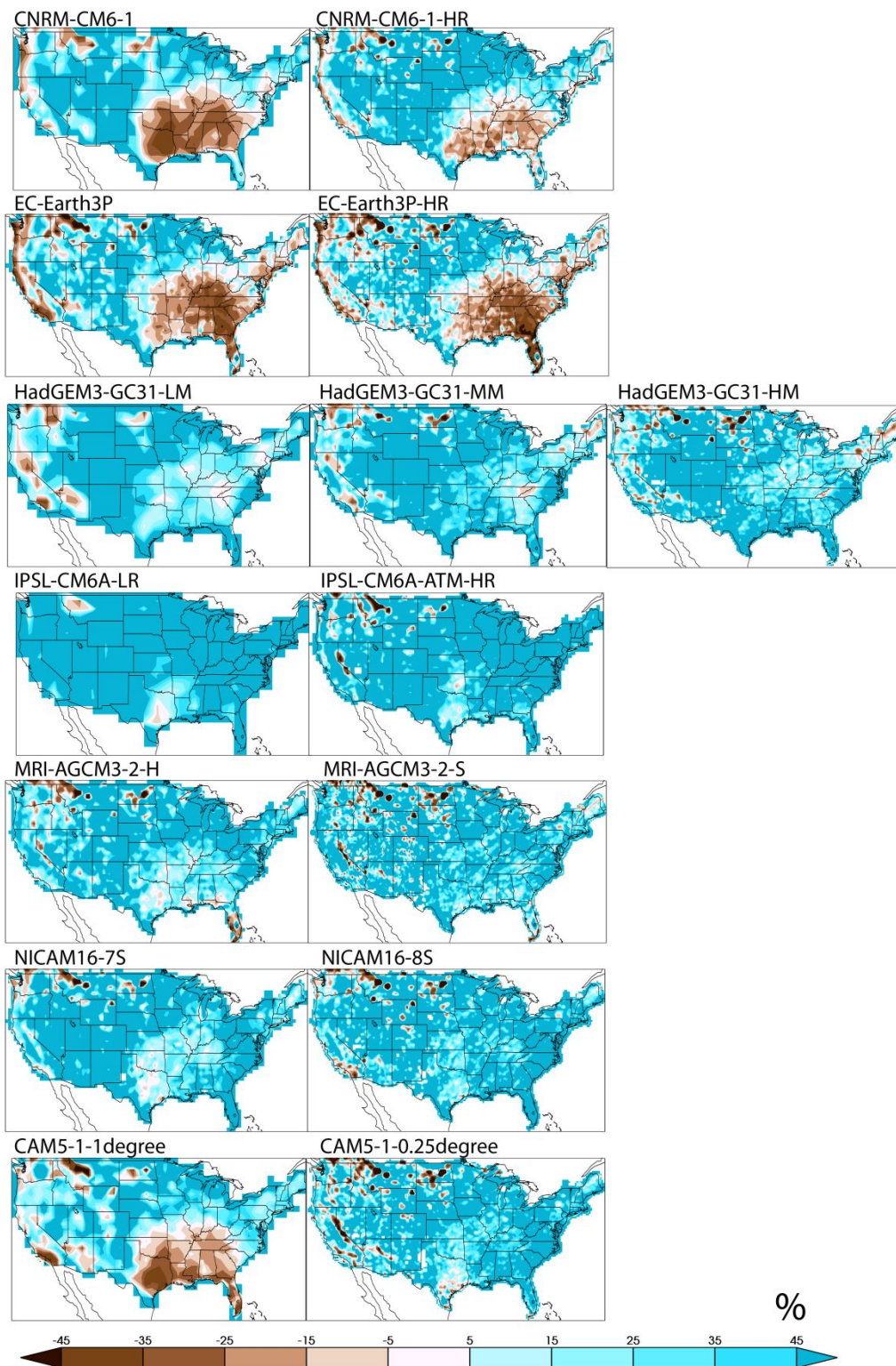
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241 3) Model errors.

242 Figure 3 shows the percent error in simulated average DJF maximum 3 hour precipitation
 243 accumulation using the native grid observations. Consistent with the expectation shown
 244 in the top row of figure 1, the high resolution models produce larger maximum values
 245 than their lower resolution counterparts. Although there is little commonality between
 246 errors across the modeling groups, the pattern of native grid errors are remarkably similar
 247 across resolution within an individual modeling group. Figure S2 shows the percent error
 248 in simulated average DJF maximum 3 hour precipitation accumulation using the non-
 249 native grid observations and highlights the importance of the order of operations in the
 250 constructing the reference maxima. Non-native grid model errors are very different than
 251 native grid errors since the non-native reference values, shown in the bottom row of
 252 figure 1, are so much larger than the native reference values of the top row of figure 1.
 253 The patterns of non-native grid model errors in figure S2 are much less similar across
 254 resolutions than the native grid model errors in figure 3 and can even be of opposite sign
 255 as summarized in table S1. This difference in error pattern can lead to very difference
 256 conclusions about the effect of horizontal resolution on simulated extreme precipitation
 257 quality.

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Figure 3. Percent native grid error in simulated average DJF maximum 3 hour precipitation accumulation. Models are arranged low to high horizontal resolution from left to right.

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Figure 4 shows the percent error in simulated average JJA maximum 3 hour precipitation accumulation using the native grid observations. Summer errors are generally considerably larger than winter errors at any resolution. Error patterns are again very different across models and for some models similar across resolutions. The notable exception to similarity across resolutions is the CAM5.1 model in the southeastern US in both seasons. Figure S3 and Table S1 show that the non-native grid errors in summer are even more different from the native grid errors than in winter.

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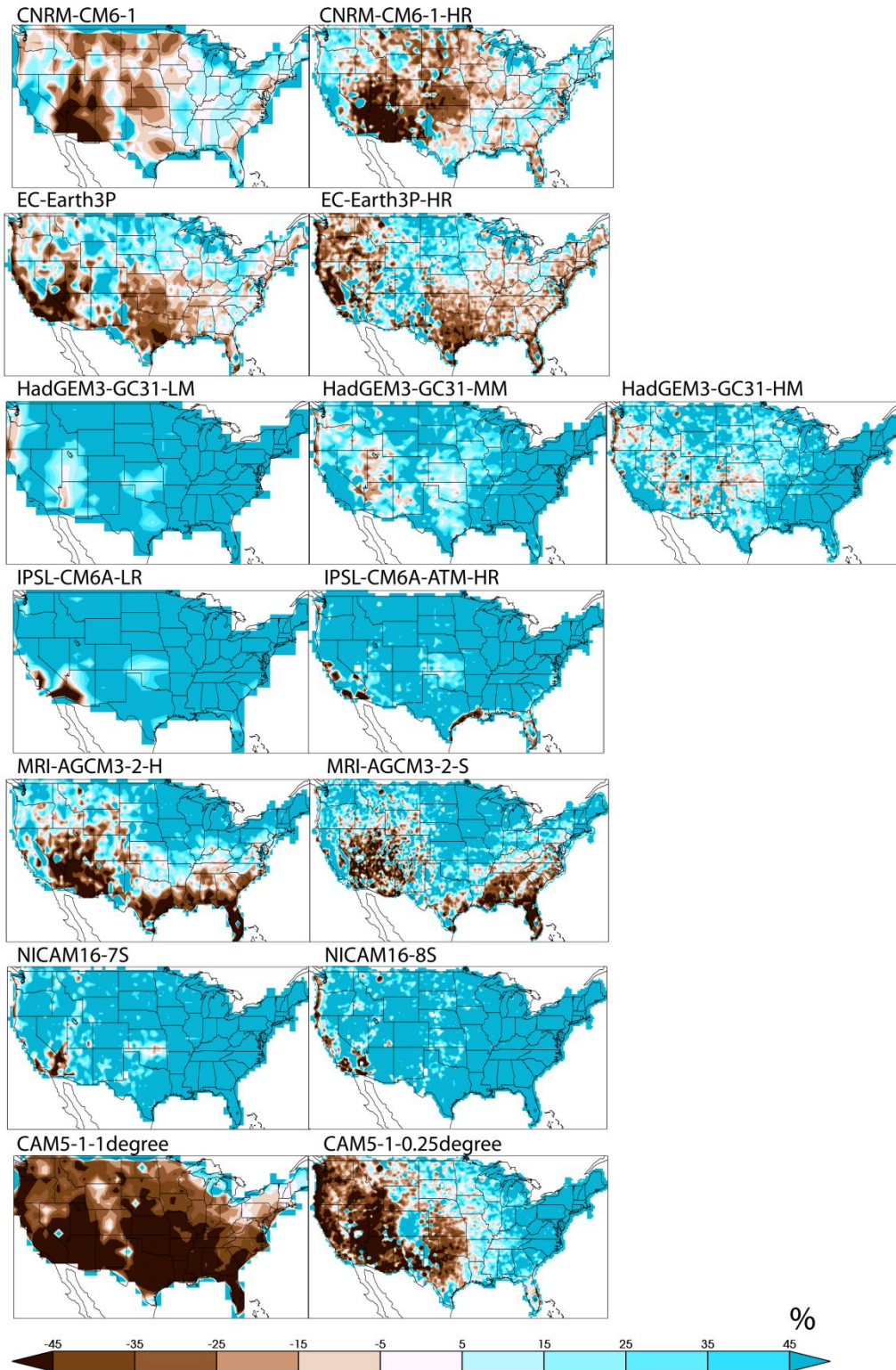
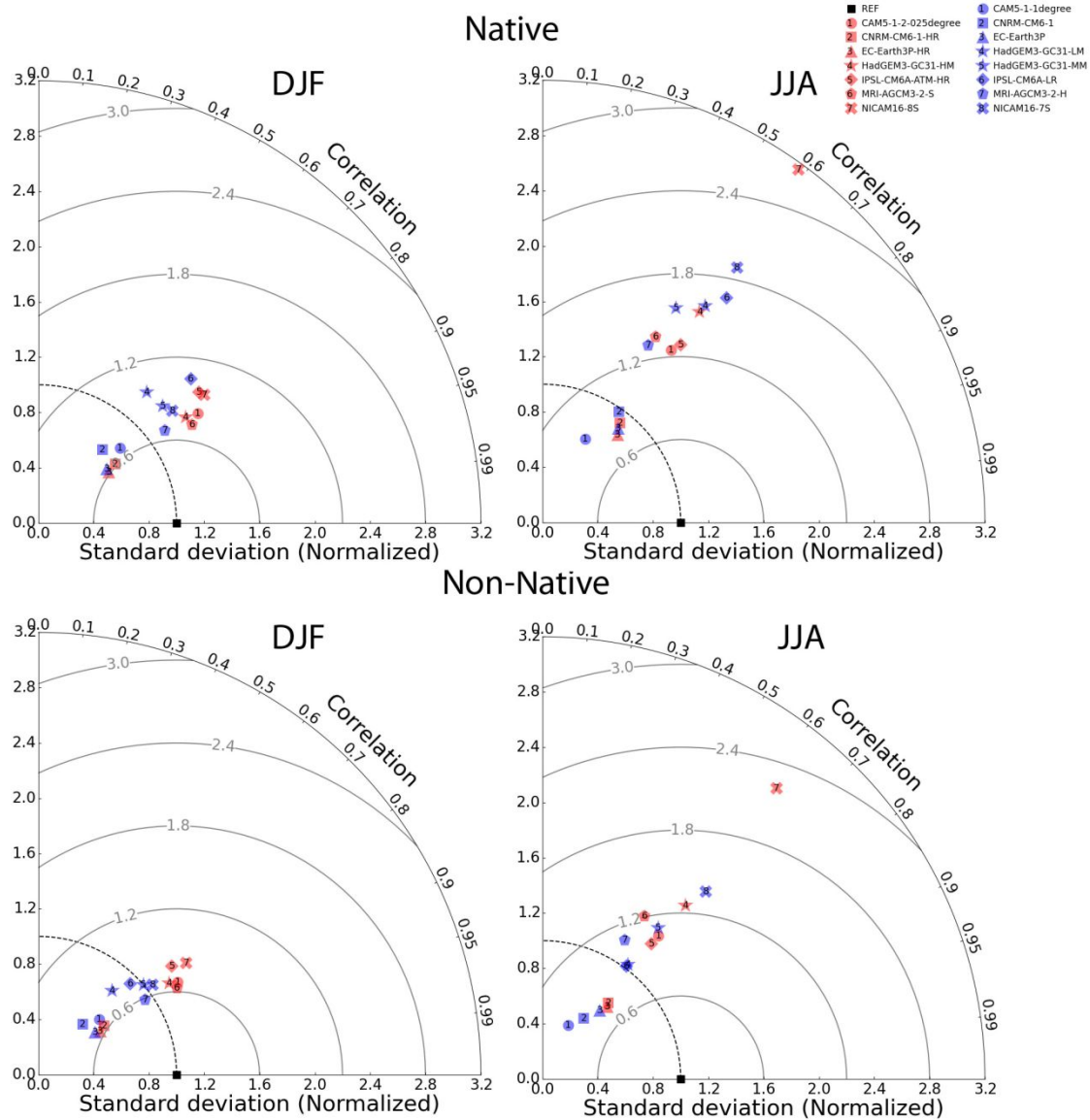


Figure 4. Percent native grid error in simulated average JJA maximum 3 hour precipitation accumulation. Models are arranged low to high horizontal resolution from left to right.

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3 280 We use Taylor Diagrams to compare differences in selected centered
4 281 statistics. Figure 5 shows Taylor Diagrams of the pattern correlation and
5 282 normalized spatial standard deviation of the simulated seasonal maximum 3 hour
6 283 precipitation accumulation for winter (left column) and summer (right column)
7 284 using both the native (top row) and non-native (bottom row) grid observations.
8 285 Traditionally, Taylor Diagrams show the different model results computed on a
9 286 common grid, but here centered statistics are calculated on each individual model's
10 287 grid to be consistent with the resolution dependent bias statistics. To facilitate
11 288 comparison, we normalize the standard deviation of each model result by the
12 289 corresponding value of the observed extremes. Consistent with the similarity in DJF
13 290 native grid error structures across resolution shown in figure 3, there is little difference in
14 291 the locations of symbols for the high (red) and low (blue) resolution simulations of a
15 292 given modeling group shown in the upper left of figure 5. Despite the dissimilar winter
16 293 error patterns across models shown in figure 3, points in the Taylor diagram are clustered
17 294 in the angular dimension with centered pattern correlations between 0.6 and 0.8.
18 295 However, there is considerable spread in the normalized spatial standard deviation
19 296 indicating that the range of maximum values varies significantly across the CONUS
20 297 region across models. Using the native grid observations, normalized Root Mean Square
21 298 Error (RMSE) ranges from 0.6 to about 1.0 in the winter. Taylor's modified skill
22 299 (Wehner, 2013) in winter using the native grid reference, shown in table 1, ranges from
23 300 0.67 to 0.82 with generally small differences between simulations from the same
24 301 modeling group.
25 302

26 303 The Taylor diagram of JJA native grid errors (upper right of figure 5) also shows a tight
27 304 cluster around pattern correlation values between 0.5 and 0.6 (the angular dimension of
28 305 the diagram) but a much larger spread in the radial dimension indicating a wider spatial
29 306 dynamic range across modeling groups. As in winter, there is little difference in the
30 307 placement of symbols across simulations from a given model group. Summer normalized
31 308 RMSE is larger than winter ranging from about 0.9 to 2.5 and Taylor's modified skill
32 309 (Table 1) ranges from 0.32 to 0.69. Differences between simulations from the same
33 310 modeling group again are small with the exception of the outlying NICAM16 models
34 311 which exhibit exceptionally large simulated JJA 3 hour maximum precipitation
35 312 accumulations.
36 313

37 314 Perhaps surprisingly, considering the difference in model biases between the native and
38 315 non-native grid standards, there is little corresponding difference in the Taylor diagrams.
39 316 Pattern correlation metrics are essentially the same and any differences come from the
40 317 normalized standard deviation.
41 318



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 320 Figure 5. Taylor diagram of average DJF (right) and JJA (left) maximum simulated 3
 321 hour precipitation accumulation from native (top) and non-native (bottom) grid errors.
 322 Blue symbols are low resolution models. Red symbols are high resolution models.
 323 Symbol shapes are the same for models from the same modeling group. The concentric
 324 semi-circles are isolines of normalized root mean square error. The dashed circle
 325 represents a normalized standard deviation of unity.

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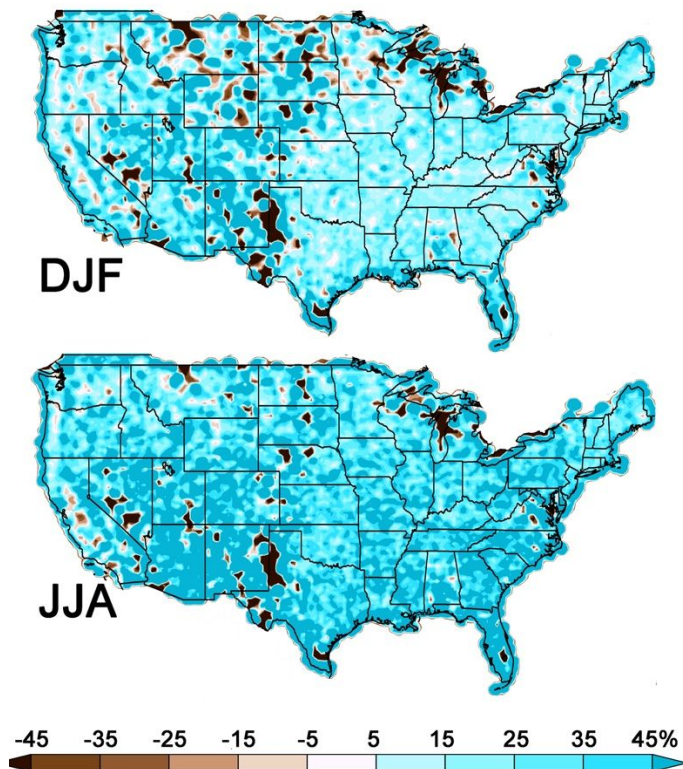
327 **4) Discussion**

328 Part of the motivation for increasing climate models' horizontal resolution to a few 10's
 329 of kilometers is to more realistically simulate the severe storms responsible for extreme
 330 precipitation. And indeed simulated seasonal maximum sub-daily precipitation
 331 accumulations increase with refined computational grids. The extrema based on
 332 appropriately coarsened sub-daily observations provide us the appropriate standard
 333 reference for model evaluation (upper panels of Figures 1 and 2). Based on that standard,
 334 we find little improvement with grid refinement in simulated 3 hour extreme precipitation
 335 accumulations when held to that expectation, at least over the CONUS region (figures 3-
 336 5).

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338 The difference in the resolution dependent standards in the upper panels of Figures 1 and
 339 2 provide an expectation of the increase in simulated extreme precipitation with
 340 resolution. Figure 6 shows the expected percent change in simulated average seasonal
 341 maximum 3 hour precipitation accumulation for a change in model horizontal resolution
 342 from ~100km to ~25km. In this figure, the ~100km standard was conservatively
 343 remapped to ~25km and is used in the denominator. This expectation, based on simple
 344 scaling arguments, is mostly of an increase. Decreases are mostly localized and confined
 345 to dry regions in areas of high orography. The shortness of record, combined with high
 346 variability in these regions is the most likely explanation for these decreases, rather than
 347 deficiency in the scaling argument.

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350 Figure 6: The expected percent change in simulated average seasonal maximum 3 hour
 351 precipitation accumulation for a change in horizontal resolution from ~100km to ~25km.

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4 353 We find that high resolution models generally exhibit similar patterns in percent errors to
5 354 their low resolution counterparts. The similarity in sub-daily precipitation errors across
6 355 resolution suggests that large scale circulation errors are not affected much by resolution.
7 356 It also suggests that the locations and frequency of winter and summer extreme storms
8 357 resulting from the simulated large scale circulation are also not greatly affected by
9 358 resolution although that aspect of the HighResMIP simulations has not yet been
10 359 evaluated. While the magnitude of extreme storms are substantially larger and hence
11 360 more realistic at high resolution, the “native grid” method of defining an extreme
12 361 precipitation standard accounts for this and little resolution dependence can be robustly
13 362 identified in percent error magnitude when models are evaluated against that standard.
14 363 Further evidence that resolution has little effect on extreme precipitation beyond what is
15 364 expected by figures 1 and 2 is provided by the normalized error metrics of the Taylor
16 365 diagrams (figure 5). The distance between points representing models of different
17 366 resolution from the same modeling groups is small and both normalized RMSE and
18 367 Taylor’s modified skill (table 1) exhibit only minor improvements at high resolution. In
19 368 fact, skill values of extreme 3 hour precipitation accumulations over the CONUS region
20 369 for the HighResMIP models are quite similar to global land skill values for extreme daily
21 370 precipitation accumulations for the CMIP5 and CMIP6 models (Wehner et al., 2020).
22 371 Indeed, as extreme daily precipitation errors are highly correlated to mean precipitation
23 372 errors (Wehner et al., 2020) it is not surprising that sub-daily errors would be closely
24 373 related to daily errors.
25 374

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27 376 There is no systematic error pattern across all modeling groups, for all but one pair of
28 377 models with an ancestral relationship. The CNRM-CM6-1 models and EC-Earth3P
29 378 models both descend from versions of the ECMWF IFS atmospheric model and have
30 379 very similar winter error patterns although differ in the summer. The other models,
31 380 except CAM5.1, are largely biased high in the winter but mixed in the sign of summer
32 381 errors.

33 382

34 383 Model evaluation is only as good as the reference data available and for sub-daily
35 384 precipitation there are many obstacles to constructing them from in-situ and remote
36 385 observations for sub-daily precipitation. While the NCEP-EMC hybrid station and radar
37 386 data set is relatively short at about 20 years, the differences between it and the model
38 387 simulations are likely much larger than natural variability, even for extreme sub-daily
39 388 precipitation accumulations. Other data sets covering larger regions and longer time
40 389 periods constructed by gridding station extrema are now becoming available (Dunn et al.,
41 390 2020; Lewis et al., 2019). While gridded station extrema are useful for assessing the
42 391 actual risk of extreme precipitation, they are inappropriate for evaluation of simulated
43 392 extreme precipitation bias due to fundamental discrepancies in their definition relative to
44 393 model representation. Climate model precipitation within a grid is best thought of as a
45 394 moisture flux and is a conserved quantity in a well-constructed climate model. While
46 395 available sub-daily *in situ* station or radar measurements within a computational grid cell
47 396 may be sparse, placing them on a grid at the same frequency as sampled by the model and
48 397 subsequently calculating maxima most closely resembles what models simulate. Clearly,
49 398 gridded station maxima is a different quantity than the maxima of gridded high frequency
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3 398 precipitation and has no conservative properties. This same statement holds true for
4 399 remapping very finely gridded observational maxima to a coarser grid. This is most clear
5 400 by recognizing that within a grid cell, not all locations will experience the maximum
6 401 precipitation accumulation at the same time. Hence, the gridded maxima is always larger
7 402 than the maxima of gridded high frequency precipitation. This effect is exacerbated as
8 403 grids coarsen as shown in figures 1, 2 and S1.
9 404

10 405 This inconsistency between gridded maxima and what climate models actually simulate
11 406 presents a challenge to comprehensive model evaluation. However, as figure 5 shows, a
12 407 standard based on gridded maxima does provide useful information about the patterns of
13 408 errors. Normalized RMSE and Taylor's modified skill from such a standard are biased
14 409 but not as much as might be expected from the biases in error magnitude. This behavior
15 410 will prove useful in a limited model evaluation over a larger fraction of the planet when
16 411 observed gridded maxima products such as from the INTENSE project become available.
17 412

18 413 We must point out that gridded extrema are indeed useful for other purposes, if not for
19 414 the evaluation of the magnitude of model bias. For if one requires the risk of extreme
20 415 precipitation at a point, long period return values calculated from some variant of gridded
21 416 extrema, preferably borrowing strength using spatial statistics, is the most credible
22 417 estimate (Risser et al., 2018) as spatial smoothing damps some of the sampling
23 418 variability.
24 419

25 420 There are important ramifications for the interpretation of simulated extreme precipitation
26 421 from the reduced expectations in the upper panels of figures 1 and 2. First and foremost,
27 422 return values or periods as calculated from climate models are not to be interpreted as
28 423 representing the probability at a point of a specified extreme value. Although beyond the
29 424 scope of this paper, they may be ways to utilize the top and bottom rows of figure 1 and 2
30 425 to bias correct the grid effect. Whether these errors cancel when inferring changes in the
31 426 future probability of extreme precipitation from simulated return periods differences
32 427 (Collins et al., 2013), remains an open question.
33 428

34 429 If the models simulate extreme precipitation statistics at values close to those from station
35 430 or radar data (i.e. the lower panels of figures 1 and 2), then they are actually biased high.
36 431 Also in extreme event attribution studies (e.g. van Oldenborgh et al., 2017), models are
37 432 often queried about the probability of a rare event of a given observed magnitude.
38 433 However, comparison of climate model precipitation return values to the station or radar
39 434 values describing a rare event leads to an overestimation of event probability in an
40 435 unbiased model, even if the observations are placed on the same grid.
41 436

42 437 Trends in average and extreme precipitation are usually presented either as absolute or
43 438 percent changes from a reference period. Maps of absolute changes tend to highlight wet
44 439 areas, while maps of percent changes tend to highlight dry areas. Because of these
45 440 reduced expectations, absolute changes in extreme precipitation of a given return period
46 441 obtained from climate models would also be low in an unbiased model, if that return
47 442 period is to be interpreted as a probability at a given point or region. The magnitude of
48 443 the reduced expectations from the high frequency gridding is likely a function of the
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3 444 rarity of the extreme precipitation considered. This would also introduce biases in point-
4 445 wise probability changes interpreted from simulated percent changes in long period
5 446 return values, although the magnitude of these errors would depend on how strong a
6 447 function of rarity the reduced expectations are.
7 448

8 448
9 449 Likewise, similar caveats should be recognized in formal Detection and Attribution
10 450 (D&A) analyses of observed trends in extreme precipitation (Min et al., 2011; Zhang et
11 451 al., 2013). “Scaling factors” are a ratio of the observed to simulated trends and are tested
12 452 against zero to infer causality in many D&A approaches. If observations are based on
13 453 gridded extrema (lower panels of figures 1 and 2) and the climate models are unbiased,
14 454 lower bounds of scaling factors of absolute extreme precipitation trends would be
15 455 overestimated, possibly leading to erroneous causal inference.
16 456

17 456 18 457 **5) Conclusion**

19 458 Increasing global atmospheric model horizontal resolution increases the magnitude of
20 459 simulated extreme sub-daily precipitation. In that sense, resolution increases are an
21 460 important step towards more realistic estimation of their behavior. However, the expected
22 461 magnitude of simulated extreme precipitation from scaling arguments is a strong function
23 462 of resolution and when held against this standard, we find improvements in simulation
24 463 quality to be nominal. In principle, horizontal resolution increases should improve the
25 464 representation of extreme storms, and in actual practice, they do with tropical cyclones
26 465 being a well-studied case in point. Hence, the lack of substantial improvement in the
27 466 quality of simulated extreme sub-daily precipitation is puzzling, at least in winter and
28 467 summer. Model errors in summer are larger than in winter, suggesting that
29 468 parameterization of cumulus convection plays a role in these errors. However, even at
30 469 high resolutions, most of the models examined herein are significantly too wet in the
31 470 winter, suggesting that moisture transport errors also play an important role.
32 471

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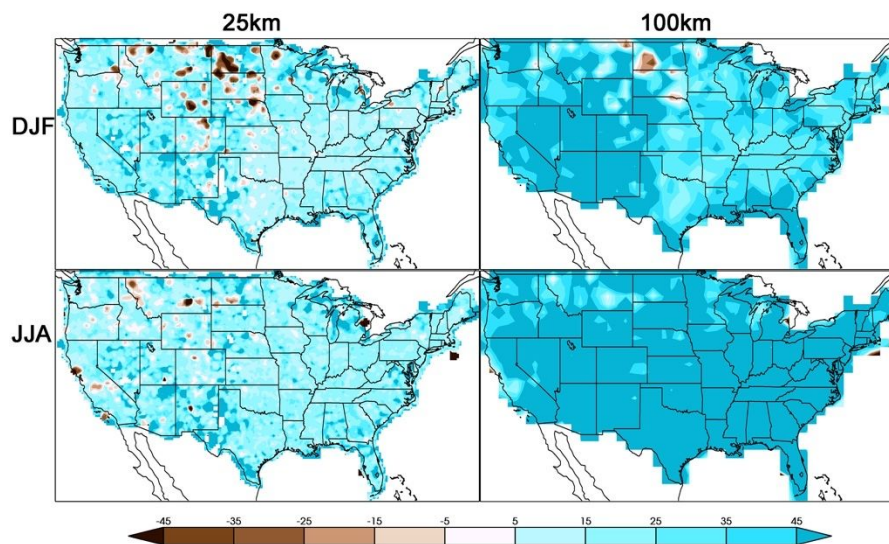
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3 490 the Regents of the University of California. The views and opinions of authors expressed
4 491 herein do not necessarily state or reflect those of the United States Government or any
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14 501

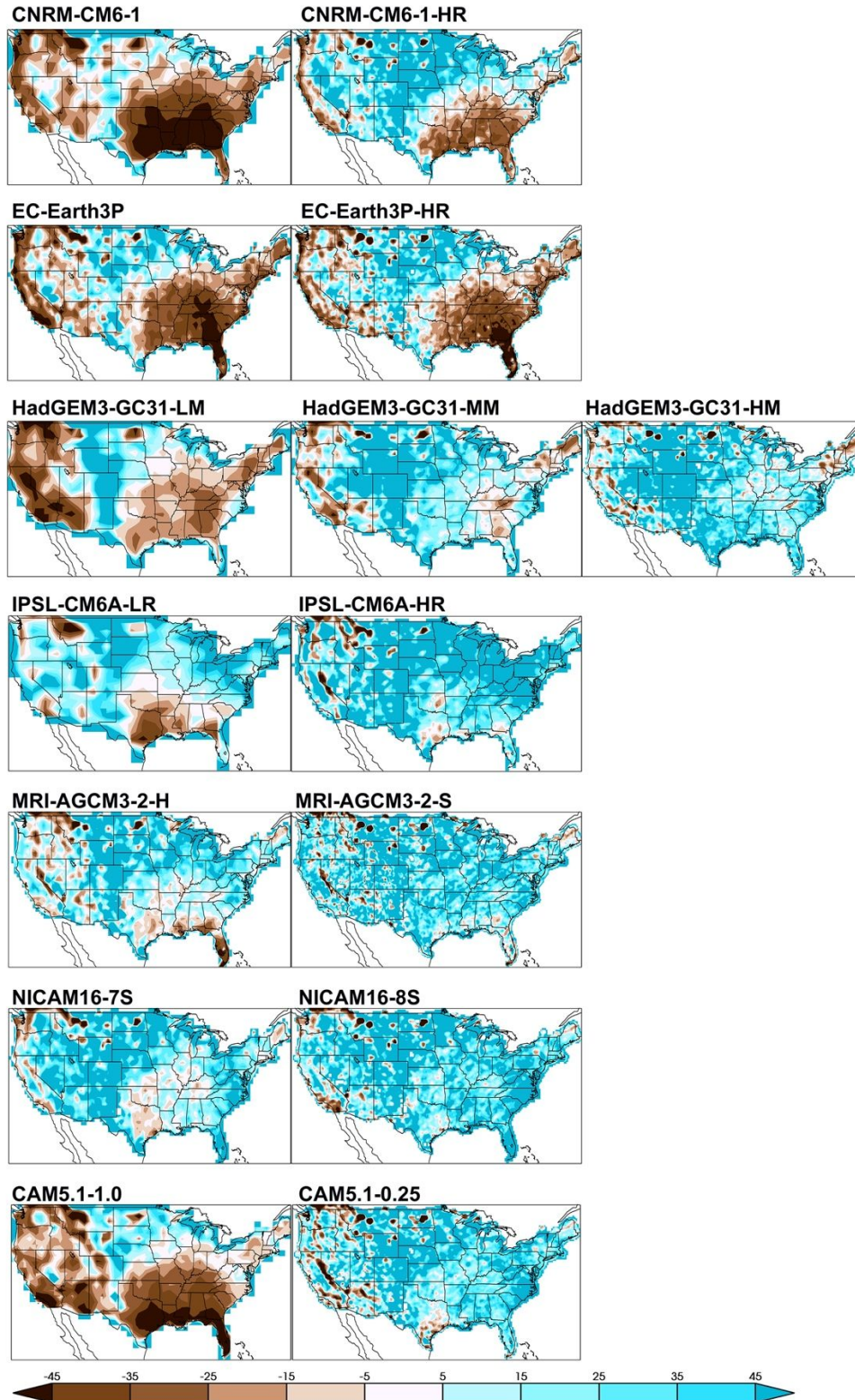
15 502 **Bibliography**

16 503 **Supplement**

17 504
18 505 Figure S1 shows the percent difference between native and non-native constructions of
19 506 NCEP-EMC average seasonal maximum 3 hour precipitation accumulation revealing the
20 507 strong dependence of resolution on the order of operations in constructing extrema.
21 508 Figures S2 and S3 show the non-native grid percent error for simulated average winter
22 509 and summer maximum 3 hour precipitation accumulation. Conclusions about changes in
23 510 model performance would be considerably different than those drawn from the errors
24 511 constructed on the native grids in figures 3 and 4.
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45 512
46 513 Figure S1. Percent difference between native and non-native constructions of NCEP-
47 514 EMC average seasonal maximum 3 hour precipitation accumulation. Top row: DJF.
48 515 Bottom row: JJA. Left column: ~25km grid. Right Column: ~100km grid.
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Figure S2. Percent non-native grid error in simulated average DJF maximum 3 hour precipitation accumulation. Models are arranged low to high horizontal resolution from left to right.

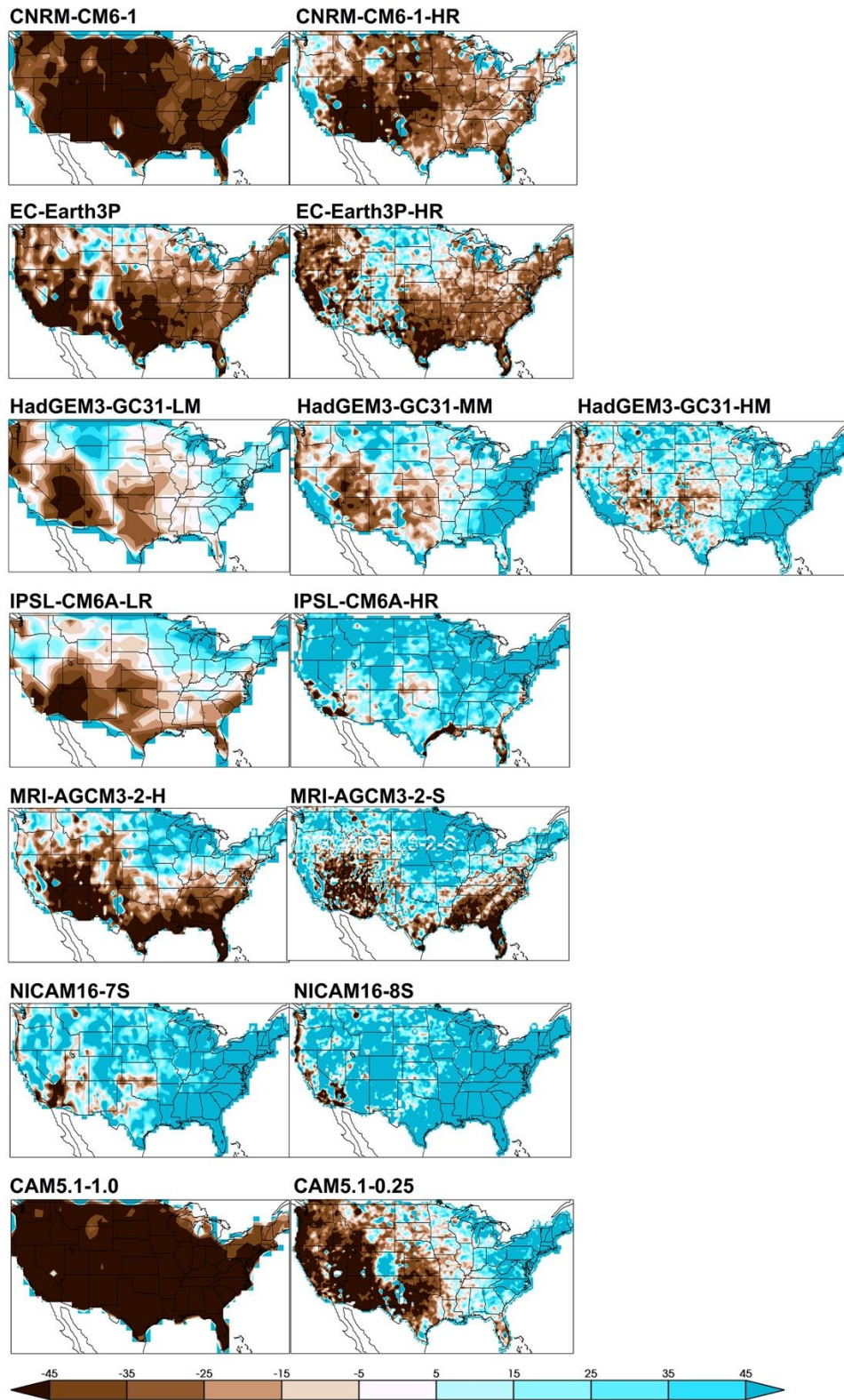


Figure S3. Percent non-native grid error in simulated average JJA maximum 3 hour precipitation accumulation. Models are arranged low to high horizontal resolution from left to right.

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Model	latitude X longitude	DJF Non- native	DJF Native	JJA Non- native	JJA Native
CAM5-1-1degree	128x256	-18%	16%	-59%	-32%
CAM5-1-2-025degree	360x720	29%	50%	4%	25%
CNRM-CM6-1	256x512	-20%	20%	-39%	13%
CNRM-CM6-1-HR	512x1024	2%	23%	-23%	1%
EC-Earth3P	144x192	-19%	4%	-25%	6%
EC-Earth3P-HR	324x432	-14%	1%	-19%	0%
HadGEM3-GC31-LM	143x144	1%	58%	13%	118%
HadGEM3-GC31-MM	361x512	22%	57%	28%	82%
HadGEM3-GC31-HM	768x1024	30%	49%	39%	68%
IPSL-CM6A-LR	320x640	23%	105%	6%	126%
IPSL-CM6A-ATM-HR	960x1920	46%	80%	44%	94%
MRI-AGCM3-2-H	320x640	16%	43%	-6%	26%
MRI-AGCM3-2-S	640x1280	32%	49%	16%	37%
NICAM16-7S	192x288	27%	56%	63%	118%
NICAM16-8S	768x1152	40%	61%	109%	152%

527 Table S1. Spatially averaged percent error over the CONUS region for average maximum
528 DJF and JJA 3 hourly precipitation using observed maxima regridded to the models'
529 resolution (3rd and 5th columns labeled "non-native") and using subdaily observations
530 regridded to the models' resolutions (4th and 6th columns labeled "native"). High
531 resolution model versions are shown in bold font.

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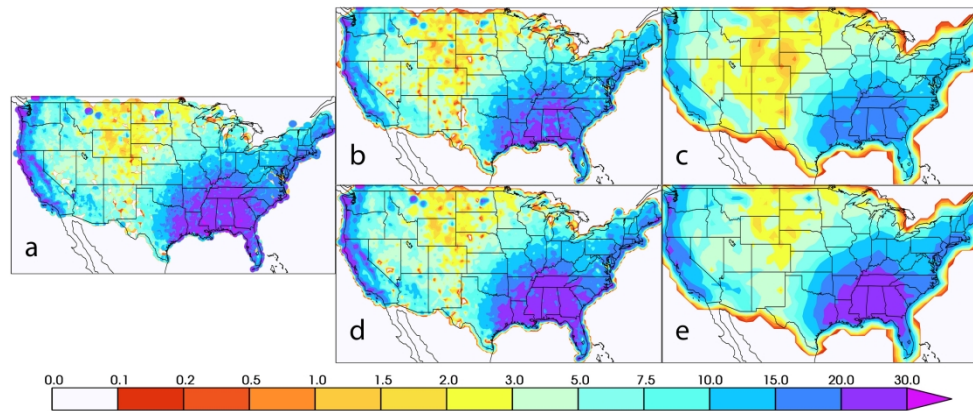


Figure 1. Average DJF maximum 3 hour precipitation accumulation. a) Maximum values calculated on the original 4km polar stereographic mesh and regridded to a 4km latitude-longitude mesh. b) Maximum values obtained by first regridding daily precipitation to a 25km mesh. c) Maximum values obtained by first regridding daily precipitation to a 100km mesh. d) Maximum values obtained by regridding 4km maxima to a 25km mesh. e) Maximum values obtained by regridding 4km maxima to a 100km mesh.

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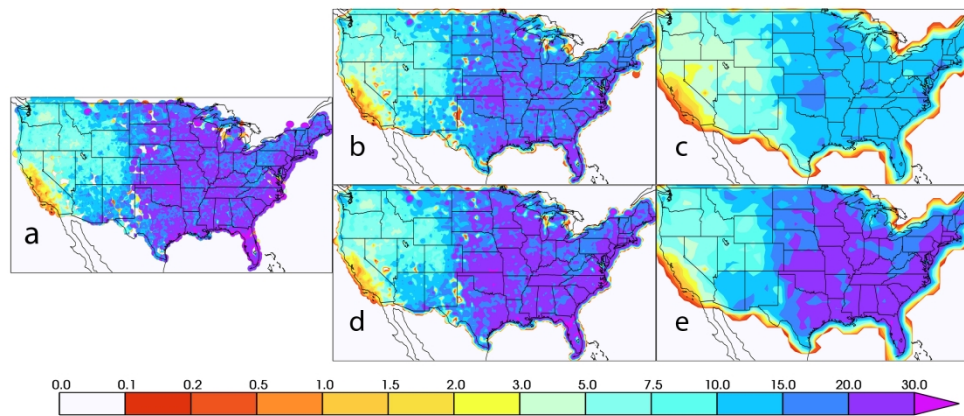


Figure 2. Average JJA maximum 3 hour precipitation accumulation. a) Maximum values calculated on the original 4km polar stereographic mesh and regrided to a 4km latitude-longitude mesh. b) Maximum values obtained by first regriding daily precipitation to a 25km mesh. c) Maximum values obtained by first regriding daily precipitation to a 100km mesh. d) Maximum values obtained by regriding 4km maxima to a 25km mesh. e) Maximum values obtained by regriding 4km maxima to a 100km mesh.

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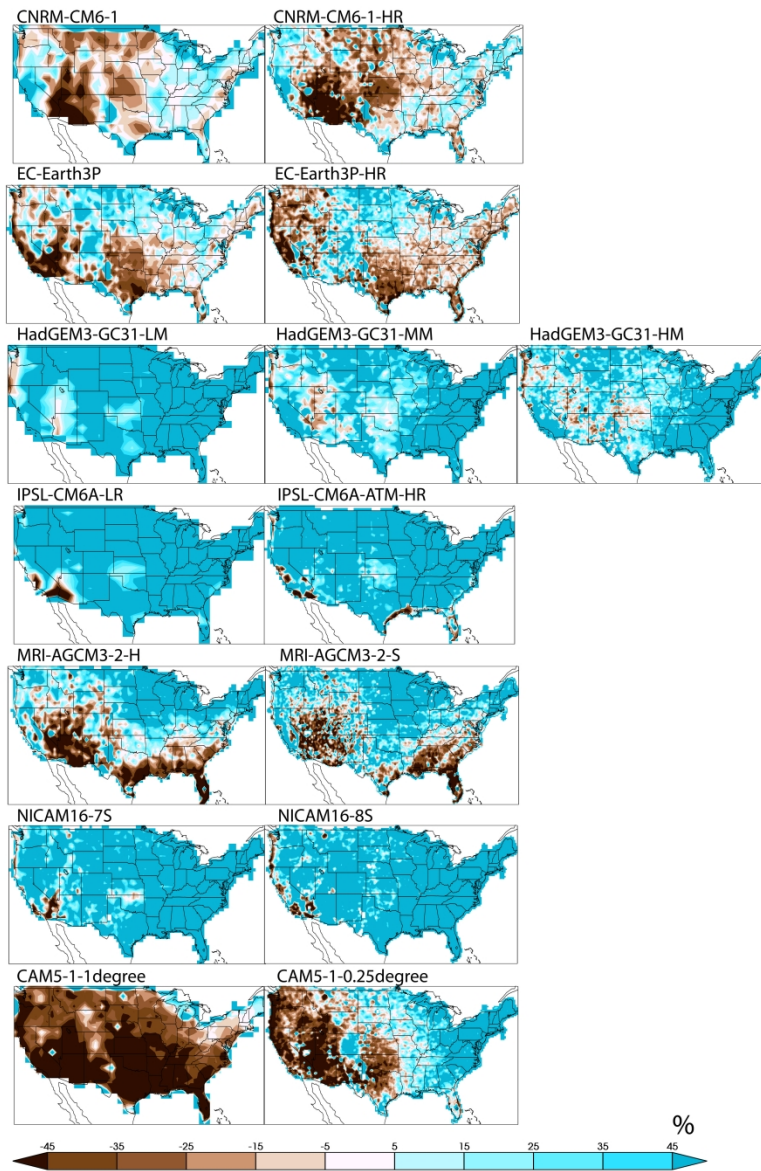


Figure 4. Percent native grid error in simulated average JJA maximum 3 hour precipitation accumulation. Models are arranged low to high horizontal resolution from left to right.

291x446mm (300 x 300 DPI)

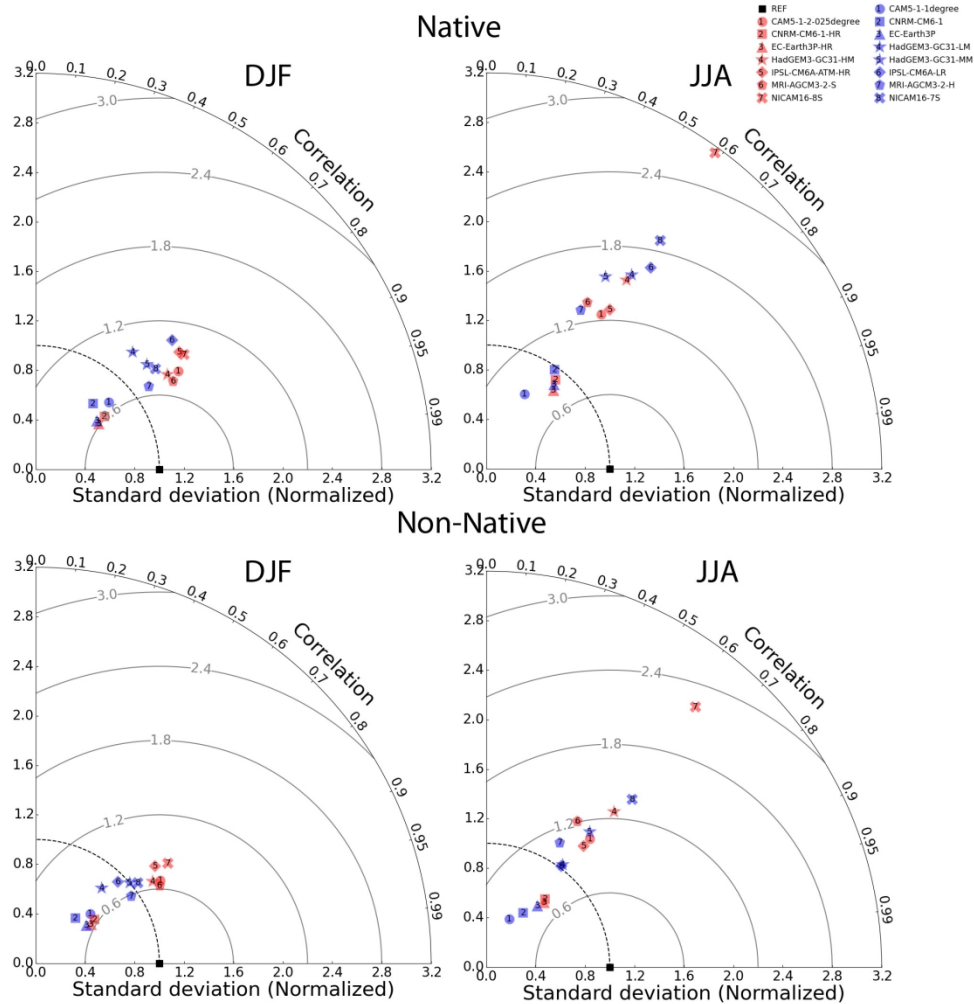
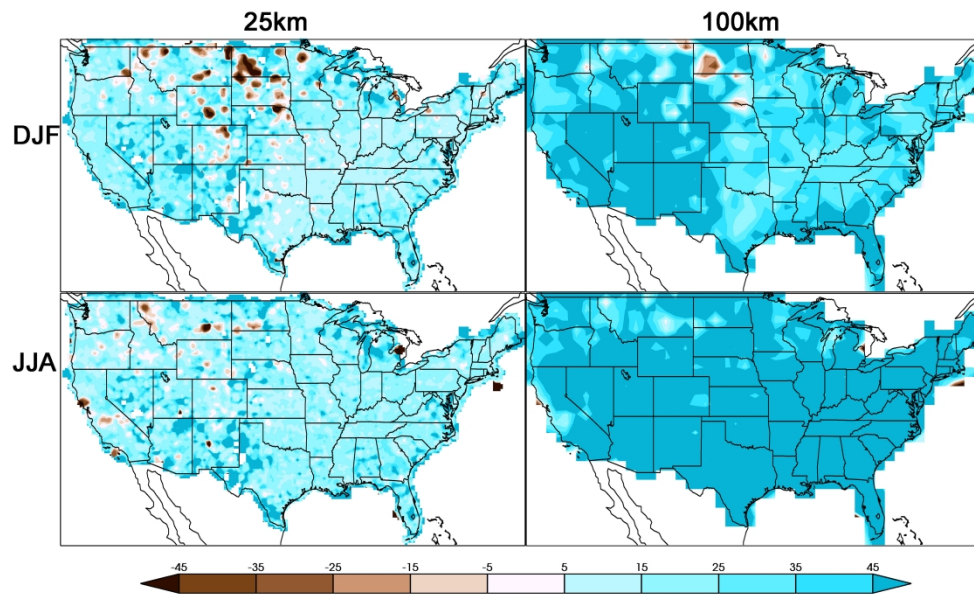


Figure 5. Taylor diagram of average DJF (right) and JJA (left) maximum simulated 3 hour precipitation accumulation from native (top) and non-native (bottom) grid errors. Blue symbols are low resolution models. Red symbols are high resolution models. Symbol shapes are the same for models from the same modeling group. The concentric semi-circles are isolines of normalized root mean square error. The dashed circle represents a normalized standard deviation of unity.

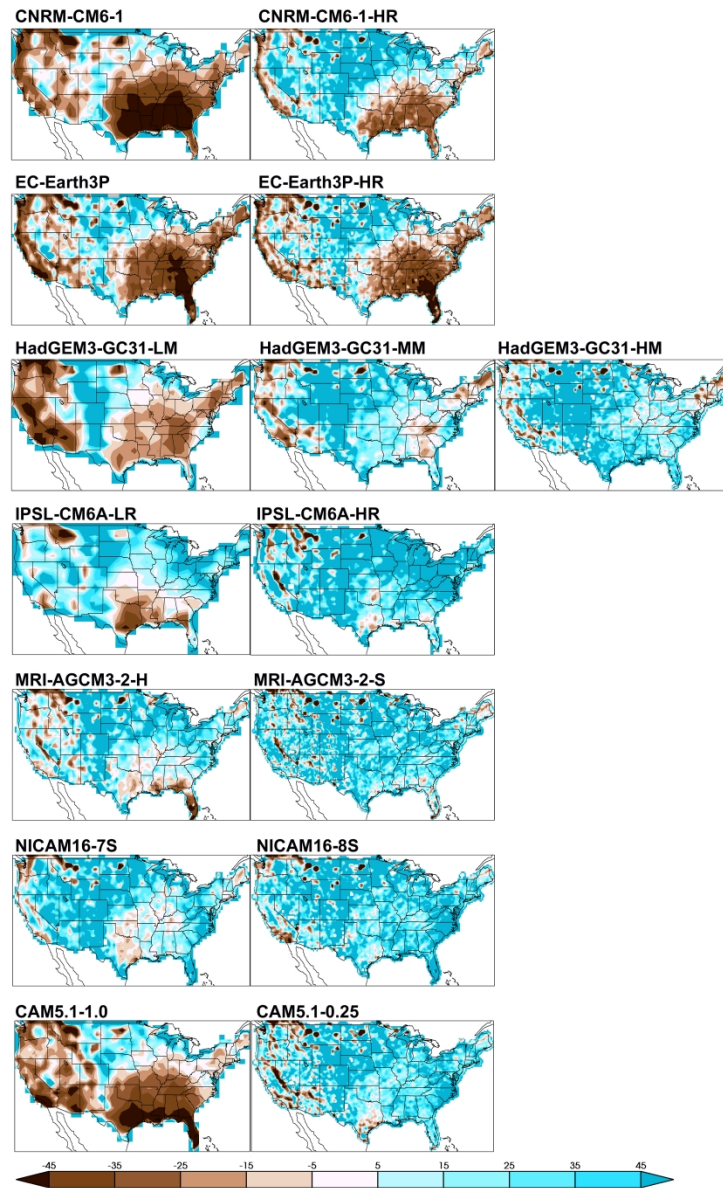
533x558mm (100 x 100 DPI)



27 Figure S1. Percent difference between native and non-native constructions of NCEP-EMC average seasonal
28 maximum 3 hour precipitation accumulation. Top row: DJF. Bottom row: JJA. Left column: ~25km grid.
29 Right Column: ~100km grid.

30 335x212mm (300 x 300 DPI)

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45 Figure S2. Percent non-native grid error in simulated average DJF maximum 3 hour precipitation
46 accumulation. Models are arranged low to high horizontal resolution from left to right.