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Influences of North Pacific Ocean Domain Extent on the Western U.S. Winter Hydroclimatology in Variable-Resolution CESM

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Authors

Rhoades, Alan M
Jones, Andrew D
O'Brien, Travis A
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1 **Influences of North Pacific Ocean domain extent on the western**
2 **US winter hydroclimatology in variable-resolution CESM**

3 **Alan M. Rhoades¹, Andrew D. Jones¹, Travis A. O'Brien¹, John P. O'Brien^{2,1}, Paul A.**
4 **Ullrich^{1,3}, Colin M. Zarzycki⁴**

5 ¹Lawrence Berkeley National Laboratory

6 ²National Center for Atmospheric Research

7 ³University of California, Davis

8 ⁴Pennsylvania State University

9 **Key Points:**

- 10 • Three variable-resolution Community Earth System Model simulations are assessed
11 for sensitivities to refinement domain size
- 12 • More extensive refinement of the Western Pacific reduces the integrated water va-
13 por transport bias to the western US
- 14 • Topographic resolution and land-surface model have greater influences on simulated
15 hydroclimatology than refinement domain extent

Corresponding author: Alan M. Rhoades, arhoades@lbl.gov

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Abstract

Variable-resolution global climate models (VRGCMs) are a dynamical downscaling method that can reach spatiotemporal scales needed for regional climate assessments. Over the years, several users of VRGCMs have assumed where the location and extent of the refinement domain should be based on knowledge of the prevailing storm tracks and resolution dependence of important regional climate processes (e.g., atmospheric rivers [ARs] and orographic uplift), but the effect of high resolution domain size and extent on the simulation of downstream hydroclimatic phenomena has not been systematically evaluated. Here, we use variable-resolution in the Community Earth System Model (VR-CESM) to perform such a test. To do this, three VR-CESM grids were generated that span the entire, two-thirds, and one-third of the North Pacific and evaluated for a 30-year climatology using Atmospheric Model Intercomparison Project protocols. Simulations are compared with reanalysis products offshore (ERA5) and onshore (Livneh, 2015 and Parameter-elevation Regressions on Independent Slopes Model) of the western US. The westward expansion of refinement domain influenced integrated vapor transport (IVT), which was generally high-biased, but minimally impacted AR characteristics. Due to slight differences in land-falling AR counts in the western US, California winter precipitation generally improved with westward expansion of the refinement domain. Western US mountain snowpack and surface temperatures were insensitive to refinement domain size and were more influenced by changes in topographic resolution and/or land-surface model version. Given minimal dependence of simulated western US hydroclimate on refinement domain size over the North Pacific we advise future VR-CESM studies to focus grid resolution on better resolving land-surface heterogeneity.

1 Introduction

Given the cost prohibitive nature of executing uniform high-resolution global climate model (GCM) experiments (e.g., *Wehner et al.* [2014]; *Haarsma et al.* [2016]), dynamical downscaling has been fundamental in reaching the spatiotemporal scales necessary to meet regional climate information needs for assessments of vulnerability, impacts, and adaptation [*Giorgi*, 2019]. Over the last thirty years, regional climate models (RCMs) have been the primary means to perform dynamical downscaling, with various internationally coordinated projects aimed at producing climate impacts and/or model sensitivity analyses [*Christensen and Christensen*, 2007; *Giorgi et al.*, 2009; *der Linden and Mitchell*, 2009;

48 *Mearns et al.*, 2012; *Evans et al.*, 2014]. These projects, and others, have shown that RCM
49 simulations can provide added value over coarser-resolution GCM simulations through the
50 enhanced representation of spatial variability in regions of complex terrain and land-sea
51 contrast and more accurate simulations of certain weather features such as hurricanes [*Di*
52 *Luca et al.*, 2015, 2016; *Poan et al.*, 2018].

53 Akin to RCMs, variable-resolution GCMs (VRGCMs) can be configured for high-
54 resolution regional modeling, with computational cost scaling with the size and resolution
55 of the most refined domain. Unique from RCMs, VRGCMs are GCMs that enable grid
56 spacing to vary by location. This capability provides some advantages over RCMs, such
57 as eliminating the need for two separate simulations and the corresponding biases that
58 arise from the specification of lateral boundary conditions and coupling disparate models.
59 However, VRGCMs also have their own issues, particularly scale sensitivity in sub-grid-
60 scale parameterizations (e.g., shallow- and deep-convection, turbulence, and cloud macro-
61 physics [*Arakawa and Jung*, 2011]). Over the last several decades, multiple VRGCMs have
62 been developed and evaluated for various climate and weather applications. As discussed
63 in *Fox-Rabinovitz et al.* [2006], VRGCMs were first developed as stretched-grid-GCMs
64 that refine resolution in one location at the expense of coarsening another [*Yessad and Bé-*
65 *nard*, 1996; *Côté et al.*, 1998; *Fox-Rabinovitz et al.*, 2001; *McGregor*, 2005]. More modern
66 VRGCMs employ techniques that do not require grid-stretching, but rather gradual tran-
67 sitions in grid-refinement including the variable-resolution capabilities in the Community
68 Earth System Model (VR-CESM; [*Zarzycki et al.*, 2014a; *Guba et al.*, 2014]), the Model
69 for Prediction Across Scales (MPAS; [*Park et al.*, 2014; *Rauscher and Ringler*, 2014]), and
70 the Finite Volume Cubed-Sphere Dynamical Core (FV3; [*Harris and Lin*, 2013; *Harris*
71 *et al.*, 2016]). A more detailed summary of the current community of VRGCMs, and the
72 specifics of their atmospheric model structural and parameter decisions, can be found in
73 *Ullrich et al.* [2017].

74 The downscaling benefits and computational cost savings enabled by VRGCMs have
75 been extensively evaluated across a hierarchy of model test-cases. *Rauscher et al.* [2013]
76 and *Rauscher and Ringler* [2014] utilized idealized model test cases in MPAS, atmospheric
77 dynamics enabled with prescribed physics (Held-Suarez) and atmospheric dynamics and
78 physics enabled with “controlled” SSTs (aquaplanet), to show that VR refinement could
79 positively impact eddy kinetic energy (i.e., storm tracks) in the mid-latitudes, but may
80 have detrimental effects on model moist-physics in equatorial regions. Similarly, *Zarzy-*

81 *cki et al.* [2014b] used VR-CESM in an aquaplanet test-case and showed that the statis-
82 tics derived from the VR refinement domain matched those of a corresponding uniform
83 high-resolution simulation and noted that cross-scale interactions in the grid-transition re-
84 gion were physically consistent (e.g., Kelvin wave phase-speeds). In relation to the find-
85 ings highlighted in *Rauscher et al.* [2013], the choice of and resolution dependence of
86 the physics scheme was noted to be responsible for the detrimental feedbacks on cloud
87 fraction, precipitation rates, and diabatic heating rates. Building on the aforementioned,
88 *Sakaguchi et al.* [2015] used MPAS in a real-world-like model test case, atmosphere-land
89 model coupling and prescribed SSTs and sea-ice observations (Atmospheric Model In-
90 tercomparison Project; AMIP), to show that when provided strong surface forcing (e.g.,
91 topography, SSTs, etc.) VR refined simulations provide comparably realistic process repre-
92 sentation compared with uniform high resolution simulations (e.g., South American mon-
93 soon and Andean induced moisture convergence over the Amazon). More recently, *Sak-*
94 *aguchi et al.* [2016] used MPAS with AMIP protocols to explore how VR refinement may
95 influence the large-scale circulation, both locally and globally, through “upscale effects”
96 and found comparable improvements as those found in uniform high-resolution simulations
97 (e.g., representation of synoptic wave activity and propagation and westerly jets) and al-
98 luded that this could improve simulated hydrologic extremes through changes in the advec-
99 tion of scalars (e.g., water vapor). This last point in *Sakaguchi et al.* [2016] is important
100 and has not been extensively evaluated in the VRGCM literature to date, particularly the
101 sensitivities of the simulated mean climate and hydrologic extremes due to the placement
102 and/or extent of the refinement domain in VRGCMs in real-world-like model test cases.

103 In the RCM literature, the implications of domain extent, placement and resolution
104 on the added value of downscaled simulations has been extensively explored [*Laprise*
105 *et al.*, 2008; *Caron et al.*, 2011; *Caron and Jones*, 2012; *Diaconescu and Laprise*, 2013;
106 *Di Luca et al.*, 2015; *Brisson et al.*, 2016; *Di Luca et al.*, 2016; *Matte et al.*, 2016; *Lucas-*
107 *Picher et al.*, 2017; *Matte et al.*, 2017; *Poan et al.*, 2018]. In particular, careful selection
108 of the RCM domain size and extent has been shown to have significant impacts on sim-
109 ulation fidelity [*Xue et al.*, 2014; *Matte et al.*, 2016, 2017]. The prevailing rule-of-thumb,
110 colloquially termed the “Goldilocks” rule, is that the RCM domain size should not be too
111 big, nor too small to allow for appropriate scale interactions between the lateral boundary
112 conditions and the innermost model domain [*Jones et al.*, 1995]. As shown in *Leduc and*
113 *Laprise* [2009], if the RCM domain is too small, there is insufficient time for meteorolog-

114 ical processes to develop small-scale features (or transient eddies), particularly higher up
115 in the troposphere where surface forcing is weak and winds are stronger. Yet if the RCM
116 domain is too large, the features within the simulated domain can become decoupled from
117 the large-scale forcing data [*Leduc and Laprise, 2009; Matte et al., 2016*], particularly if
118 domain nudging methods are not used [*Miguez-Macho et al., 2004*]. Therefore, the RCM
119 domain size should be “just right” with an even balance between the forces associated
120 with the large-scale boundary conditions and transient eddy spin-up in the RCM domain(s)
121 in order for the RCM to recreate and spatially enhance the GCM simulation. In a practical
122 sense, this tradeoff also has significant implications with respect to computational expense
123 of the simulation, with larger domains resulting in greater costs.

124 The “Goldilocks” rule evidenced in the RCM literature may also apply to VRGCMs,
125 but to date has been sparsely studied. The VRGCM literature has primarily explored the
126 role of horizontal resolution and sub-grid-scale parameterization sensitivities. In particular,
127 *Hagos et al. [2015]* used both aquaplanet and real-world-like AMIP simulations in MPAS
128 at ~240km to ~30km to explore resolution sensitivity of storm tracks and counts, in par-
129 ticular atmospheric rivers (ARs), over the North Pacific using uniform-resolution grids.
130 For the AMIP simulations, the number of AR events that impinge on the western US
131 showed little dependence on resolution at ~120 km vs ~30 km and were low compared
132 with reanalysis estimates due to an overall drier subtropics and poleward-shifted storm
133 track. Most recently, *Goldenson et al. [2018]* utilized MPAS-AMIP simulations with VR
134 refinement over the western US coast at ~30 km and showed that the simulation of ARs
135 was high biased compared with reanalysis, but improved compared with coarser uniform-
136 resolution simulations and previous versions of MPAS with differing dynamical cores and
137 sub-grid-scale physics parameterizations. Similar to MPAS-based studies, a plethora of
138 VR-CESM-based studies has been published that assess the resolution and sub-grid-scale
139 physics dependence of simulations across the continental US. For example, VR-CESM
140 has shown comparable skill in reproducing results from a uniform high-resolution GCM
141 simulation across a hierarchy of simulations including baroclinic wave tests, aquaplanet,
142 and full physics test-cases over the continental US [*Gettelman et al., 2018*], extratropi-
143 cal and tropical cyclone characteristics [*Zarzycki and Jablonowski, 2014; Zarzycki et al.,*
144 *2015, 2016; Zarzycki, 2016*] and has been shown to produce comparable results to RCMs
145 in coastal and mountain climates [*Huang et al., 2016; Huang and Ullrich, 2016, 2017;*
146 *Rhoades et al., 2016, 2018a,b; Wang and Ullrich, 2018; Wang et al., 2018; Wu et al., 2017,*

147 2018; *Xu et al.*, 2018; *Burakowski et al.*, 2019; *Rahimi et al.*, 2019; *van Kampenhout et al.*,
148 2019]. Yet, akin to the aforementioned MPAS studies, most have assumed what size the
149 refinement domain should be for their particular regional application by identifying the
150 region's prevailing storm direction, resolution dependence of the most extreme storms,
151 and necessary resolution to appropriately characterize the surface heterogeneity. Given
152 the aforementioned literature on the "Goldilocks" rule in shaping the climate information
153 produced by RCMs, the effect of refinement domain size and placement on the simulated
154 storm characteristics that shape regional hydroclimates needs to be explored in VR-CESM
155 as well.

156 Evaluation of regional hydroclimate, particularly in mountainous regions, has shown
157 a clear added value of dynamical downscaling approaches [*Xue et al.*, 2014]. Accurately
158 capturing regional hydroclimate requires models to represent multiple spatiotemporal scales
159 and large-scale teleconnections, the near surface and free atmosphere, and statistical mo-
160 ments – as pointed out by *Di Luca et al.* [2015] this is essential in evaluating the added
161 value of a particular downscaling approach. Furthermore, hydroclimatic extremes can have
162 significant socioeconomic impacts, particularly on water management [*Ullrich et al.*, 2018;
163 *Vano et al.*, 2019], and should be a model benchmark if the end-goal of model develop-
164 ment is usability outside of academic circles. The western US provides a useful multi-
165 scale domain test bed as the hydroclimatology is largely shaped by inter-annual variability
166 caused by large-scale teleconnections (e.g., El Niño Southern Oscillation, ENSO; [*Harri-
167 son and Larkin*, 1998; *Williams and Patricola*, 2018; *O'Brien et al.*, 2019; *Patricola et al.*,
168 2019]) and hydrometeorological extremes (e.g., ARs; [*Ralph et al.*, 2018, 2019]). In par-
169 ticular, ARs have been shown to be crucial to western US accumulated precipitation totals.
170 Notably, California receives 50% of its water year totals in under 10-40 (60-120) hours in
171 the southern (northern) part of the State [*Lamjiri et al.*, 2018] with an average of 14 land-
172 falling ARs per year [*Neiman et al.*, 2008]. ARs also directly influence inter-annual vari-
173 ability in mountain snowpack with estimates ranging between 22-73% of annual snowpack
174 totals associated with ARs in the California Sierra Nevada [*Guan et al.*, 2013]. Greater
175 flood potential in California is also associated with ARs due to their punctuated extreme
176 precipitation totals when combined with saturated soil moisture conditions [*Ralph et al.*,
177 2006] and/or large antecedent snowpacks [*Guan et al.*, 2016; *White et al.*, 2019]. Over
178 the years, several GCM simulations at 1° and 0.5° resolution have shown skill in rep-
179 resenting AR characteristics over the North Pacific [*Dettinger*, 2011], CESM being one

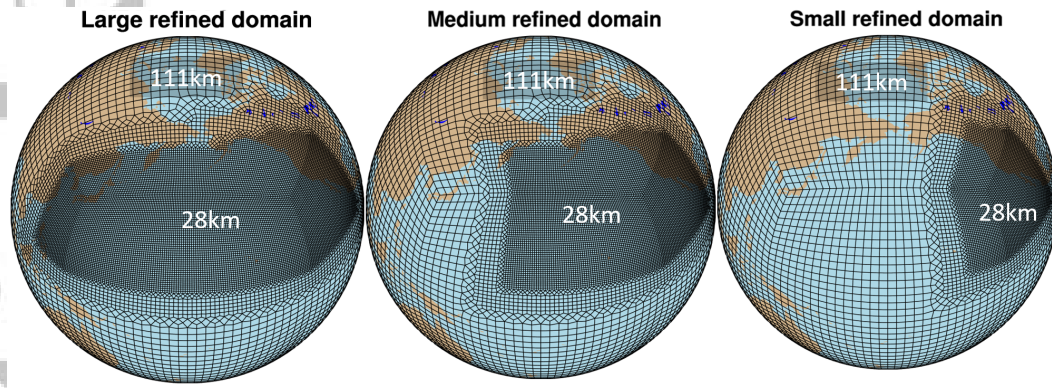


Figure 1. The three VR-CESM grids used for this study. Each cubed-sphere grid has a quasi-uniform 111km (1.00°) global resolution and a 28km (0.25°) refinement region over the north Pacific and western US.

such model [Hagos *et al.*, 2016; Shields and Kiehl, 2016a,b; Benedict *et al.*, 2019]. It was noted in some of these studies that commonly used GCM resolutions may bias the interactions between landfalling ARs and orography. With that said, VR-CESM provides a model framework to explore the interactions between refinement domain size and fidelity in representing AR characteristics over the North Pacific and the interactions between landfalling ARs and their influence on the simulated western US hydroclimate.

To evaluate the “Goldilocks” rule in VR-CESM, we have designed an experiment where a 28km refinement domain size varies longitudinally, yet is fixed latitudinally, over the North Pacific Ocean basin. Our hypothesis is that these different model configurations will modify the simulated hydroclimatology of the western US through its impact on the dynamic and thermodynamic processes that influence key storm types (e.g., ARs). The remainder of the paper is organized as follows: Section 2 discusses the experimental design for the VR-CESM domain sensitivity experiments and the reanalysis datasets, statistical approaches, and atmospheric river detector used to benchmark model performance. Section 3 includes the results of the study, followed by the discussion and conclusions outlined in section 4.

2 Experimental Design and Reference Datasets

CESM Overview

CESM is a widely used and community-supported GCM co-developed by the National Center for Atmospheric Research (NCAR) and the US Department of Energy (DoE)

202 over the last several decades and is comprised of stand-alone atmospheric, land-surface,
203 oceanic, sea-ice, and land-ice components that can either be fully and/or selectively cou-
204 pled or data prescribed [Collins *et al.*, 2006; Gent *et al.*, 2011; Hurrell *et al.*, 2013]. For
205 the domain size sensitivity simulations, we chose to use the Atmosphere Model Intercom-
206 parison Project (AMIP) protocols with active, coupled atmosphere and land-surface, and
207 prescribed ocean and sea-ice models using monthly observations of sea-surface tempera-
208 ture and sea-ice extent [Gates *et al.*, 1999; Hurrell *et al.*, 2008]. Figure 1 depicts the three
209 VR-CESM grids that were generated using an open-source grid generator, SQuadGEN
210 [Guba *et al.*, 2014; Ullrich, 2014]. The three VR-CESM grids span resolutions of 111km-
211 >55km->28km (not including grid-transition regions) with a fixed latitudinal extent (i.e.,
212 15°N to 60°N), a fixed eastern boundary (100°W), and a varied longitudinal extent of
213 141 degrees (large refined domain), 94 degrees (medium refined domain), and 47 degrees
214 (small refined domain) over the North Pacific Ocean. The latitudinal and longitudinal ex-
215 tents of the 28km refinement domain were chosen based on work done by Payne and Mag-
216 nusdottir [2014], who identified AR source-to-terminus pathways using the Modern-Era
217 Retrospective Analysis for Research and Applications (MERRA) reanalysis data. Each
218 of the VR-CESM simulations were run from 1984-2015, with 1984 discarded as spin-up.
219 Table 1 provides a summary of the aforementioned and highlights the number of grid ele-
220 ments, simulated years per day using 48 nodes on the National Energy Research Scientific
221 Computing Center (NERSC) Cori-Haswell supercomputer, and the simulation output fre-
222 quencies.

223 The atmospheric model used for these experiments was the Community Atmosphere
224 Model (CAM) version 5.4 with the cubed-sphere spectral element (CAM5.4-SE) dynam-
225 ical core, which features variable-resolution capabilities and demonstrated computational
226 scalability [Dennis *et al.*, 2012]. The CAM5.4-SE physics time-step for each simulation
227 was set to 7.5 minutes (4 times shorter than the default), and the convective time-scale
228 parameter (τ) is set to 15 minutes (2 times shorter than the default). These timescales
229 were chosen to more comprehensively capture processes governing the finer features sim-
230 ulated in the high-resolution domain. In addition, we utilized the newest publicly released
231 version of the Morrison and Gettelman microphysics scheme, version 2 (MG2), which al-
232 lows for prognostic rainfall and snowfall [Gettelman and Morrison, 2015; Gettelman *et al.*,
233 2015], an essential feature to simulate mountainous hydroclimate correctly [Rhoades *et al.*,
234 2018b]. All other physics parameterizations and prescription files are default to the CAM5

235 release including bulk aerosols [*Ghan et al.*, 2012], deep convection [*Neale et al.*, 2008],
236 macrophysics [*Park et al.*, 2014], radiation [*Iacono et al.*, 2008], and shallow convection
237 [*Park and Bretherton*, 2009]. Further specifics of CAM-SE can be found in *Neale et al.*
238 [2010] and *Lauritzen et al.* [2018].

239 The newest version of the Community Land Model available at time of writing, ver-
240 sion 5 with satellite phenology (CLM5.0-SP), was used. CLM5.0-SP was chosen as it has
241 considerable process advancements compared with CLM4.0-SP and CLM4.5-SP such as
242 carbon and nitrogen cycling, soil evaporation and decomposition, vegetation hydraulics
243 and traits, representative hillslope based river routing, surface and subsurface hydrology
244 and, in particular to western US hydroclimate, snow hydrology [*Lawrence et al.*, 2019].
245 The snow hydrology module in CLM5.0-SP explicitly models the mass of water, the mass
246 of ice, layer thickness, and temperature. Compared with CLM4.0-SP, CLM5.0-SP includes
247 12 dynamic snow layers (rather than 5), enables snow water equivalent to develop to 10-
248 meters (rather than 1-meter), calculates the snow cover fraction separately for the accu-
249 mulation and melt phases of the snow season, and allows the forest canopy to capture and
250 store ice and liquid precipitation separately (rather than just liquid precipitation). Further,
251 snow cover depletion in CLM5.0-SP now depends on the ratio of the current and max-
252 imum mass of snow and a melt parameter that accounts for sub-grid-scale topographic
253 variability. Furthermore, the bulk density of snow now depends on both temperature and
254 wind (rather than just temperature) [*van Kampenhout et al.*, 2017]. Similar to CLM4.0-SP,
255 CLM5.0-SP allows for black carbon, organic carbon, and dust deposited and encapsulated
256 by the snowpack. The snowpack layers are then free to compact and age by pressure and
257 melt.

264 **Reference Dataset Overview**

265 We evaluate our VR-CESM simulations against three reanalysis products: ERA5
266 [*Copernicus Climate Change Service (C3S)*, 2017], Livneh, 2015 (L15; [*Livneh et al.*,
267 2015]) and the Parameter-elevation Relationships on Independent Slopes Model (PRISM;
268 [*Daly et al.*, 2008]). All reference datasets in this study were either conservatively (L15
269 and PRISM, original data $\leq 28\text{km}$ resolution) or bilinearly (ERA5, original data $\geq 28\text{km}$
270 resolution) interpolated using TempestRemap [*Ullrich and Taylor*, 2015; *Ullrich et al.*,
271 2016] from their base resolutions to the highest resolution of the VR-CESM simulations
272 (i.e., 28km). Similarly, each of the VR-CESM simulations are bilinearly interpolated from

258 **Table 1.** VR-CESM North Pacific Ocean domain size experiment metadata including the case name, num-
 259 ber of spectral elements in the model grid, simulated years per day (SYPD), and 28km domain size extent in
 260 latitude and longitude. All CESM simulations were conducted for 1984-2015 with all of 1984 discarded as
 261 spin-up. For each of the CESM simulations all default CAM5.4-SE variables were output at monthly inter-
 262 vals, most variables (including those from CLM5.0-SP) were output at daily intervals, and a select number of
 263 CAM5.4-SE variables were output at 6-hourly, 3-hourly, and 1-hourly intervals to evaluate atmospheric rivers.

<i>CESM Case Name</i>	<i>Number of Spectral Elements</i>	<i>SYPD (48 nodes)</i>	<i>28km Refinement Domain Extent</i>
Large refined domain	17,715	3.74	Lat: 15N to 60N Lon: 119E to 100W
Medium refined domain	13,905	4.25	Lat: 15N to 60N Lon: 166E to 100W
Small refined domain	9,879	4.55	Lat: 15N to 60N Lon: 147W to 100W
No refined domain	5,400	8.47	N/A

273 unstructured to regular latitude–longitude at 28km resolution over the entire extent of the
 274 largest refined domain. ERA5 was used to evaluate offshore fields in VR-CESM, whereas
 275 PRISM and L15 were used for onshore fields. When comparing the climatological and
 276 seasonal differences between model simulations and reanalysis products, we utilize the
 277 Kolmogorov-Smirnov two-sample test made available from the NCAR Command Lan-
 278 guage [*The NCAR Command Language (Version 6.6.2)*, 2019]. To ensure that we minimize
 279 Type-I error in spatial map comparisons we also employ the false discovery rate (FDR;
 280 *Benjamini and Hochberg* [1995]; *Wilks* [2016]) combined with a strict p-value choice (i.e.,
 281 0.001).

282 ERA5 is a newly available fifth generation reanalysis product developed at the Eu-
 283 ropean Centre for Medium-Range Weather Forecasts (ECMWF) that uses a mixture of
 284 aircraft, satellite, and in-situ measurement data assimilated into the Integrated Forecasting
 285 System (IFS) to estimate climate variables globally across 137 vertical levels at 30km spa-
 286 tial and hourly temporal resolution. To evaluate domain size influence on integrated vapor
 287 transport (IVT), and therefore AR activity, ERA5 zonal and meridional winds and specific
 288 humidity across 17 vertical levels, or every 50 hPa, were used. The 17 vertical levels in-
 289 clude: 100, 150, 200, 250, 300, 350, 400, 450, 500, 550, 600, 650, 700, 750, 800, 850,

290 900, 950, and 1000 hPa. In comparison, CAM5.4-SE has 32 terrain-following vertical lev-
291 els which include: 4, 8, 14, 25, 36, 43, 52, 62, 74, 88, 103, 122, 143, 168, 198, 233, 274,
292 322, 379, 446, 525, 610, 691, 763, 821, 860, 887, 913, 936, 957, 976, and 993 hPa (as
293 well as the terrain surface). To evaluate potential IVT sensitivity to vertical level choice in
294 ERA5 an analysis, not shown, was conducted across a smaller time-period (2006-2015) to
295 evaluate how the number of vertical levels used in ERA5 (17 vs 38) would impact com-
296 puted IVT. An average difference over the North Pacific of ~ 20 kg/m/s was found (or a
297 $\sim 10\%$ difference).

298 L15 utilizes 21,137 quality assured and quality controlled in-situ meteorological sta-
299 tions that encompass a large swath of spatial coverage of North America and a temporal
300 period of 1950-2013. *Livneh et al.* [2015] then applies several adjustments to the in-situ
301 derived meteorological variables using NCEP-NCAR reanalysis data along with other key
302 spatiotemporal adjustments such as correcting the climate normal fields towards PRISM,
303 assuming a fixed lapse-rate of 6.5 K/km, and modifications to orographic precipitation.
304 This spatially continuous daily meteorological field is then used to bound variable infil-
305 tration capacity (VIC) hydrologic model simulations that then output key hydroclimate
306 variables (e.g., snow water equivalent) to produce a 6km resolution reanalysis product.

307 PRISM was developed at Oregon State University and is a spatially continuous high-
308 resolution estimate (either 800m, proprietary, or 4km, free) of precipitation, max and min
309 surface temperature, max and min surface vapor pressure deficit, and mean dewpoint tem-
310 perature over the continental US for the time period of 1970 to present day. To create the
311 spatially continuous climate fields, *Daly et al.* [2008] used a digital elevation model and
312 quality assurance and quality control protocols on $\sim 13,000$ precipitation and $\sim 10,000$ tem-
313 perature in-situ measurement stations. To ensure that proper spatiotemporal variation was
314 incorporated into the PRISM climate fields, their algorithm incorporated geographic vari-
315 ables, including coastal proximity, elevation, location, terrain slope, topographic orienta-
316 tion and position, and vertical atmospheric layer. PRISM was used for this analysis due
317 to its improved characterization of coastal effects, cold air drainage, elevational gradients,
318 inversion layers, and rain shadows compared with other publicly available reanalysis prod-
319 ucts.

320 The use of both PRISM and L15 provides juxtaposition for known tradeoffs in re-
321 analysis products widely used in the western US hydroclimate community. For example,

the assumption of a fixed lapse rate of 6.5 K/km in L15 has been shown to be particularly influential on minimum surface temperature in mountainous regions [Walton and Hall, 2018]. Similarly, L15 and PRISM (and other reanalysis products) have shown considerable differences in precipitation amount and structure due to differences in spatial interpolation technique and quality controls used to account for the spatiotemporal variation of measurement networks and extreme events, particularly at higher elevation in mountainous regions [Henn et al., 2018a,b; Timmermans et al., 2019]. Further, as discussed in Rhoades et al. [2018c], L15 is one of only a handful of reanalysis products that provide daily snow water equivalent estimates across the western US and has shown comparable skill to a high quality snow water equivalent reanalysis product that is only available in the California Sierra Nevada, the Sierra Nevada Snow Reanalysis (SNSR; [Margulis et al., 2016]).

Atmospheric River Tracking with TempestExtremes

To evaluate the potential influence of domain size on AR characteristics, we employ a publicly-available Lagrangian tracking algorithm, TempestExtremes [Ullrich and Zarzycki, 2017; Zarzycki and Ullrich, 2017]. Specifically, the AR algorithm in TempestExtremes when used “out-of-the-box” has tended to be a good representation of the median of the community of AR trackers [Shields et al., 2018]. For detecting ARs, TempestExtremes necessitates the use of five parameter choices to filter fields of IVT. The parameter definitions (units) and our choices include:

- (1) minimum threshold of IVT to be considered an AR (min_val ; $\text{kg m}^{-1} \text{ s}^{-1}$) = 250
- (2) minimum laplacian of IVT (min_laplacian ; $\text{kg m}^{-1} \text{ s}^{-1} \text{ degrees}^{-2}$) = 50000 (default)
- (3) minimum area of IVT to be classified as an AR (min_area ; # of grid-cells) = 25
- (4) radius of the discrete Laplacian (size_laplacian ; # of grid-cells) = 35
- (5) absolute latitude at which AR detection is not warranted (min_abslat ; degrees) = 15

These choices are specific to the 28km grid on which major analysis for this study is performed. To choose the AR algorithm parameters we use a combination of AR community suggested values (e.g., min_val and min_area , Ralph et al. [2018]) and conducted a parameter sensitivity analysis (e.g., min_laplacian , size_laplacian , and min_abslat). The AR algorithm generated fields are then stitched together in time using another TempestEx-

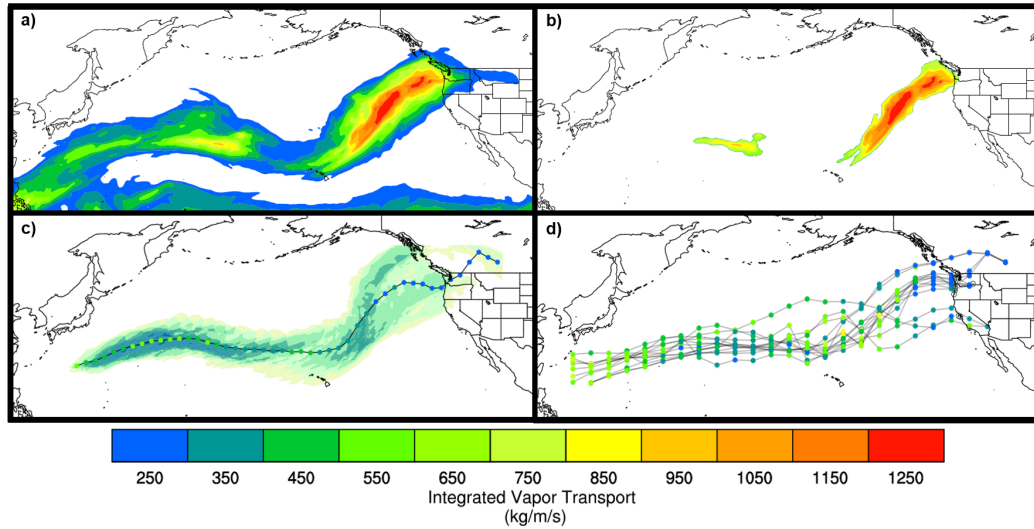
353 tremes algorithm that we set to have an overlap constraint of, at least, 8 time steps (or 2
354 days with 6-hourly data) and, at least, 35 grid-cells (which meets the *Ralph et al.* [2018]
355 average AR width constraint of 850km assuming ~25km resolution data). The qualitative
356 sensitivity analysis evaluated TempestExtremes filtered IVT data for AR characteristics
357 such as AR life cycle coherence, thickness and length and tried to ensure that little-to-no
358 equatorial blobs (i.e., tropical cyclones and/or storms associated with equatorial deep con-
359 vection) were present in the filtered data to minimize the number of false positives in AR
360 detection.

361 A novel extension to the TempestExtremes AR tracking algorithm was developed
362 for this work to identify potential influences of domain size on the characteristics of ARs.
363 This new algorithm takes the spatiotemporally stitched outputs from TempestExtremes
364 to create a composite mask over the lifetime of each unique AR identified. The methods
365 used in our algorithm share some commonality with other published methods including
366 *Payne and Magnusdottir* [2014] and *Zhou et al.* [2018]. These composite masks are then
367 used to find the latitudinal center-of-mass at each of several longitudinal cross-sections for
368 each AR to generate the source-to-terminus pathways. Figure 2 shows an example of a
369 single AR identified using the composite mask and center-of-mass approach and an entire
370 DJF season worth of AR source-to-terminus pathways using one of the VR-CESM simula-
371 tions. Once generated, these AR source-to-terminus pathways allow for the compilation of
372 various summary statistics of the ARs. These summary statistics include:

- 373 (1) the number of unique ARs (total and western US landfalling)
- 374 (2) the lifetime of each unique AR (total and after western US landfall)
- 375 (3) the latitude and longitude of AR western US landfall location
- 376 (4) the average maximum IVT over the lifetime of the AR (total and after western US
377 landfall)
- 378 (5) the duration of the AR (total and after western US landfall)
- 379 (6) the resultant *Ralph et al.* [2019] AR category for each AR that made landfall over
380 the western US

387 **3 Results**

388 The goal of this work is to identify the extent to which the size of the refinement
389 domain within a VR-CESM simulation can influence the simulated western US hydro-
390 climate. To do this, we first examine if there are any discernible differences in the simu-

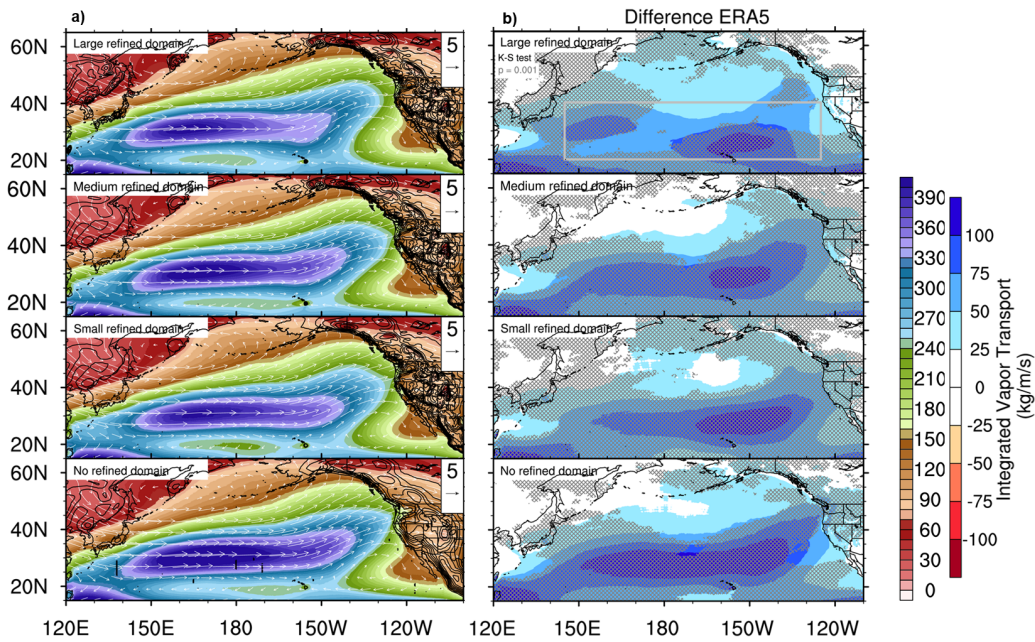


381 **Figure 2.** A step-by-step visual depiction of the TempestExtremes based workflow which takes a) 6-hourly
 382 integrated vapor transport (IVT) fields b) filters the fields into atmospheric river (AR) masks based on user
 383 selected parameter thresholds c) stitches and composites the AR tracks in time and space and d) compiles
 384 the AR source-to-terminus pathways and summary statistics over an entire DJF season. For a) and b), IVT
 385 magnitudes are shown for a particular 6-hourly time slice, whereas in c) and d) the maximum IVT over the
 386 lifetime of the AR is shown via circles at each longitude.

391 lations due to dynamical and/or thermodynamical properties of the atmosphere over the
 392 North Pacific Ocean. Next, we evaluate how these potential differences influence the at-
 393 mospheric response to key climate modes of variability (e.g., the El Niño Southern Oscil-
 394 lation [ENSO]) and storm characteristics (e.g., ARs). Last, we examine how the character-
 395 istics of the western US hydroclimatology, particularly in mountainous regions, is shaped
 396 by the influence of refinement domain size. Throughout each of these analyses we focus
 397 on the boreal winter, specifically December, January, and February (DJF).

398 North Pacific Ocean Integrated Vapor Transport

407 IVT is a primary variable of interest for assessing how well models can simulate the
 408 western US hydroclimate [Zhu and Newell, 1998; Ralph et al., 2006; Neiman et al., 2008;
 409 Ralph and Dettinger, 2011; Gimeno et al., 2014; Lamjiri et al., 2018; Shields et al., 2018].
 410 As discussed by Lavers et al. [2016], IVT is a key driver of western US precipitation and
 411 has been shown to be easier to prognose than precipitation given that it is not as depen-
 412 dent on localized processes that shape precipitation intensity and spatial variability that



399 **Figure 3.** (a) DJF climatological average integrated vapor transport (IVT) for a uniform-resolution 1°
 400 CESM simulation (no refined domain) and three variable-resolution CESM cases with a 28km refinement
 401 domain that varies in extent longitudinally. Total wind vectors are overlaid along with 500m interval to-
 402 pography contours. (b) ERA5 differenced DJF climatological average IVT. The gray box region is used
 403 for analysis and spans across the three VR-CESM 28km refinement domains. The hatching overlay repre-
 404 sents a statistically significant difference between ERA5 and CESM simulations (p-value = 0.001) using the
 405 Kolmogorov-Smirnov two-sample test (K-S test) adjusted using the *Benjamini and Hochberg* [1995] FDR
 406 (dark gray).

413 often need to be parameterized at the sub-grid-scale (e.g., convective precipitation due to
414 frontal convergence and land-atmosphere feedbacks).

415 Total IVT is calculated as

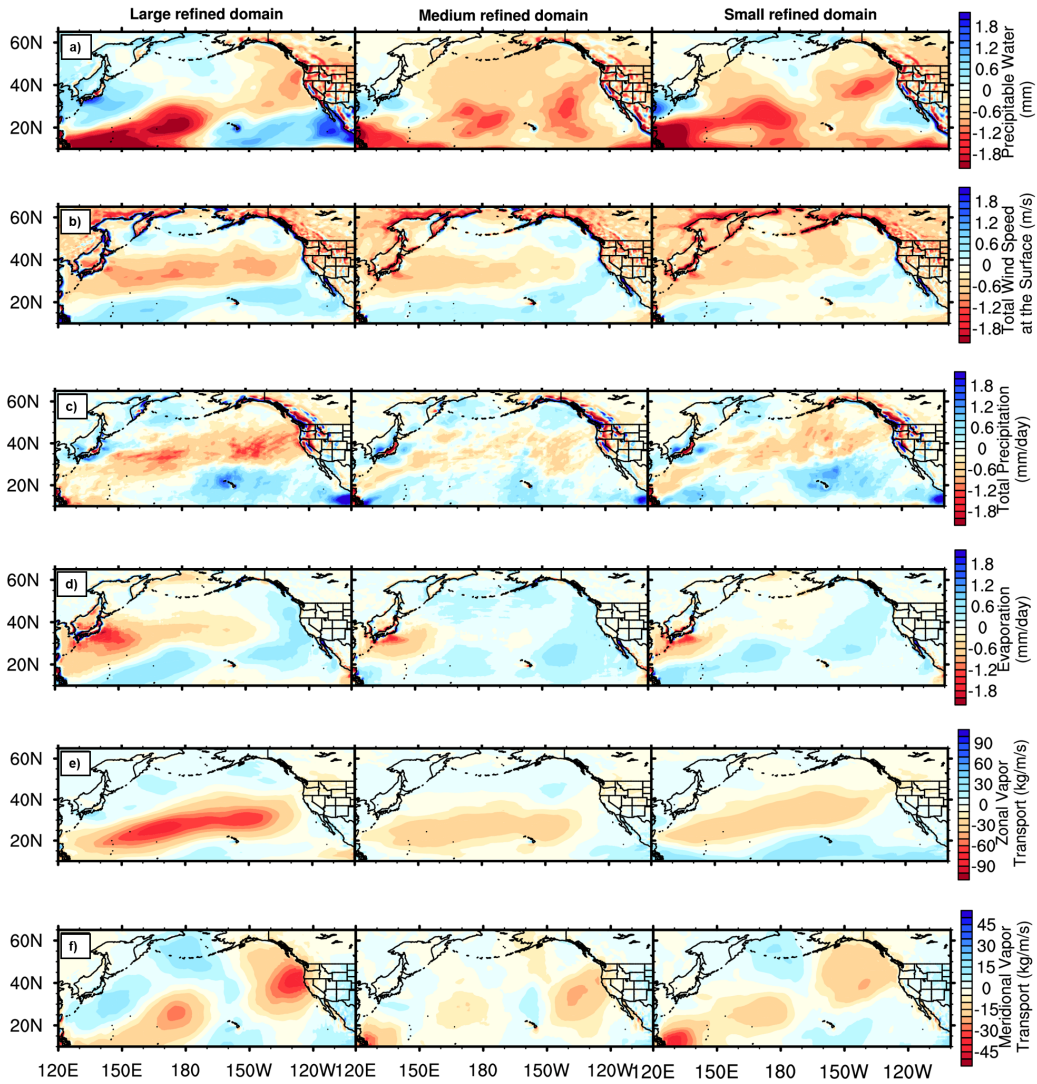
$$IVT = \frac{1}{g} \int_{P_s}^{P_t} qV dp, \quad (1)$$

416 where g is the gravitational acceleration (9.8 m/s^2), P_s is the surface pressure level (Pa),
417 P_t is the top of atmosphere pressure level (Pa), q is specific humidity (kg/kg), and V is
418 the total wind (m/s; $\sqrt{u^2 + v^2}$ where u is the zonal wind component and v is the merid-
419 ional wind component).

420 Figure 3a shows the IVT and total wind fields across CESM simulations for the DJF
421 climatological period of 1985-2015. Figure 3b shows the difference in IVT over this same
422 period from ERA5, where all IVT values with gray stitching are statistically significant at
423 a p-value of 0.001 using the Kolmogorov-Smirnov two-sample test and further adjusted
424 using the FDR. Interestingly, the magnitude of IVT bias generally decreases as the 28km
425 refinement domain is expanded westward over the North Pacific Ocean. Across the box re-
426 gion highlighted in Figure 3b, all CESM simulation estimates of IVT are positively biased
427 compared with the ERA5 dataset, however, the large refined domain has the lowest mean
428 bias of +70 kg/m/s and the no refined domain has the highest mean bias of +87 kg/m/s.
429 Notably, although the analysis is not shown, Kolmogorov-Smirnov significance testing of
430 IVT differences between all CESM simulations at p-values of 0.001 and 0.01 (corrected
431 using FDR) are not significantly different over most of the North Pacific and western US
432 (save for the southern coast of Japan and a portion of the Northern Rockies in the large
433 refined domain).

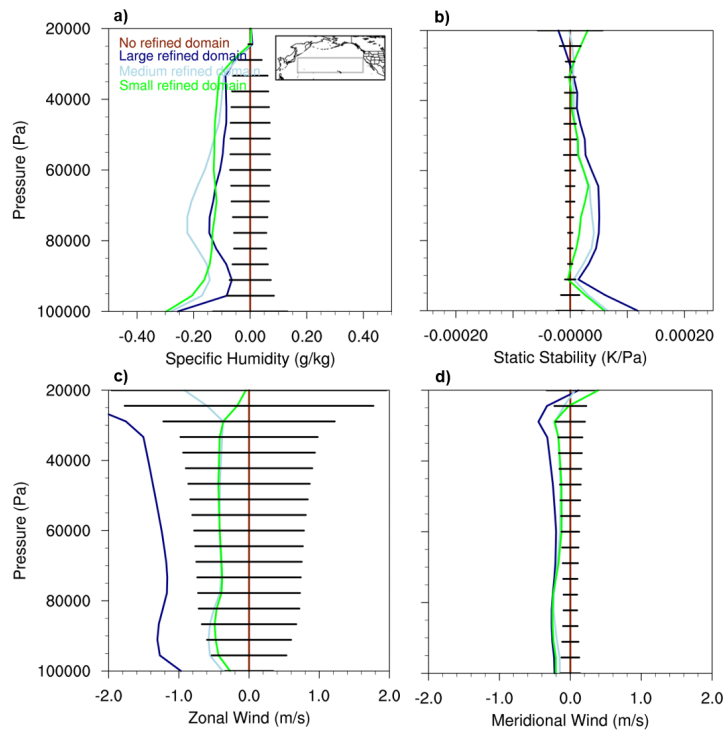
441 To understand why IVT increases as the longitudinal extent of the 28km refine-
442 ment domain decreased over the North Pacific Ocean, we compare the water budgets of
443 the VR-CESM simulations to the no refined domain. The water budget, similar to the
444 technique used in *Dacre et al.* [2019], includes precipitable water, total precipitation (lo-
445 cal sink), evaporation (local source), and zonal and meridional vapor transport (non-local
446 source/sink) (Figure 4). We evaluate these water budget terms in the same region identi-
447 fied in Figure 3, which represents the core-region of IVT in DJF across the North Pacific.
448 As shown by the precipitable water fields in Figure 4 the atmospheric column was drier
449 in the large refined domain, particularly over the western equatorial Pacific Ocean. An
450 indication of potential resolution-dependent processes that led to this drying of the atmo-

icle



434 **Figure 4.** DJF climatological average difference in a) precipitable water b) total surface wind speed c) total
 435 precipitation, d) evaporation, e) zonal vaport transport, and f) meridional vapor transport compared against
 436 the no refined domain.

Acc



437 **Figure 5.** DJF climatological average vertical profile difference in a) specific humidity, b) static stability, c)
 438 zonal wind, and d) meridional wind against the no refined domain. Horizontal black bars represent the 95%
 439 confidence intervals based on DJF seasonal averages. The North Pacific Ocean box region over which the
 440 vertical profiles are generated is shown in the upper right corner of a).

451 spheric column is shown via the source terms in Figure 4 which highlight that as the lon-
452 gitudinal extent of the 28km refinement domain is extended westward towards the Asian
453 coastline, surface wind speeds and evaporation are diminished, particularly off the coast of
454 Japan and into the north-central Pacific where IVT is highest in Figure 3. Slower surface
455 wind speeds combined with drier lower levels of the atmosphere in turn diminishes the
456 water vapor available to be transported eastward and northward via the zonal and merid-
457 ional vapor transport and, importantly, along one of the main source regions, southwest
458 of Hawaii, and terminus regions, Pacific Northwest, of IVT. Figure 5 confirms this as the
459 vertical profiles of the atmosphere across the North Pacific Ocean are more stable, drier,
460 and the zonal wind speeds are dampened, particularly near the surface up to the region in
461 which low-level jets usually occur within the warm-conveyor belt of North Pacific extra-
462 tropical cyclones (i.e., ~1000-700 hPa, [Dacre *et al.*, 2019])

463 The net result of this dampened IVT is shown in Figure 4 where a westward expan-
464 sion of the 28km refinement domain leads to less total precipitation throughout the North
465 Pacific. This is shown primarily through a reduction in the contribution of convective pre-
466 cipitation to total precipitation and, interestingly, is not completely compensated for by a
467 concomitant increase in stratiform precipitation (Supplemental Figure 1). The resolution
468 dependence of convective precipitation is corroborated by other global and regional cli-
469 mate modeling literature [Williamson, 2008; Bacmeister *et al.*, 2014; Zarzycki *et al.*, 2014b;
470 O'Brien *et al.*, 2016; Rauscher *et al.*, 2016; Benedict *et al.*, 2017; Herrington and Reed,
471 2017]. In some of these studies, precipitation fidelity is shown to improve with refinement
472 of model resolution and is associated with an overall reduction in drizzle events (i.e., a de-
473 crease in the initiation of parameterized convective precipitation) along with an increase in
474 extreme precipitation (i.e., precipitation intensity has been shown to scale with vertical ve-
475 locity which is directly related with grid resolution in hydrostatic models). However, other
476 studies evaluating multiple versions of CAM have shown that model simulated precipita-
477 tion extremes at more refined resolutions (i.e., 0.25°) do not converge and even overshoot
478 observations due to model adjustment changes (i.e., performance of model dynamics and
479 physics at multiple resolutions) in intensity, duration, and/or frequency, potentially due to
480 the cumulus parameterization and its allowance of overly saturated model columns too fre-
481 quently [Wehner *et al.*, 2014; Chen and Dai, 2018]. More specifically, in a recent study
482 by Chen and Dai [2019], CAM precipitation frequency and duration has been shown to

483 decrease at coarser grid spacing, particularly for convective precipitation, and intensity in-
484 creases at more refined grid spacing, especially for stratiform precipitation.

485 The decrease in western equatorial convective precipitation and meridional and zonal
486 vapor transport (i.e., 120-170°E, 10-20°N) has an important influence on IVT over the
487 North Pacific, particularly in regions in close proximity to Hawaii and off the coast of the
488 Pacific Northwest. This indicates that refinement domain size may have also had an influ-
489 ence on the atmospheric response at sub-seasonal scales through the Madden Julian Oscil-
490 lation (MJO) and at inter-annual scales through the El Niño Southern Oscillation (ENSO).
491 Although a comprehensive analysis of sub-seasonal scale phenomena is out-of-scope for
492 this climate sensitivity study, we note a few of the important atmosphere-ocean couplings
493 given their importance to western US hydroclimate. At sub-seasonal timescales, the re-
494 gion southwest of Hawaii has been shown to be a source region of IVT to the western
495 US through its association with the Madden Julian Oscillation (MJO), or eastward migra-
496 tion of equatorial convection, during the northern hemisphere winter season. As shown
497 by *Guan et al.* [2012] and *Zhou et al.* [2018], MJO phases can be directly linked to IVT
498 anomalies which in turn have a particular influence on the strength and variability of win-
499 tertime ARs that make landfall in the western US (e.g., MJO Phase 6-7 increase both the
500 number and lifetime of AR events over the North Pacific). Supplemental Figure 1 shows
501 how refinement domain size has a direct influence on the convective precipitation in the
502 simulations, particularly equatorial deep convection, which may be an indication that the
503 representation of particular phases of MJO and, consequently, anomalous IVT were also
504 dependent on refinement domain size. Meridional vapor transport may also have been
505 impacted by other sub-seasonal atmosphere-ocean feedbacks that led to the inhibition of
506 local evaporation in the East China Sea and Sea of Japan such as the East Asian Cold
507 Surge (EACS) associated with southerly movement of polar air masses [*Jiang and Deng,*
508 2011]. Supplemental Figure 3 compares the surface sensible and latent heat fluxes and
509 minimum and maximum surface temperatures across simulations. A general warming of
510 Siberia and Northern China occurs as the 28km refinement domain is expanded westward
511 which, as shown by surface sensible and latent heat fluxes, would act to suppress the sea-
512 sonal strength of EACS events as they move into the Sea of Japan and East China Sea.
513 This regional warming could be a response to a strengthening of the Siberian High which
514 in turn would augment the prevalence of onshore (relatively warm, moist) or offshore (rel-
515 atively cold, dry) winds due to sharper gradients in land-sea contrast at more refined res-

516 olution [Kumar *et al.*, 2019]. Diminished EACS would in turn minimize the sub-seasonal
517 atmospheric disturbances that are induced by these events which would feedback onto the
518 North Pacific trough-ridge patterns and, inevitably, dampen IVT. These two sub-seasonal
519 processes would make for interesting avenues to explore in future research using these
520 VR-CESM domain sensitivity experiments.

521 ***Representation of the Extreme 1998 El Niño***

522 The El Niño Southern Oscillation (ENSO) is a coupled ocean-atmosphere inter-
523 action, which alternates between its positive phase (El Niño) and its negative phase (La
524 Niña) every 2-7 years [Philander, 1985; Neelin *et al.*, 1998; McPhaden *et al.*, 2006]. ENSO
525 accounts for the largest fraction of inter-annual climate variability and alters global circu-
526 lation and weather patterns around the world via an atmospheric bridge, or teleconnec-
527 tion [Rasmusson and Wallace, 1983; Alexander *et al.*, 2002]. During El Niño, anomalous
528 oceanic heat builds up in the tropical east-Pacific as a result of slackening tradewinds as-
529 sociated with a weakened Walker circulation, downwelling oceanic Kelvin waves, and a
530 deepening thermocline [Neelin *et al.*, 1998; Timmermann *et al.*, 2018]. This in turn, al-
531 ters the zonal temperature gradient of the tropical Pacific exciting deep convection far
532 out into the east-Pacific, where the climatologically cool sea surface temperatures (SSTs)
533 would normally prevent deep convection from occurring [Hoerling *et al.*, 1997; Sabin
534 *et al.*, 2013]. The anomalous convection excites a quasi-stationary Rossby wave that deep-
535 ens the Aleutian low and moves its center of action to the East [Bjerknes, 1969; Hoskins
536 and Karoly, 1981; Rasmusson and Wallace, 1983; Trenberth *et al.*, 1998]. This has the ef-
537 fect of strengthening and extending the North Pacific stormtrack and moving it south re-
538 sulting in enhanced western US precipitation, and in particular, for California [Trenberth
539 *et al.*, 1998; Cayan *et al.*, 1999; Feldl and Roe, 2011; O'Brien *et al.*, 2019; Patricola *et al.*,
540 2019].

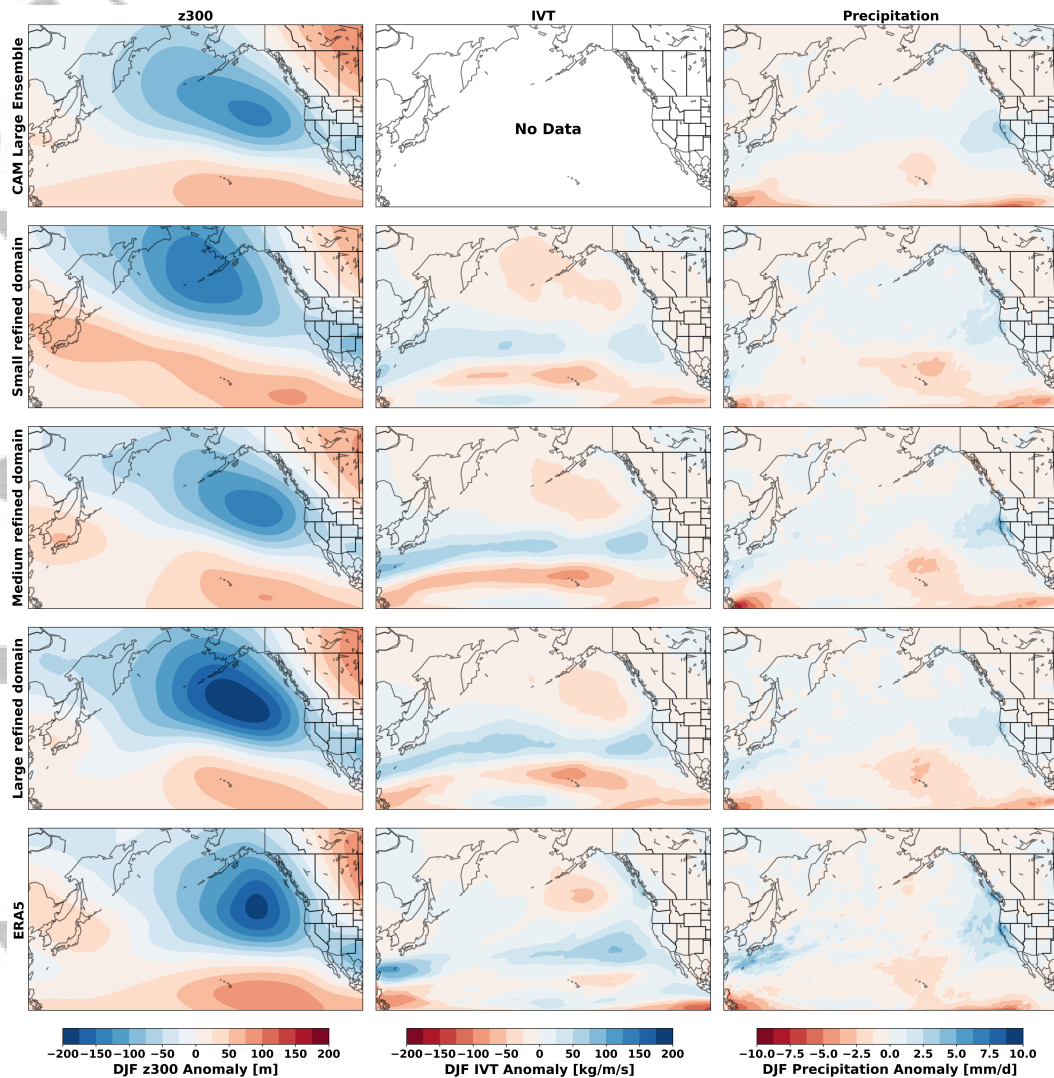
541 Given that El Niño's primary region of action is across the eastern Pacific, it is
542 reasonable to suspect that there may be sensitivity to the longitudinal extent of the VR-
543 CESM refinement domain in the representation of the El Niño tropical Pacific - North-
544 east Pacific teleconnection and resultant precipitation response across the western US. For
545 this analysis we focus on the DJF precipitation response to El Niño in California as the
546 transpacific teleconnection signal tends to be the largest here among all regions across
547 the western US [Cayan *et al.*, 1999; Feldl and Roe, 2011; Patricola *et al.*, 2019]. The VR-

548 CESM simulations span December 1986 through February 2014, thus simulating the ex-
549 treme El Niño year of 1998, where California received near record levels of precipitation
550 and sustained significant infrastructure and property damage resulting in large financial
551 losses due to the widespread flooding that occurred that year [Hoell *et al.*, 2016; Lee *et al.*,
552 2018; Corringham and Cayan, 2019]. That the physical driver of the El Niño teleconnec-
553 tion to California is tropical deep convection, which transmits energy north and east across
554 the Pacific, the placement and extent of the refined grids makes its representation in the
555 VR-CESM simulations important for understanding domain size sensitivity. Supplemen-
556 tal Figure 2 shows the 1998 DJF tropical east-Pacific SST anomaly with the four CESM
557 grids overlain. Additionally, the dot in each panel represents the estimated 1998 DJF av-
558 erage center of deep convection as indicated by the ENSO Longitude Index [Williams and
559 Patricola, 2018] and the gray box indicates the more conventional Niño3.4 region.

560 The results of any single initialized simulation are subject to variability introduced
561 by its unique initial conditions and subsequent evolution in time. Thus, the atmospheric
562 response to the 1998 El Niño and associated precipitation response in California in each
563 of the three refined domain experiments represents a single outcome of a range of plau-
564 sible outcomes. Therefore, to isolate the El Niño forced response in each of the three re-
565 fined domains we ran 10 additional perturbed initial condition simulations of 1998 at each
566 domain extent. This is done to account for internal variability and isolate the signal-to-
567 noise of the effect of refinement domain extent. Given the large computational costs of
568 running multi-member ensembles of global simulations we chose 10 ensemble members
569 for 1998 following from Deser *et al.* [2012, in press 2019] (plus the simulation of 1998 in
570 the climatological runs).

571 As a benchmark by which to compare the VR-CESM domain sensitivity simula-
572 tions, we use both a large-ensemble of 1° resolution global atmospheric model (CAM5.1)
573 simulations and a reanalysis (ERA5). The CAM simulations make up a 50 member large-
574 ensemble extending from 1959-2018 and are, similar to the VR-CESM simulations, of the
575 AMIP class where each member is forced by the observed SSTs and radiative forcings, but
576 differentiated by slight perturbations in their initial conditions. The CAM simulations are
577 part of the Climate of the Twentieth Century (C20C) Project and are a subset of a larger
578 multi-model ensemble [Folland *et al.*, 2014; Stone *et al.*, 2019]. Additionally, we employ
579 the ERA5 reanalysis product as the ground truth representation of California DJF precip-

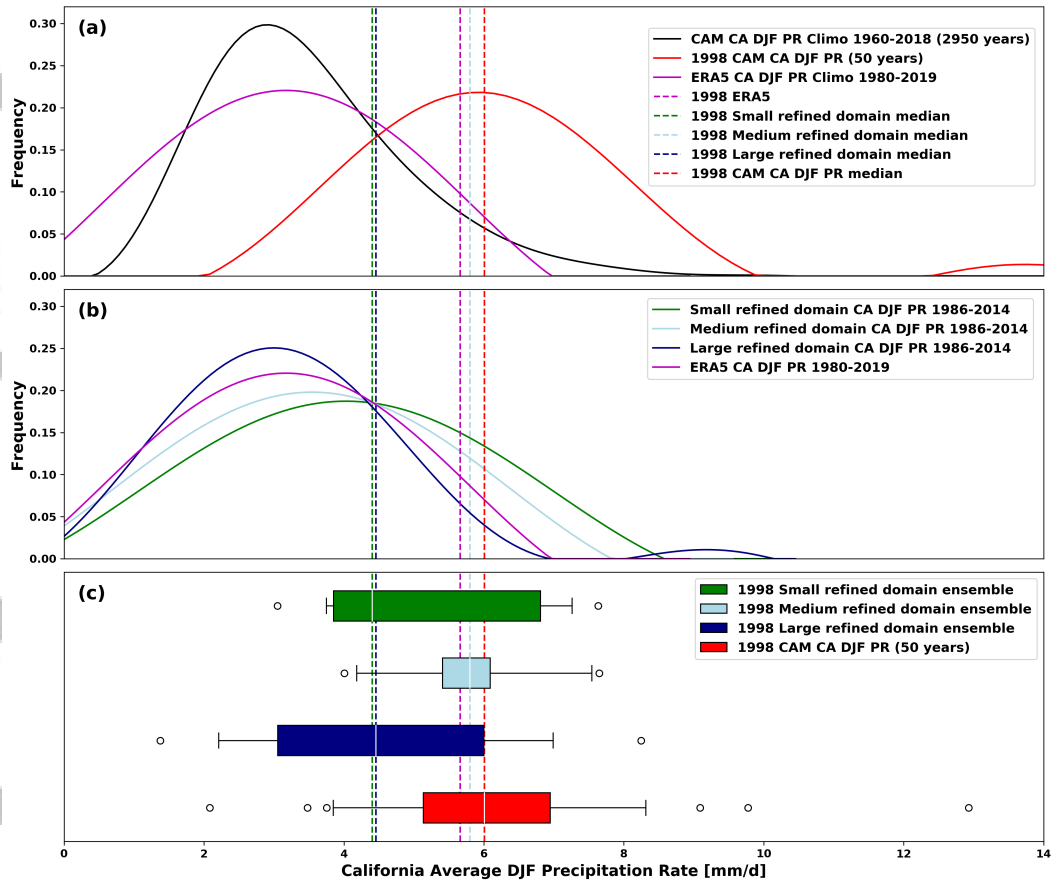
580 itation climatology and the 1998 El Niño response [*Copernicus Climate Change Service*
 581 (*C3S*), 2017].



582 **Figure 6.** The ensemble mean representation of the extreme 1998 El Niño among three key atmospheric
 583 variables: left column, the 300-hPa geopotential height anomaly; center column, the Integrated Vapor Trans-
 584 port (IVT) anomaly; and right column, the precipitation anomaly. Each variable is represented by a different
 585 model product in each row: top row, the uniform 1° resolution of the CAM large ensemble; top middle row,
 586 the small refined domain ensemble; middle row, the medium refined domain ensemble; bottom middle row,
 587 the large refined domain ensemble; and bottom row, ERA5 reanalysis. The ensemble means are comprised
 588 of 50 and 11 simulations of 1998 for the CAM and the three VR-CESM domain experiments respectively.
 589 Anomalies are calculated with respect to the all-year DJF climatologies for each simulation.

590 Figure 6 shows the representation of the strong 1998 El Niño event among several
591 key variables. In the left column, the geopotential height anomaly at 300-hPa, the center
592 column shows the IVT anomaly, and the right column shows the precipitation anomaly
593 all corresponding to their respective DJF climatologies. The top row shows the ensemble
594 mean anomalies of 50 simulations of 1998 from the uniform 1° CAM large ensemble,
595 while the top center, middle center, and bottom center rows show the ensemble mean
596 anomalies of 11 simulations of 1998 for each VR domain experiment. We were unable to
597 calculate the IVT field for the CAM ensemble as the 3D specific humidity variable was
598 not output for this experiment. The broad similarities of the geopotential height anomalies
599 across the different VR-CESM domains are consistent with the atmospheric response to
600 El Niño ocean forcing, in particular, the deepening of the Aleutian Low [Bjerknes, 1969;
601 Hoskins and Karoly, 1981; Rasmusson and Wallace, 1983; Trenberth *et al.*, 1998]. How-
602 ever, each model experiment has its own unique character and differ in their respective
603 representations of the atmospheric response to El Niño. For example, relative to ERA5,
604 the center of z300 height anomaly is moved further to the Northwest in the small refined
605 domain, whereas in the CAM simulations and the medium/large refined domains the lo-
606 cation is approximately correct, however the response is weaker/stronger than what is ob-
607 served in ERA5. Similarly with IVT (Figure 6 middle column), the small refined domain
608 simulates a stormtrack that is most inconsistent with ERA5 while the medium and large
609 refined domains broadly simulate the correct strength and position. The precipitation re-
610 sponse shows the most heterogeneity across simulations (Figure 6 right column) likely
611 reflecting model sensitivity to the complexity of processes and parameterizations neces-
612 sary to generate precipitation. In terms of the spatial footprint of the western US precipi-
613 tation anomaly in each simulation, the CAM large ensemble simulations and the medium
614 refined domain most closely match ERA5. Though it is notable that both the CAM large
615 ensemble simulations and all of the refined domain simulations fail to capture the precipi-
616 tation near Washington State and British Columbia. In the refined domain experiment
617 that best simulates precipitation in California, the medium refined domain, the effect of
618 the increased resolution is apparent relative to the uniform 1° resolution in the CAM large
619 ensemble simulations. This is likely because the refined domain simulations better resolve
620 orthographically enhanced precipitation in the Sierra Nevada mountains.

629 Figure 7 panel (a) shows that the distribution of the 1998 CAM simulations (red)
630 clearly separate from the climatological distribution (black) indicating a clear and strong



621 **Figure 7.** Probability Density Functions (PDFs) of the California DJF spatiotemporal average precipitation
 622 rate. Panel (a) corresponds to the CAM large ensemble all-year DJF climatology (black curve) and the
 623 50 member ensemble representation of the extreme 1998 El Niño year (red). Panel (b) shows the DJF climatolo-
 624 gies of the three different VR-CESM simulations. Both panels (a) and (b) have the ERA5 climatology overlain
 625 (magenta). Panel (c) shows box and whisker plots of the ensemble of 1998 simulations for each VR-CESM
 626 experiment. Box edges indicate the 25th/75th percentiles and the whiskers indicate the 5th/95th percentiles
 627 with outlier points plotted beyond the whiskers. For reference, each panel has a vertical dashed line to indicate
 628 the ensemble median for each experiment and the single year representation derived from ERA5.

631 ocean forced response from the extreme El Niño. Moreover, relative to the ERA clima-
 632 tology (magenta), the CAM ensemble accurately captures California's DJF climatologi-
 633 cal precipitation (black) albeit with more refined tails due to greater sampling of internal
 634 variability. Within a small margin of error, the ensemble median of the 1998 CAM sim-
 635 ulations accurately captures the outcome of the 1998 El Niño precipitation response in
 636 California indicated by the proximity of vertical dashed red and magenta lines. We note

637 here that throughout Figure 7 medians rather than means are shown only to be consistent
638 with the standard interpretation of box and whisker plots, however, the normality of the
639 distributions ensures that results are not sensitive to whether means or medians are used
640 to show ensemble averages. Additionally, it is notable that the 50 member ensemble of
641 CAM simulations for the 1998 El Niño include both members that fall far below (near the
642 climatological mean) and far above the 1998 response estimated by ERA5. This clearly
643 demonstrates that any single initialized simulation may result in a wide range of simu-
644 lated outcomes for the same event and that it is only with an ensemble of perturbed initial
645 condition simulations that the true forced response can be separated from internal vari-
646 ability [Deser *et al.*, 2012, 2016, in press 2019]. However, the ensemble median of the 50
647 simulations of 1998 provides a close approximation of the response estimated by ERA5
648 indicating that the DJF precipitation 1998 in California was indeed primarily the result of
649 large-scale ocean forcing. Panel (b) shows that the DJF precipitation climatologies of all
650 VR-CESM domain sizes are roughly the same, suggesting that the representation of aver-
651 age California DJF precipitation is not sensitive to domain refinement extent. In the ERA5
652 data, the extreme El Niño of 1998 occupies the 95th percentile of the distribution. Only in
653 the CAM simulations and the medium refined domain experiment does the 1998 ensemble
654 median occupy approximately the correct percentile of the climatological distribution. No-
655 tably, both the small and large refined domain ensemble median simulates a much weaker
656 representation of the extreme 1998 El Niño (falling closer to the climatological mean).
657 However, that said, panel (c) shows the box and whisker plots for the 10 member ensem-
658 ble of simulations of the extreme 1998 El Niño and each experiment spans the range of
659 internal variability as indicated by the CAM large ensemble. Therefore, from a statistical
660 perspective, we cannot say that one domain extent represents El Niño better than another.
661 Despite this null result, the lack of sensitivity of the El Niño teleconnection to western
662 US precipitation is still important in that it appears that a large refined domain may not
663 be required to ensure simulation precipitation fidelity in the western US. Thus, computa-
664 tional resources can be focused elsewhere such as longer duration simulations and/or more
665 ensemble members.

666 ***Western US Landfalling Atmospheric Rivers***

667 As discussed in Gimeno *et al.* [2014], and in more detail in Ralph and Dettinger
668 [2011] and Jiang and Deng [2011], the aforementioned dynamical and thermodynamical

669 differences induced by refinement domain size across CESM simulations likely influenced
670 the most extreme form of IVT, ARs. Furthermore, *Hagos et al.* [2015] posited that al-
671 though their MPAS simulated estimates of AR counts in the North Pacific did not show
672 strong dependence on resolution, that AR position at landfall and associated precipitation
673 may have been influenced. Given these assumptions, we evaluate the impact of the 28km
674 refinement domain extent on the characteristics of ARs prior to and after western US land-
675 fall. We employ the *Ullrich and Zarzycki* [2017] TempestExtremes AR detection algorithm
676 along with a novel AR lifecycle stitching algorithm developed specifically for this study.
677 Table 2 gives an overview of the various summary statistics of AR characteristics over the
678 1985-2015 DJF climatology. Summary statistics were compiled by using the AR tracking
679 algorithms to filter individual AR events for each DJF season, averaging these individual
680 statistics across a given DJF season, and then compiling each DJF season into a clima-
681 tology and providing a 95% confidence interval based on the seasonal averages. The AR
682 metrics evaluated include: the total number of ARs identified, the number of ARs that
683 made landfall in the western US, the average latitude and duration of the AR after land-
684 fall, the maximum IVT identified over the lifetime of the AR after landfall, and, finally,
685 the *Ralph et al.* [2019] AR category scale.

686 The total number of annual ARs have been identified in several studies to date using
687 various satellite and/or reanalysis datasets. *Waliser et al.* [2012] found that a typical AR
688 count over the North Pacific ranged between 122 to 137 per year over a two-year period
689 using IWV derived from the Atmospheric Infrared Sounder observations from the NASA
690 Aqua satellite. *Payne and Magnusdottir* [2014] showed a higher estimate in AR counts
691 over the North Pacific of 156 per year from 1979-2011 using the MERRA reanalysis prod-
692 uct, although, importantly, daily extreme precipitation has been shown to be quite different
693 in MERRA versus other global precipitation products [*Sun et al.*, 2018]). Importantly, AR
694 count can depend on the detection method used [*Shields et al.*, 2018]. Using TempestEx-
695 tremes, we find a comparable AR count over our 30-year period of 1985-2015 of 133 per
696 year when we use the ERA5 dataset. As indicated previously, each of the CESM simula-
697 tions had higher IVT than ERA5 and, not surprisingly, this resulted in a higher number
698 of total ARs identified (Figure 3). This AR count varied from 139 per year (large refined
699 domain) to 141 per year (small refined domain). However, for DJF, both ERA5 and all
700 of the CESM simulations show comparable seasonal AR count statistics with overlapping
701 counts at the 95% confidence interval (Table 2).

702 Although total AR counts are relevant in identifying if CESM is simulating the var-
703 ious dynamical and thermodynamical processes that seed and propagate ARs over the
704 North Pacific, water managers in the western US are primarily interested in the number
705 of ARs that make landfall due to their role as both a boon and bane on reservoir man-
706 agement [Ralph *et al.*, 2006; Vano *et al.*, 2019]. To estimate AR landfall counts, Neiman
707 *et al.* [2008] used 8-years of Special Sensor Microwave Imager observations to identify
708 that ARs made landfall in 27-49 (10-19) days per year in Oregon/Washington (California).
709 Payne and Magnusdottir [2014] identified that there were an average of 6, 5, and 3 AR
710 landfall dates in the months of DJF (14 total), respectively, with 749 out of the 4992 to-
711 tal dates (15%) associated with landfalling ARs. Our estimates of DJF landfalling ARs in
712 ERA5 are similar, yet slightly higher (17), compared with those in Payne and Magnusdot-
713 tir [2014]. Interestingly, all CESM simulations overestimate the number of ARs that make
714 landfall save for the large refined domain, 20, at the 95% confidence interval. Regardless
715 of differences in landfalling AR counts, the average latitude in which they make landfall
716 are agreed upon between CESM simulations and ERA5 (41 N near the California/Oregon
717 border).

718 In addition to the number of landfalling ARs, it's also necessary to quantify the du-
719 ration and magnitude of these events, as both are important for assessing impacts [Ralph
720 *et al.*, 2019]. For example, Ralph *et al.* [2013] showed that landfalling ARs over Califor-
721 nia typically have durations of 20 hours, but can last up to 40 hours in extreme cases. Our
722 evaluation of the ERA5 dataset complements this finding and shows that the average du-
723 ration of the AR events identified in DJF last 18 hours (Table 2). Interestingly, CESM
724 model simulated ARs on average last 6-12 hours longer than those found in the ERA5
725 dataset. This is likely related to the fact that the average max IVT is also ~80-100 kg/m/s
726 higher in CESM simulations than in the ERA5 dataset. The result of this high bias in IVT
727 is that CESM simulations have a concomitant increase in Ralph *et al.* [2019] scores during
728 DJF (2.38-2.47) compared with ERA5 (1.83). Albeit only a difference of 1 category in the
729 Ralph *et al.* [2019] scale, the qualitative difference between category 1 versus category 2 is
730 the difference between ARs being primarily beneficial to water resources versus beginning
731 to pose some type of hazard.

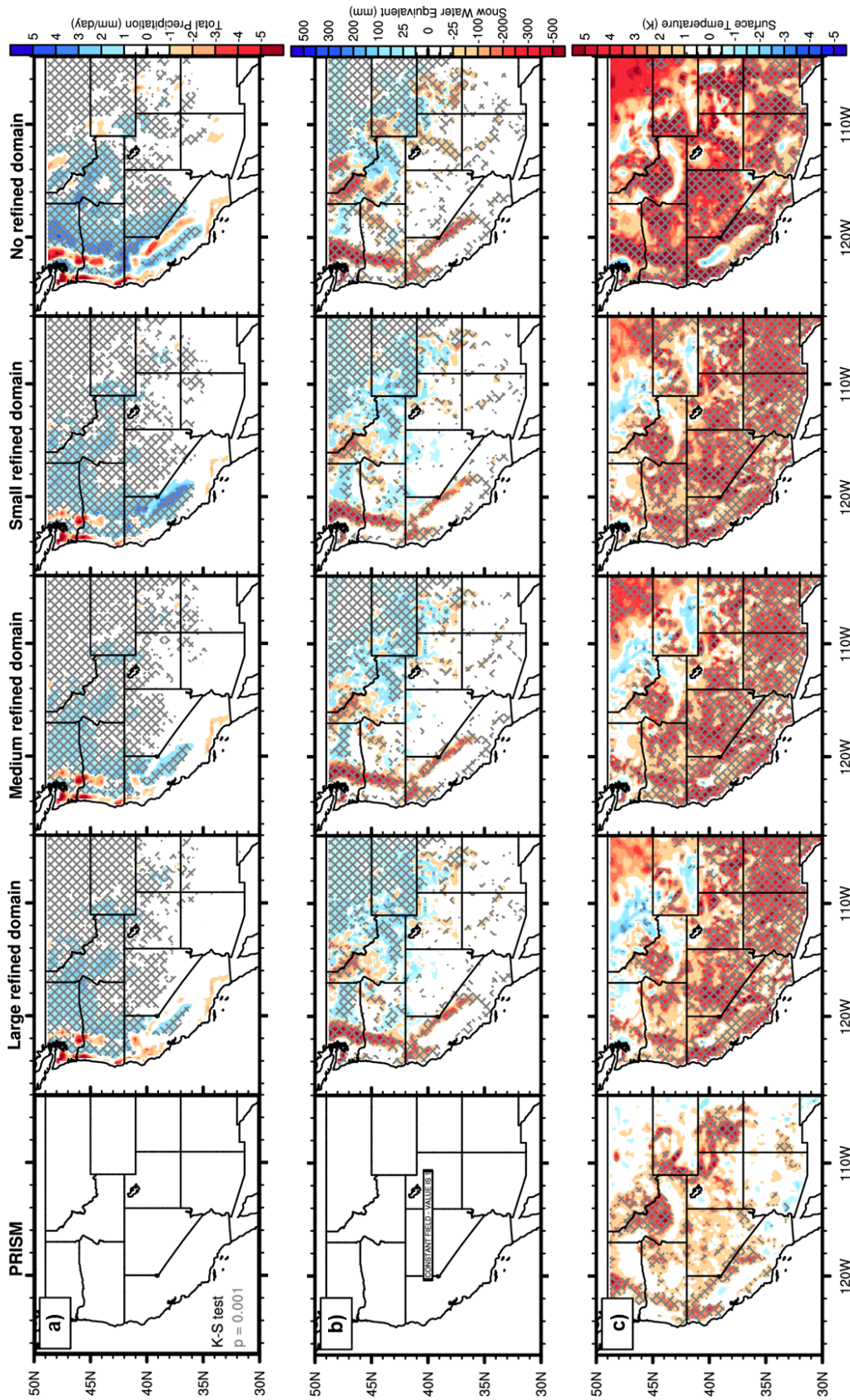


Figure 8. DJF climatological average a) total precipitation, b) snow water equivalent, and c) surface temperature for a uniform-resolution 1° resolution CESM simulation (no refined domain) and three variable-resolution CESM cases (large refined domain, medium refined domain, and small refined domain) differenced against the L15 reanalysis dataset. For comparison, the PRISM reanalysis dataset is shown in the left most column. The hatching overlay represents a p-value exceedance of 0.001 (dark gray) using the Kolmogorov-Smirnov two-sample test (K-S test) adjusted using the *Benjamini and Hochberg [1995]* False Discovery Rate and compared with L15.

732 **Table 2.** DJF climatological average summary statistics for western US landfalling ARs over the years
 733 1985-2015 with 95% confidence intervals. In the landfalling ARs column, emboldened numbers represent the
 734 percentage of landfalling ARs relative to the total number of ARs.

<i>Dataset Name</i>	<i>Total ARs</i>	<i>Landfalling ARs</i>	<i>Average Latitude</i>	<i>Average Duration (days)</i>	<i>Average Maximum IVT (kg/m/s)</i>	<i>Average Ralph et al. 2019 AR category</i>
ERA5	37±1	17±2 (46%)	41.6±0.68	0.76±0.11	746±28.1	1.83±0.16
Large refined domain	35±2	20±2 (57%)	41.4±0.83	1.26±0.19	842±32.4	2.44±0.20
Medium refined domain	35±1	22±1 (63%)	41.3±0.66	1.13±0.12	830±22.8	2.38±0.14
Small refined domain	36±2	22±1 (61%)	41.1±0.76	1.23±0.19	842±28.1	2.47±0.20
No refined domain	34±1	21±2 (62%)	41.4±0.84	1.20±0.15	824±26.1	2.44±0.19

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 736 ***ature***

737 The differences in AR landfall counts between the large refined domain and the
 738 other CESM simulations likely played a role in shaping the precipitation totals in the
 739 western US. To explore this we compare the DJF hydroclimatology (i.e., total precipita-
 740 tion, snow water equivalent, and surface temperature) between the CESM simulations and
 741 two widely used reanalysis products, L15 and PRISM (Figure 8). Across the western US,
 742 CESM simulations are generally positively-biased in total precipitation and surface tem-
 743 perature and negatively-biased in snow water equivalent when compared against L15. The
 744 large refined domain simulated the DJF climatology most closely with L15 with total pre-
 745 cipitation at +0.3 mm/day, snow water equivalent at -5.3 mm, and surface temperature at
 746 +2.3 K, whereas the no refined domain was least similar with total precipitation at +0.5
 747 mm/day, snow water equivalent at -16 mm, and surface temperature at +3.3 K. Therefore,
 748 all VR-CESM simulations outperform the uniform-resolution 1° resolution simulation.
 749 This highlights the added value of high-resolution modeling over the western U.S. com-
 750 pared with conventional GCM simulations (e.g., better representation of complex terrain

751 and land-surface cover). However, in concert with the positively-biased surface temper-
752 atures, which likely altered general storm precipitation phasing from snowfall to rainfall
753 too regularly, in CESM simulations it appears that 28 km resolution was insufficient in
754 representing the various topographic dependent processes in the Oregon and Washington
755 Cascades. This is shown by the clear negative-bias in total precipitation and snow water
756 equivalent throughout much of the Cascades which consists of a chain of highly localized
757 and intermittent volcanic peaks.

758 Across the VR-CESM simulations there are important regional differences, particu-
759 larly in the coastal ranges of the western US, that are likely related to refinement domain
760 size. The impact of refinement domain size is indicated most clearly in California. As
761 shown for the California Central Valley and Sierra Nevada, the large refined domain pro-
762 vides the best skill in representing the expected total precipitation climatology of L15 and
763 PRISM, whereas the small refined domain is high-biased with statistically significant er-
764 rors across most of the central-to-northern portions of California. This is likely because
765 of better IVT representation in the large refined domain over the North Pacific (Figure 3).
766 In terms of precipitation phasing, all VR-CESM simulations are significantly low-biased
767 in their DJF climatology of snow water equivalent compared with the reanalyses datasets,
768 akin to other regions of the western US. This lack of DJF snow water equivalent is in-
769 sensitive to refinement domain size and is more likely related to the overall warm-bias
770 in CLM5.0-SP simulated surface temperatures. The warm-bias is important because a
771 discrete range of surface temperatures dictate precipitation phase partitioning (i.e., +2 C
772 [all rain] \geq 0 C [mixture of rain-snow] \geq -2 C [all snow]) and ripening, or changes in
773 density and albedo, of the snowpack over the water year in CLM5.0-SP [Lawrence *et al.*,
774 2019]. Interestingly, surface temperature biases appear to be dictated more by minimum
775 than maximum surface temperatures (Supplemental Figure 4). As noted before, Walton
776 and Hall [2018] has shown that L15 surface temperatures are likely at the lower end of
777 reanalysis dataset estimates, due to fixed assumptions in lapse-rates, and this is confirmed
778 with the DJF climatology comparison with PRISM indicating that surface temperature
779 biases may be inflated when comparing simulation results to L15. Regardless of assump-
780 tions in L15, comparisons with PRISM indicate that there is a systematic warming and
781 over correction of previously identified surface temperature biases across the western US
782 when CESM simulations with CAM5.4-SE are run with CLM4.0-SP versus CLM5.0-
783 SP [Rhoades *et al.*, 2018b] with deleterious impacts on seasonal dynamics of mountain

784 snowpack. Previous VR-CESM simulations using CAM5.4-SE coupled with CLM4.0-
785 SP showed much better agreement with observational estimates of western US mountain
786 snowpack.

787 To expand our analysis beyond DJF and explore how refinement domain size may
788 have influenced the accumulation and melt seasons in western US mountains we present
789 daily climatologies across the water year (Figure 9). Similar to the DJF climatologies, VR-
790 CESM simulations perform well for accumulated total precipitation in western US moun-
791 tains with all VR-CESM simulations falling inside of the 95% confidence intervals of L15
792 throughout the entire water year. Accumulated total precipitation is slightly low-biased in
793 the large refined domain and the medium refined domain (-9 to -34 mm) and high-biased
794 in the small refined domain (+28 mm) across western US mountain ranges. The moun-
795 tain region with most disagreement across VR-CESM simulations is the California Sierra
796 Nevada where the large refined domain has a bias of -144 mm and the small refined do-
797 main has a bias of +87 mm (both within ~10% of L15; Supplemental Figure 5). This is
798 likely related to the previously mentioned difference in AR landfall counts of 2 per DJF,
799 associated with refinement domain size (Table 2). Although, total precipitation is generally
800 well represented across VR-CESM simulations, daily snow water equivalent is low-biased
801 across all VR-CESM simulations. Peak snow water equivalent estimates are low biased by
802 -68 to -75 mm across the western US mountains in all VR-CESM simulations. With that
803 said, all VR-CESM simulations still outperform peak snow water equivalent estimates pro-
804 vided by the uniform 1° resolution CESM simulation (-124 mm bias). Further, although
805 coastal mountains show poor snow water equivalent simulation performance across VR-
806 CESM simulations the interior mountain ranges are better simulated (Supplemental Figure
807 5). For example, in the Rockies peak snow water equivalent estimates are low biased by
808 -18 to -28 mm (within ~15% of L15). Regardless of mountain range, VR-CESM simu-
809 lations using CLM5.0-SP still exhibit a systematic bias whereby snow water equivalent
810 peaks too early and melts too fast, an holdover identified in previous VR-CESM studies
811 using CAM5.4-SE coupled with CLM4.0-SP over the western US [Rhoades *et al.*, 2016,
812 2018a,b].

813 As mentioned previously, the warm-bias in surface temperature was likely the ma-
814 jor reason for the deleterious impacts on seasonal mountain snowpack. VR-CESM sim-
815 ulated surface temperatures are biased between +2.9 and +3.0 (+1.6 to +1.7) K on av-
816 erage throughout the water year when compared with L15 (PRISM). This warm-bias is

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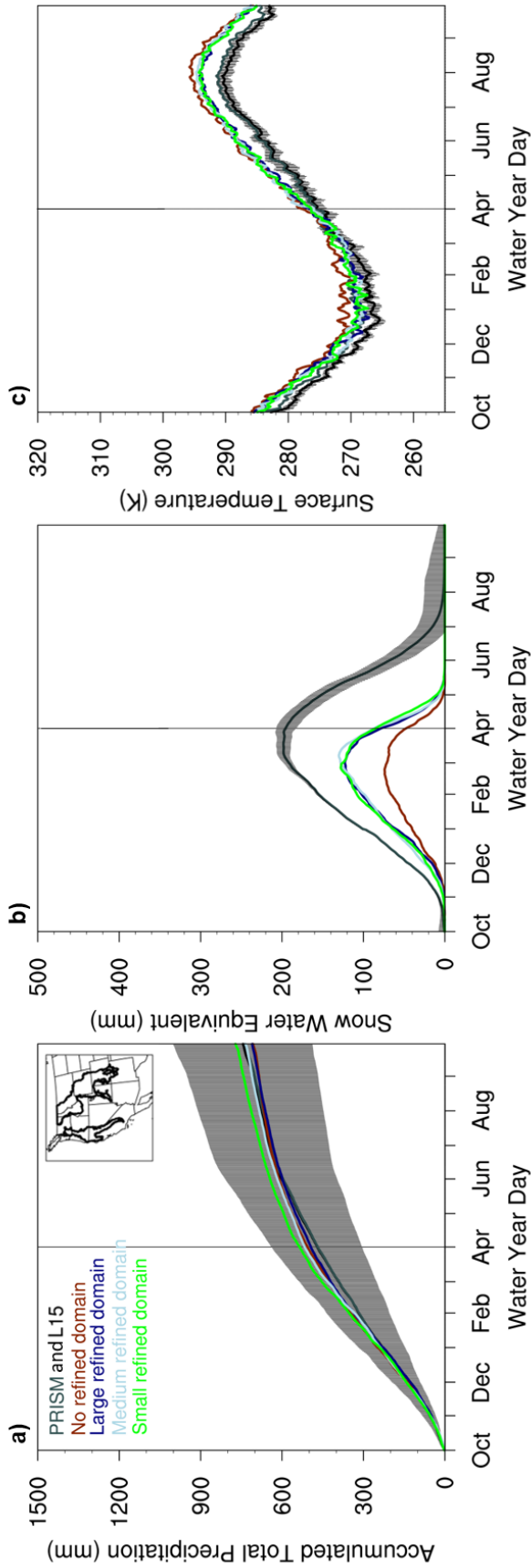


Figure 9. Western US mountain daily climatological average a) accumulated total precipitation, b) snow water equivalent, and c) surface temperature for each of the CESM simulations, no refined domain (red), large refined domain (navy blue), medium refined domain (light blue), and small refined domain (green), compared with the L15 reanalysis dataset (black). For comparison, the PRISM reanalysis dataset (gray) is also shown. The vertical black lines overlaid onto the L15 curves represent the 95% confidence interval based on daily average values.

817 pronounced and is particularly impactful in the accumulation season where precipitation
818 is unable to change its phase from rain to snow and/or preserve at the land-surface and
819 in the melt season where the snowpack ripens too quickly (i.e., snow density increases
820 too fast) lowering the albedo which leads to earlier spring-season melt [Colombo *et al.*,
821 2019]. Supplemental Figure 6 shows this by highlighting the frost ($T_{\min} < 273\text{K}$), freez-
822 ing ($T_{\text{avg}} < 273\text{K}$), and ice day ($T_{\max} < 273\text{K}$) deficits across CESM simulations, the
823 naming conventions are consistent with the World Meteorological Organization [Contosta
824 *et al.*, 2019]. Freezing days are a proxy for the days available to accumulate snowfall at
825 the surface and frost days are a proxy for the number of days in which snow can be pre-
826 served into late-winter to early-spring. VR-CESM freezing day deficits range from -12 to
827 -24 days with the uniform-resolution 1° simulation having the largest freezing day deficit
828 of -43 days. This 2-3 week freezing day deficit in early-winter inhibits the VR-CESM
829 simulations from allowing precipitation events to precipitate as snowfall and accumulate
830 as snowpack (and is most pronounced in the coastal mountain ranges). In late-winter to
831 early-spring, VR-CESM simulations have another 2-3 week frost day deficit which forces
832 the snowpack to ripen and melt more abruptly than is expected in L15. Therefore, it ap-
833 pears that none of the snow-process enhancements in CLM5.0-SP could compensate for
834 these surface temperature biases including the new upper limit of snow water equivalent
835 (10,000 mm), the updated partitioning of snow cover fraction (depletion) curves for the
836 snow accumulation (melt) seasons, and/or the new snow density parameterization that now
837 depends on both temperature and wind, to account for wind-driven snow compaction [van
838 Kampenhout *et al.*, 2017]. Of note, Rhoades *et al.* [2018c] and Rhoades *et al.* [2018d] have
839 shown that these systemic snow water equivalent lifecycle biases are prevalent in other
840 global and regional climate models of comparable and/or refined model resolutions too,
841 particularly in the melt season. This was similarly confirmed in Xu *et al.* [2019] who de-
842 vised an error decomposition framework to quantitatively show that simulated SWE biases
843 in regional climate models are resolution-dependent, however are also related to biases,
844 that can sometimes offset, in the spatial and elevational distribution of precipitation (i.e.,
845 microphysics scheme), lapse-rates (i.e., boundary layer scheme), and rain-snow partitioning
846 in the land-surface model (i.e., surface temperature threshold choice). Future work should
847 evaluate this systematic increase in surface temperature from CLM4.0-SP to CLM5.0-SP.
848 A hypothesis as to why a general warming occurred is due to several new modifications
849 to soil evaporation and/or transpiration in CLM4.0-SP versus CLM5.0-SP. More specifi-

850 cally, CLM5.0-SP soil evaporation now includes a resistance parameterization and transpi-
851 ration includes a hydraulic stress parameterization. These two modifications likely led to
852 drier soil and vegetation and enhanced the surface sensible heat flux, but need to be more
853 robustly explored using an error decomposition framework mentioned previously and/or
854 energy budget analysis to confirm this hypothesis.

855 **4 Discussion and Conclusions**

856 The effects of refinement domain size on simulation fidelity in the RCM litera-
857 ture has been extensively explored, however this same analysis has not been methodically
858 tested in the VRGCM literature. Therefore, the goal of this study was to identify if the
859 refinement domain size in VR-CESM had a significant impact on the simulated dynami-
860 cal and thermodynamical characteristics of the atmosphere over the North Pacific Ocean
861 and, if so, what were the concomitant impacts on the simulated hydroclimatology over the
862 western US.

863 We found that the westward expansion of the 28km refinement domain over the
864 North Pacific Ocean led to a decrease in IVT in DJF resulting in a closer approximation to
865 ERA5. Lower DJF IVT can be attributed to the atmosphere becoming more stable, drier,
866 and less windy near the surface. In turn, lower simulated DJF IVT led to a decrease in to-
867 tal precipitation. Interestingly, refinement domain size (or more refined resolution in gen-
868 eral) did not have a significant impact on the total count of DJF ARs, but does seem to re-
869 duce the number of landfalling ARs, specifically in California. The lower number of land-
870 falling ARs was shown to improve DJF precipitation in the western US, but was mostly
871 evident over California. At inter-annual timescales, the simulated atmospheric response to
872 strong El Niño events does not seem to be influenced by refinement domain size.

873 Regardless of 28km refinement domain size over the North Pacific Ocean, we found
874 that DJF simulated IVT is high-biased across all CESM simulations when compared against
875 ERA5. The high-bias in IVT resulted in landfalling ARs that are generally too strong ac-
876 cording to the *Ralph et al.* [2019] scale (i.e., max IVT is too high and AR duration is too
877 long). Although DJF total precipitation was better simulated with the westward expansion
878 of the 28km refinement domain, snow water equivalent was low-biased throughout most of
879 the western US, save for the interior mountain ranges. The low-bias in snow water equiva-
880 lent in the VR-CESM simulations is intuitive as topographic resolution was still too coarse

881 to properly represent certain western US mountain ranges, in particular the intermittent
882 and localized peaks of the Cascades and sharp elevation gradients of the eastern Sierra
883 Nevada. However, even when comparing 28km resolution VR-CESM simulations using
884 CLM4.0-SP in past studies to the simulations using CLM5.0-SP in this study, a systematic
885 increase in surface temperature was evident. This systematic increase in surface tempera-
886 ture altered precipitation phase partitioning and overall residence time of snowpack in the
887 mountains.

888 Therefore, although the DJF simulated climatology across the VR-CESM simulations
889 did produce some differences, particularly in North Pacific IVT, minimal differences were
890 actually seen on AR characteristics and resultant influences on the simulated western US
891 hydroclimate, save for precipitation over California. Topographic resolution and/or the ver-
892 sion of land-surface model used appears to be more of a factor in simulation fidelity than
893 the refinement domain extent, at least for the western US. This corroborates assumptions
894 made by previous VRGCM studies that refinement domain size need only extend out as
895 far as Hawaii when evaluating the western US and instead finer refinement should be ap-
896 plied over areas of complex terrain. Practically, this finding enables a core-hour saving
897 of ~30% when running VR-CESM with the small refined domain versus the large refined
898 domain using 48 nodes on the NERSC Cori-Haswell supercomputer.

899 These findings are likely generalizable to other VRGCMs that have comparable nu-
900 merical order accuracy in grid-transition regions and physics parameterizations. For exam-
901 ple, CAM-SE has third-order numerical accuracy in grid-transition regions, therefore other
902 VRGCMs that have lower order accuracy may require a larger grid-transition region for
903 comparable results. However, these findings are likely not generalizable to RCMs. This
904 is because VRGCMs allow for two-way feedbacks between coarser and finer domains,
905 whereas RCMs only enable a one-way feedback with varying degrees of influence based
906 on domain size configuration. More specifically, using a similar experimental design to
907 this one, western US hydroclimate simulations in RCMs may be more influenced by a
908 westward expansion of the refinement domain over the North Pacific due to a more pro-
909 nounced decoupling of larger scales (GCM boundary conditions) from regional scales
910 (RCM simulation). Further, if boundary conditions are provided by a reanalysis dataset
911 the relative quality of the RCM simulation would likely be impacted by the number of
912 available observations that are assimilated in the generation of the reanalysis dataset, par-
913 ticularly over the Pacific Ocean.

914 As mentioned previously, there are still several avenues of future research that could
915 be explored with these VR-CESM domain sensitivity experiments. One such path would
916 be a robust evaluation of the implications of refinement domain size on the atmospheric
917 response to teleconnections at sub-seasonal timescales (e.g., the MJO and EACS events).
918 Given the minimal influence that refinement domain size had on North Pacific AR char-
919 acteristics, particularly between the large and small refined domain, another path could be
920 an exploration of how a warmer world may influence AR characteristics (using any of the
921 VR-CESM grids from this study).

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934 The aforementioned reanalysis datasets used in this study are publicly available at their
935 source repositories. The CESM simulations generated for this study are made available at
936 the following NERSC Science Gateway - [https://portal.nersc.gov/archive/home/
937 a/arhoades/Shared/www/Hyperion/](https://portal.nersc.gov/archive/home/a/arhoades/Shared/www/Hyperion/). Please notify arhoades@lbl.gov if you access and
938 use any of the CESM datasets.

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