# The Influence of a Resolved Gulf Stream on the Decadal Variability of Southeast US Rainfall

Wei Zhang<sup>1</sup>, Ben P. Kirtman<sup>2</sup>, Leo Siqueira<sup>2</sup>, Baoqiang Xiang<sup>3</sup>, Johnna M. Infanti<sup>2</sup>, and Natalie Perlin<sup>4</sup>

<sup>1</sup>Princeton University <sup>2</sup>University of Miami <sup>3</sup>NOAA/Geophysical Fluid Dynamics Laboratory, UCAR <sup>4</sup>Oregon State University

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#### Abstract

Ocean variability is a dominant source of remote rainfall predictability, but in many cases the physical mechanisms driving this predictability are not fully understood. This study examines how ocean mesoscales (i.e., the Gulf Stream SST front) affect decadal southeast US (SEUS) rainfall, arguing that the local imprint of large-scale teleconnections is sensitive to resolved mesoscale features. Based on global coupled model experiments with eddying and eddy-parameterizing ocean, we find that a resolved Gulf Stream improves localized rainfall and remote circulation response in the SEUS. The resolved Gulf Stream influences the boundary layer, driving a barotropic circulation response, thus affecting decadal SEUS rainfall due to a westward extension of the North Atlantic Subtropical High. The eddy-parameterizing simulation fails to capture the sharp SST gradient associated with the Gulf Stream and overestimates the role of tropical SST in the SEUS rainfall due to its classical wintertime connection with the El Niño/Southern Oscillation.

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3 4 5	Wei Zhang <sup>1,2</sup> *; Ben Kirtman <sup>3</sup> ; Leo Siqueira <sup>3</sup> ; Baoqiang Xiang <sup>2,4</sup> ; Johnna Infanti <sup>5</sup> ; Natalie Perlin <sup>3</sup>
6	1 Program in Atmospheric and Oceanic Sciences, Princeton University, Princeton, NJ, USA,
7	2 NOAA/Geophysical Fluid Dynamics Laboratory, Princeton, NJ, USA.
8	3 Rosenstiel School of Marine and Atmospheric Science, University of Miami, Miami, USA.
9	4 Cooperative Programs for the Advancement of Earth System Science, University Corporation for
10	Atmospheric Research, Boulder, CO, USA.
11	5 NOAA/NWS/NCEP/Climate Prediction Center, College Park, Innovim, LLC, Greenbelt, MD, USA.
12	* Corresponding author: Wei Zhang (wz19@princeton.edu)
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16	Key Points
17	<ul> <li>The Gulf Stream influences regional rainfall patterns in the Southeast US</li> </ul>
18	Eddying CCSM4 improves the representation of the North Atlantic Subtropical High variability and
19	its connection to the Southeast US rainfall
20	Eddy-parameterizing CCSM4 and CMIP5 models may overestimate the role of tropical sea
21	surface temperature in decadal Southeast US rainfall
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#### 35 Abstract

36 Ocean variability is a dominant source of remote rainfall predictability, but in many cases the physical 37 mechanisms driving this predictability are not fully understood. This study examines how ocean 38 mesoscales (i.e., the Gulf Stream SST front) affect decadal southeast US (SEUS) rainfall, arguing that the 39 local imprint of large-scale teleconnections is sensitive to resolved mesoscale features. Based on global 40 coupled model experiments with eddying and eddy-parameterizing ocean, we find that a resolved Gulf 41 Stream improves localized rainfall and remote circulation response in the SEUS. The resolved Gulf 42 Stream influences the boundary layer, driving a barotropic circulation response, thus affecting decadal 43 SEUS rainfall due to a westward extension of the North Atlantic Subtropical High. The eddy-44 parameterizing simulation fails to capture the sharp SST gradient associated with the Gulf Stream and 45 overestimates the role of tropical SST in the SEUS rainfall due to its classical wintertime connection with 46 the El Niño/Southern Oscillation.

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# 51 Plain Language Summary

52 Current global climate models (GCMs) typically fail to fully resolve mesoscale ocean features (with length 53 scales on the order of 10 km) such as western boundary currents, which potentially limit rainfall 54 predictability over decadal timescales. Improvements in high-performance climate modeling enable us to 55 incorporate high-resolution ocean models (0.1°) that capture these important mesoscale features with 56 increased fidelity. Here we show that the inclusion of ocean mesoscales produces a more realistic Gulf 57 Stream and improves both localized rainfall patterns and large-scale teleconnections. A resolved Gulf 58 Stream drives a nearly barotropic circulation response and generally reproduces the observed variability 59 of the North Atlantic Subtropical High that regulates Southeast US rainfall. The results further imply that 60 high-resolution GCMs with increased ocean model resolution may be needed in future climate prediction 61 systems.

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#### 68 **1 Introduction**

69 The ability to predict decadal rainfall variability over land remains one of the grand challenges in climate 70 prediction. Regional prediction of rainfall has limited skill on timescales from seasons to decades 71 (Hawkins & Sutton, 2011; Knutti & Sedláček, 2013; Kushnir et al., 2019; Pathak et al., 2019; Shepherd, 72 2014). For example, several recent studies have shown the underestimated signals in models, or the so-73 called "signal-to-noise paradox" (e.g., Scaife et al. 2014; Scaife & Smith, 2018; Siegert et al. 2016; 74 Strommen & Palmer, 2019; Zhang et al., 2021; Zhang & Kirtman, 2019b) in decadal rainfall predictability 75 (Smith et al., 2019, 2020), implying potentially serious issues in current modeling systems that fail to 76 capture the observed decadal rainfall signals.

77 The ocean plays a crucial role in modulating low-frequency rainfall variability (see Battisti et al., 2019 for 78 review of current understanding). Variations in sea surface temperature (SST) (e.g., El Niño/Southern 79 Oscillation, ENSO) can result in substantial impacts on local air-sea feedbacks and teleconnection 80 patterns affecting regional US precipitation variability (Grondona et al., 2000; Infanti & Kirtman, 2016; 81 Mamalakis et al., 2018). However, extra-tropical mesoscale oceanic drivers of precipitation are not 82 necessarily well represented in current GCMs (e.g., the fifth Coupled Model Intercomparison Project, 83 CMIP5). In recent years, improvements in high-performance computing have enabled high-resolution 84 GCMs with eddying (e.g., eddy-resolving and eddy-permitting) ocean models to include more mesoscale 85 ocean processes (e.g., Delworth et al., 2012; Roberts et al., 2020; Wang et al., 2019; Zhang, 2020; 86 Zhang et al., 2021). Studies with eddying GCMs show considerable benefits, for example, with better 87 representation of ocean surface climatology (Kirtman et al., 2012; Sigueira & Kirtman, 2016), 88 improvements in air-sea interactions (Bryan et al., 2010; Kirtman et al., 2017), and implications for 89 remarkable impacts on precipitation changes especially over ocean regions (He et al., 2018).

90 Compared with their lower-resolution counterparts, eddying GCMs more accurately simulate fronts and 91 the sharpness of SST gradients in the Gulf Stream (e.g., Siqueira & Kirtman, 2016) that are necessary to 92 reproduce the observed distributions of the rainfall climatology (Bryan et al., 2010; Johnson et al., 2020; 93 Minobe et al., 2008). Mesoscale air-sea interaction processes in the western boundary currents may 94 influence the overlying atmospheric boundary layer and the upper troposphere and atmospheric 95 circulation (Feliks et al., 2011; Sigueira et al., 2021; Small et al., 2008). However, whether and the degree 96 to which the inclusion of ocean mesoscales affects remote regional precipitation over land - particularly 97 decadal southeast US (SEUS) rainfall and teleconnections - remains unclear.

98 Low-frequency SEUS rainfall significantly responds to ocean surface conditions and large-scale patterns 99 of SSTs such as ENSO, the Pacific Decadal Oscillation (PDO) (e.g., Fuentes-Franco et al., 2016; Li et al., 2012) and the Atlantic Multi-decadal Oscillation (AMO) (e.g., Burgman & Jang, 2015; Kwon et al., 2009). 101 For instance, ENSO can play an essential role in modulating seasonal to interannual SEUS rainfall 102 variability, especially during winter seasons (Hoerling et al., 1997; Infanti & Kirtman, 2019; Schmidt et al., 103 2001; Trenberth et al., 1998). The impacts of tropical cyclones (Chan & Misra, 2010; Knight & Davis, 104 2007; Nogueira & Keim, 2011) and surface soil moisture (Koster et al., 2004; Yoon & Leung, 2015) on 105 SEUS rainfall have also been addressed in previous studies. Of particular interest here is the North 106 Atlantic subtropical high (NASH). Li et al. (2011) and Li et al. (2012) have noted that the displacement of 107 the NASH western ridge influences the SEUS rainfall in summer by changing the moisture transport and 108 vertical motion. The westward extension of the NASH towards the continental US contributes to increased 109 northward flow and low-level convergence, leading to upward motion and more precipitation over the 110 SEUS.

Here we diagnose how mesoscale ocean features affect decadal-scale SEUS precipitation and teleconnections based on the hypothesis that SST variability associated with the Gulf Stream front affect the position of the NASH and hence rainfall over SEUS. Possible influences of SSTs and the NASH on the SEUS rainfall at decadal timescales is discussed based on a suite of global coupled model simulations with the Community Climate System Model Version 4.0 (CCSM4; Gent et al., 2011) using eddying and eddy-parameterizing ocean component models.

## 117 **2 Data and Method**

### 118 2.1 Data

119 Observed monthly precipitation data are obtained from the Global Precipitation Climatology Project 120 (GPCP) version 2.3 combined precipitation dataset (1979-present; Adler et al., 2018) and the gauge-121 based Global Precipitation Climatology Center (GPCC) precipitation product (1901-2016; Schneider et al., 122 2017) from the National Center for Atmospheric Research (NCAR). The GPCP data has a 40-year record 123 and lower resolution on global 2.5° grids, whereas the GPCC provides land-surface precipitation with 124 1°x1° spatial resolution and a long-time record. To represent the NASH variability, we use the 125 geopotential heights at 850 hPa from the NOAA's twentieth-century reanalysis version-2c data (20CV2c; 126 Compo et al., 2011).

We assessed thirty coupled models from CMIP5 that were used as supplementary analyses (Table S1).
All CMIP5 models are considered as low-resolution GCMs with an eddy-parametrized ocean. To equally
weight each model, we only consider the first realization of each model's historical simulation. The results
based on CMIP5 models are analyzed and compared with observational estimates.

### 131 **2.2 Model Experiments**

To examine the influence of ocean mesoscales on climate simulations, we perform two different sets of experiments using CCSM4 with eddy-parameterizing (1° ocean; hereafter, LRC) and eddying (0.1°; hereafter, HRC) ocean components, respectively. CCSM4 is a fully coupled climate model consisting of component models for atmosphere, land, ocean, sea ice, and the coupling infrastructure. A general description of CCSM4 can be found in Gent et al. (2011).

137 In this study, the LRC experiment is a present-day control simulation (greenhouse gas concentrations for

138 1990) using 1° atmosphere/land coupled to the ocean and sea-ice models with the nominal 1° horizontal 139 resolution. LRC is initialized with an ocean at rest and allows for 200 years of spin-up period and then a 140 300-year simulation is integrated for analysis (the same simulation as used in Zhang & Kirtman, 2019a). 141 HRC experiments include three high-resolution simulations that are identical except for a small 142 perturbation in the initial conditions. The initial condition for our first HRC simulation is taken from the end 143 of the previously completed LRC experiment, and we ran the HRC model for 155-years and only 144 analyzed the last 55-years. The two other HRC simulations are initialized, with small initial perturbations, 145 at year 48 of the first, and run for 70-years. We drop the first 20-years of both of these simulations in our 146 analysis. The details of CCSM4 HRC and LRC model experiments are discussed in Zhang et al. (2021).

To diagnose the potential impact of atmospheric resolutions, we perform an additional experiment (hereafter, LRC-OCN) with a pre-released version of CCSM4, which has the same ocean and sea-ice model resolution (1°) as LRC and the exact atmospheric and land model resolution (0.5°) as HRC (see details in Kirtman et al., 2012). LRC-OCN has a present-day control simulation of 150 years, and the first 50-years are taken as spin-up periods.

# 152 **3 Results and Discussion**

153 We first show the observed (GPCC and GPCP) and model simulated (HRC and LRC) decadal variance of 154 rainfall over the SEUS and western North Atlantic in Figure 1 (left panels). We removed any linear trend 155 from the datasets and applied a 5-year low-pass Butterworth filter to the anomalies to represent internal 156 rainfall variability at decadal timescales. Here we define the SEUS as land regions bounded by 25°N to 157 38°N and 266°E to 284°E. Compared with both observational estimates, the model simulations generally 158 show smaller decadal variance. CMIP5 multi-model mean estimates (based on thirty model historical 159 simulations in Table S1) show 21% lower decadal SEUS rainfall variance than observational estimates 160 based on GPCP. Overall, CMIP5 models (73%), including CCSM4, underestimate decadal rainfall 161 variance in the SEUS.

162 We identify an increase in the decadal variance of the SEUS rainfall in HRC compared to LRC (Figs. 1c 163 and 1d). Whether this improvement is due to finer ocean resolution remains unassessed in Fig. 1 given 164 that both the atmospheric and oceanic resolutions are different between LRC and HRC. However, the 165 role of the ocean resolution is isolated in Fig. S1a. Here we note that the slightly larger decadal variance 166 in SEUS rainfall detected in LRC-OCN (0.5° atmosphere; Fig. S1) compared to LRC (1° atmosphere; Fig. 167 1d) implies that the increased atmospheric resolution is also partially responsible for the increased 168 variance, but the resolved ocean meso-scale features also remain important. We also note that even 169 though the decadal SEUS rainfall variability is slightly larger in LRC-OCN compared to LRC, the rainfall 170 climatology only indicates small differences (not shown).



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Figure 1. Decadal variance and leading EOF patterns (unit: mm/day) of monthly rainfall anomalies over the Southeast US and western North Atlantic region: (a, e) GPCP, (b, f) GPCP, (c, g) LRC, and (d, h) HRC. The land region within the black dashed box (25°N to 38°N, 266°E to 284°E) indicates the region of the Southeast US.

The leading spatial pattern of decadal rainfall variability (EOF1) in HRC (Fig. 1g) suggests that a tilted zonal dipole over the ocean in HRC, similar to the GPCP observations (Fig. 1f), is possibly linked to the Gulf Stream with maximum rainfall over the SEUS. However, the signal is weaker over SEUS than observational estimates (Figs. 1e and 1f). The center of action in LRC (and LRC-OCN, Fig. S1b) is further

- 181 south and east of the observed and HRC, and indicates relatively weak connectivity with the Gulf Stream.
- 182 Based on these differences we hypothesize that resolved mesoscale processes in the Gulf Stream affect
- 183 the center of decadal rainfall variability upstream and over SEUS.



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Figure 2. Correlation between decadal Southeast US rainfall index (25°-38°N, 266°-284°E) and global SST anomalies based on (a) CMIP5 (median correlation coefficients at each grid for thirty CMIP5 models), (b) OBS, (c) LRC, and (d) HRC. All the data have been applied with a 5-year low-pass filter. The maps only show the 95% confidence interval for the correlations based on the Student's *t* test (two-tailed).

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191 To examine the role of SST variability in modulating decadal SEUS rainfall, we show in Figure 2 the 192 correlation between decadal SEUS rainfall index and global SST anomalies for the observational 193 estimates and the models, with shading significant at 95% confidence level based on the Student's t test 194 (two-tailed). The decadal SEUS rainfall index is defined as the area-averaged values of 5-year low-pass 195 filtered rainfall anomalies over the SEUS (25°-38°N, 266°-284°E) land points. Both LRC and CMIP5 196 models (median correlation coefficients for thirty CMIP5 models) show a strong correlation between the 197 decadal SEUS rainfall index and the (ENSO-like) eastern tropical Pacific SST anomalies (Figs. 2a and 2c). 198 A similar pattern is also identified with LRC-OCN with finer atmospheric resolution than LRC (not shown). 199 This dominant role of ENSO SST in decadal SEUS rainfall in LRC and CMIP5 models can be attributed to

the typical strong wintertime connection between ENSO and SEUS rainfall that may persist on decadal timescales (Fig. S2). During boreal winter, near the peak of El Niño events, warm tropical SSTs affect the corresponding tropical convection, leading to a shift in the subtropical jet streams that brings more moisture to the SEUS (e.g., Infanti & Kirtman, 2019; Ropelewski & Halpert, 1986; Schmidt et al., 2001). La Niña generally leads to the opposite response.

205 However, the strong positive link between the decadal SEUS rainfall index and ENSO SST signal is weak 206 or even missing in HRC and observational estimates (Figs. 2b and 2d). Interestingly, HRC and 207 observational estimates suggests that decadal SST in the Gulf Stream and its surrounding regions can be 208 the dominant contributor to decadal SEUS rainfall variability. We note that the correlation between 209 decadal SEUS rainfall and Gulf Stream SST is detected in HRC is stronger than observational estimates, 210 possibly because the spatial resolution of the currently available observed SST dataset - HadISST - is 211 still too low to reproduce realistic decadal SST variability (Deser et al., 2010; Solomon & Newman, 2012), 212 but we cannot eliminate the possibility that HRC overemphasizes the importance of the Gulf Stream 213 variability. Nevertheless, HRC produces an improvement of decadal SEUS rainfall induced 214 teleconnections compared with LRC, indicating the significant impact of ocean mesoscales on the SEUS 215 rainfall-SST teleconnections. We further argue that LRC and most CMIP5 models may overestimate the 216 role of tropical Pacific SST in the SEUS rainfall over decadal timescales. This overestimation can be 217 explained by the classical wintertime connection between SEUS rainfall and tropical Pacific SST 218 anomalies due to ENSO (Fig. S2). A similar finding was presented by Infanti and Kirtman (2019), who 219 argued that instead of tropical Pacific SST, the Gulf Stream played a leading role in the 36-month 220 prediction of the SEUS drought based on high-resolution CCSM4 initialized prediction experiments.

221 The influence of the NASH on interannual variations of the SEUS rainfall has been discussed in several 222 earlier studies (e.g., Li et al., 2011; Li et al., 2012). Here we aim to investigate the role of the NASH in 223 decadal SEUS rainfall variability by comparing HRC with LRC. We focus on 850 mb geopotential heights 224 as it is a common indicator for the NASH. Figure 3 shows the composite of standardized decadal 850hPa 225 geopotential height anomalies during wet and dry conditions over the SEUS. The corresponding 226 composite of standardized decadal SST anomalies during wet and dry conditions is also shown in Figure 227 S3. During the SEUS wet conditions, the warm SST and strong high-pressure anomalies along the Gulf of 228 Mexico, SEUS, and Gulf Stream in HRC produce increased northward moisture transport and low-level 229 convergence, which leads to upward motion and ultimately more precipitation over the SEUS. We argue 230 this increased rainfall is due to the westward extension of the NASH (Li et al., 2011; Li et al., 2012; Jones, 231 2019). During the SEUS dry conditions, we find cold SST anomalies along the Gulf Stream and a robust 232 low-pressure anomaly centered around the Gulf Stream extension in HRC, contributing to southward flow 233 (with dry moisture advection) and low-level divergence and thus downward motion and less precipitation 234 over the SEUS. HRC generally resembles the spatial patterns of the NASH variability based on 235 observational estimates (Figs. 3a-d), though HRC somewhat overestimates the amplitude of the decadal 236 NASH pressure anomalies and its connection to the SEUS rainfall (Figs. 4a and 4b).



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Figure 3. Composite of standardized decadal 850hPa geopotential height anomalies (unit: m) during wet and dry conditions over the SEUS based on (a, b) OBS, (c, d) HRC, and (e, f) LRC. Wet (dry) condition is identified when decadal SEUS rainfall index is above (below) plus (minus) one standard deviation.

LRC, conversely, fails to capture decadal NASH variability and its connection to the SEUS rainfall. For example, as seen in Figure 4, LRC largely fails to capture the westward expansion or shift of the NASH that is apparent in the observational estimates and in HRC. Changes in decadal SEUS rainfall in LRC are possibly due to variations of the pressure anomaly centers over the western US (Figs. 3e and 3f) and tropics.

248 Comparison between LRC and HRC suggests that a resolved Gulf Stream may improve the 249 representation of the NASH that affects decadal SEUS rainfall. The resolved Gulf Stream in HRC 250 influences the boundary layer, driving a nearly barotropic circulation response, and bringing more 251 moisture, and ultimately increasing the SEUS rainfall owing to the westward extension of the NASH, as 252 shown conceptually in Figure 5. It is possible that the North Atlantic Oscillation (NAO) can play a role in 253 decadal SEUS rainfall variability (e.g., Hurrell & Van, 1997; Ning & Bradley, 2016; Whan & Zwiers, 2017), 254 though we find no significantly larger NAO amplitude in HRC compared with LRC.



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Figure 4. Correlation between decadal Southeast US rainfall index and 850hPa geopotential height anomalies based on (a) OBS, (b) HRC, and (c) LRC. The maps only show the correlation at the 95% level based on the Student's *t* test (two-tailed).





#### **4 Summary and Conclusion**

This study investigates decadal SEUS rainfall and its teleconnections using high-resolution eddying CCSM4 simulations compared with its lower-resolution counterparts that are eddy parameterized. The inclusion of ocean mesoscales produces more realistic and warmer SST, sharper SST gradient (Siqueira & Kirtman, 2016), improved surface wind speed-SST coupling (Bryan et al., 2010), and betterrepresented subsurface ocean thermal and vertical structures (Zhang et al., 2021) along the Gulf Stream and its extension. An increase in decadal SST variance is also detected with HRC compared to LRC (not shown), especially along the Gulf Stream extension region.

271 With a better resolved Gulf Stream, the simulations indicate an improved annual mean rainfall climatology 272 that is generally consistent with observational estimates. We find no notable improvement in the annual 273 mean rainfall climatology over the SEUS, whereas enhanced decadal SEUS rainfall variance is detected 274 with HRC in better agreement with observational estimates. Though atmospheric resolution may partly 275 contribute to the increase in the decadal variance of the SEUS rainfall, the leading EOF pattern in HRC 276 shows consistency with observations, indicating the influence of the resolved Gulf Stream with a local 277 maximum over the SEUS. This dominant rainfall pattern in HRC and observational estimates is not the 278 leading pattern in LRC or LRC-OCN, and thus, we conclude that this decadal variability is connected to 279 resolved Gulf Stream variability.

280 The above conclusion is further supported by the decadal SEUS rainfall teleconnections with global SST. 281 Consistent with Infanti and Kirtman (2019), the SEUS rainfall shows a higher correlation with the North 282 Atlantic SST than the tropical Pacific SST on decadal timescales in HRC and observations. HRC 283 suggests an even higher correlation between decadal SEUS rainfall and the Gulf Stream SST than 284 observational estimates, perhaps indicating that HRC over-predicts the connectivity between Gulf Stream 285 variability and decadal SEUS rainfall variability. Conversely, LRC and CMIP5 models overestimate the 286 role of tropical Pacific SST in decadal SEUS rainfall due to the classic wintertime connection between the 287 SEUS rainfall and ENSO. Although the seasonality of decadal SEUS rainfall is not our focus in this 288 manuscript, we re-examine the SEUS rainfall-SST relationship in the summer and winter seasons, 289 respectively (Fig. S2). Perhaps surprising is that the overall correlation patterns, as shown in Figure 2, 290 pick up the wintertime relationships (Fig. S2). Interestingly, HRC and observation show a positive 291 (negative) correlation between the SEUS rainfall and tropical Pacific SST during winter (summer), which 292 may explain why decadal SEUS rainfall shows no discernable connection with ENSO SST.

A resolved Gulf Stream has both a localized impact and a remote circulation response affecting the SEUS. The resolved Gulf Stream influences the boundary layer and forces a near barotropic circulation response, and ultimately modulates the SEUS rainfall over decadal timescales. The representation of the NASH and its connection to the SEUS rainfall are improved in HRC with better represented ocean mesoscales. HRC can generally reproduce the observed westward extension and retreat of the NASH that regulates the variations of decadal SEUS rainfall (Figs. 3-5), despite that HRC may overestimate the correlation between the SEUS rainfall and NASH. As suggested in HRC and observations, the westward extension of the NASH brings increased northward moisture transport and low-level convergence, leading to rising motion and ultimately more rainfall in the SEUS, which can be explained by a steady-state quasigeostrophic balance. However, the LRC simulation fails to capture the realistic Gulf Stream, the westward extension of the NASH, and its relationship with the SEUS rainfall.

304 Uncertainty remains in this study as the length of high-resolution observation and model simulations is 305 limited, and the results may be model-dependent. Many other factors that may influence decadal SEUS 306 rainfall such as tropical cyclone activities and surface soil moisture are not addressed. However, this 307 study, for the first time, demonstrates the potential benefits of an ocean eddying GCMs for regional 308 rainfall simulations and predictions over land. Arguably, the results presented here demonstrate that 309 using models that capture oceanic mesoscale features have the potential to improve the representation of 310 rainfall variability remotely and regionally. How well this translates across models remains an open 311 question and whether this improved simulated low-frequency variability of remote rainfall translates into 312 improved predictions remains an open question.

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335 All the observational, reanalysis data and CMIP5 historical simulations are properly referenced and 336 publicly available. The GPCP and GPCC precipitation datasets are downloaded through 337 https://psl.noaa.gov/data/gridded/data.gpcp.html and https://psl.noaa.gov/data/gridded/data.gpcc.html, 338 respectively. The twentieth century reanalysis of geopotential height at 850 hPa can be found from 339 NOAA's Physical Sciences Laboratory (https://psl.noaa.gov/data/20thC Rean). Thirty CMIP5 model 340 historical simulations and the associated model descriptions can be obtained from the Natural 341 Environment Research Council's Data Repository for Atmospheric Science and Earth Observation 342 (http://archive.ceda.ac.uk). The southeast US rainfall index (5-year low-pass filtered) derived from 343 observations and models can be accessed by using the DOI http://doi.org/10.5281/zenodo.4433147. 344 Besides, the model codes of CCSM4 used in this study can be achieved freely from 345 http://www.cesm.ucar.edu/models/ccsm4.0/. The CCSM4 HRC and LRC model codes, experiments, and 346 data outputs are archived at the University of Miami Center for Computational Science, which are 347 available from the authors upon request.

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