

A Library of Large-eddy Simulations for Calibrating Cloud Parameterizations

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Key Points:

- A library of high-resolution simulations of clouds is created using LES driven by a GCM.
- The LES library can be used to train parameterizations in a GCM and to investigate cloud feedbacks.

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Abstract

Advances in high-performance computing have enabled large-eddy simulations (LES) of turbulence, convection, and clouds, but their potential to improve parameterizations in global climate models (GCMs) is only beginning to be harnessed. We design an experimental setup in which LES can be driven by large-scale forcings from GCMs. This can be done anywhere in the atmosphere, and we use this setup to create a library of LES of clouds across tropical and subtropical regimes. The LES are used to simulate the transition from stratocumulus to shallow cumulus over the East Pacific. The results are not very sensitive to the choice of the host GCM driving the LES. The setup is also used to simulate clouds under climate change. The LES simulate a positive but weak shortwave cloud feedback. The LES library expands the datasets available for calibrating parameterizations in GCMs.

Plain Language Summary

Clouds remain one of the largest uncertainties in our understanding and predictions of climate change because it is challenging to represent their small-scale dynamics in climate models. High-resolution simulations can provide faithful simulations of clouds and turbulence in limited areas, which can be used to calibrate climate models. However, only a limited set of simulations has been used for calibration of climate models, with focus on a few specific locations. This study presents an experimental setup that allows the high-resolution simulations to be run anywhere on the globe, driven by output from climate models. The setup is used to create a library of high-resolution simulations of clouds across different tropical and subtropical low-cloud regimes in both current and warmer climates. The library expands the training data available for the calibration and development of climate models.

1 Introduction

Low clouds play an important role in Earth’s energy budget, but they are poorly represented in global climate models (GCMs). Despite some improvements in recent decades, large biases remain in the clouds simulated by the current generation of GCMs. Most GCMs underestimate low cloud cover in the tropics and subtropics (Klein et al., 2013; Cesana & Waliser, 2016; Vignesh et al., 2020). The negative model bias can be as large as 50% in stratocumulus regions near the coast (Brient et al., 2019). In shallow cumulus regions, most GCMs overestimate the optical thickness of low clouds to achieve a reasonable global-mean energy balance despite the low bias in cloud cover. This is referred to as the “too few, too bright” problem (Nam et al., 2012). How low clouds respond to global warming is a key source of uncertainty in predictions of climate change. While the low cloud feedback is generally positive in GCMs, the magnitude of the feedback has a large intermodel spread and is strongly correlated with the equilibrium climate sensitivity (Bony & Dufresne, 2005; Bony et al., 2006; Schneider, Teixeira, et al., 2017; Zelinka et al., 2020).

It is challenging for GCMs to simulate low clouds because their resolution, which is on the order of 100 km in the horizontal, is too coarse to resolve the boundary layer turbulence and convection controlling the clouds. As a result, GCMs rely on parameterizations to represent these processes, and inadequacies in the parameterizations lead to biases in GCM-simulated clouds. However, large-eddy simulations (LES) can directly resolve cloud dynamics and provide high-fidelity simulations in limited areas. While global LES will not be feasible for decades, data from LES can be used to train and improve GCM parameterizations with data assimilation and machine learning approaches (Schneider, Lan, et al., 2017). So far, LES used for evaluating GCM parameterizations have typically been run at a few specific locations, usually associated with field campaigns (e.g. Siebesma et al., 2003; Stevens et al., 2005; Rauber et al., 2007). Idealized large-scale forc-

64 ing fields are often used in studies comparing LES with GCMs and/or single column mod-
 65 els (Zhang et al., 2012, 2013). The potential of using LES to systematically inform GCM
 66 parameterizations has not yet been fully harnessed.

67 In Shen et al. (2020), we presented a framework in which LES are driven by large-
 68 scale forcings from GCMs. This study aims to use the framework to expand the dataset
 69 for training GCM parameterizations by generating a library of LES across a range of cloud
 70 regimes. We simulate low-cloud over the East Pacific using LES driven by large-scale forc-
 71 ings from comprehensive GCMs in both current and warmer climates. Section 2 describes
 72 the GCM and LES used in the study and key features of the forcing framework. Section
 73 3 describes simulation characteristics in the LES and compares the LES with the GCMs.
 74 Section 4 summarizes the conclusions and discusses potential uses of the data presented
 75 in this study.

76 2 Methods

77 2.1 Experimental Setup

78 The large-scale forcing is derived from the cfSites output in the Coupled Model In-
 79 tercomparison Project Phase 5 (CMIP5) archive. cfSites includes high-frequency out-
 80 put at different locations of instrumented sites and field campaigns, as well as a num-
 81 ber of climate regimes where the inter-model spread of cloud feedbacks is large (Bony
 82 et al., 2011). In this study, we focus on low cloud (cloud top height lower than 3km) re-
 83 gions over the East Pacific (Figure 1). We use 5-year (2004-2008) averaged large-scale
 84 forcings in different months (January, April, July, and October) from the AMIP exper-
 85 iment, which is forced by observed sea surface temperatures (SSTs) and sea ice concen-
 86 tration. The time-averaged forcing does not have a diurnal cycle. To test the sensitiv-
 87 ity of the results to the host model, we use large-scale forcings from two GCMs: HadGEM2-
 88 A and CNRM-CM5. We choose these two models as the tropical low-cloud reflection re-
 89 sponse to global warming in HadGEM2-A and CNRM-CM5 are at the higher and lower
 90 end of the range of CMIP5 models, respectively (Brient & Schneider, 2016). To explore
 91 how clouds change in a warmer climate, we run simulations with large-scale forcings from
 92 the AMIP4K experiment, where SSTs are increased uniformly by 4 K from the AMIP
 93 experiment.

94 The LES are performed using the Python Cloud Large-Eddy Simulation (PyCLES)
 95 code (Pressel et al., 2015). PyCLES solves the anelastic equations with specific entropy
 96 and total water specific humidity as prognostic thermodynamic variables and uses a third-
 97 order, three-stage strong stability preserving Runge-Kutta scheme (Shu & Osher, 1988).
 98 The performance of the model on standard test cases has been described in previous pa-
 99 pers (Pressel et al., 2015; Tan et al., 2016; Pressel et al., 2017). The simulations are forced
 100 with prescribed SSTs from the GCM. Surface fluxes are calculated using a bulk scheme
 101 with drag coefficients obtained from Monin-Obukhov similarity theory (Byun, 1990). Ra-
 102 diative energy fluxes are calculated with the Rapid Radiative Transfer Model (RRTM)
 103 (Iacono et al., 2008). The top-of-atmosphere insolation and the insolation-weighted av-
 104 erage of solar zenith angle are prescribed from the GCM. Cloud microphysical processes
 105 are represented using a one-moment warm-rain microphysics scheme based on Kessler
 106 (1995). Subgrid-scale turbulent fluxes are modelled using the Smagorinsky-Lilly closure
 107 (Lilly, 1962; Smagorinsky, 1963). We use a doubly periodic domain that is 6000 m wide
 108 in the horizontal and 4000 m tall in the vertical. The horizontal and vertical resolutions
 109 are 75 m and 20 m, respectively. The time step is dynamically adjusted to maintain the
 110 Courant number close to 0.7, and is on the order of 1 s. The simulations are initialized
 111 from the 5-year averaged GCM profiles and are run for 6 days. The results are averaged
 112 over the last day, when most simulations reach a quasi-steady state.

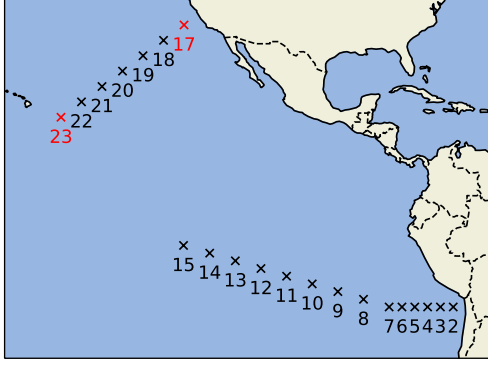


Figure 1: cfsites locations used in this study. The sites cover the transition from stratocumulus to shallow cumulus over the East Pacific. The red crosses highlight site 17 and site 23, two locations on which we focus in the paper. They represent cloud regimes of stratocumulus and shallow cumulus, respectively.

113

2.2 Forcing Framework

114

The forcing framework is similar to that in Shen et al. (2020). Here we briefly summarize the large-scale forcings in the LES and describe the difference to Shen et al. (2020).

115

116

2.2.1 Subsidence

117

Large-scale subsidence gives rise to a source in the specific entropy (s) and specific humidity (q_t) equations:

118

119

$$\frac{ds}{dt} = -\langle \tilde{w} \rangle \frac{\partial s}{\partial z}, \quad (1)$$

120

121

$$\frac{dq_t}{dt} = -\langle \tilde{w} \rangle \frac{\partial q_t}{\partial z}. \quad (2)$$

122

Here, $w = dz/dt$ is the vertical velocity, $\tilde{(\cdot)}$ denotes a GCM value, and $\langle \cdot \rangle$ denotes the time mean. The time-averaged vertical velocity is approximated by $\langle \tilde{w} \rangle \approx -\langle \tilde{\omega} \rangle \langle \tilde{\alpha} \rangle / g$, where we have ignored small terms associated with the horizontal advection of pressure and assumed that the pressure-coordinate vertical velocity $\tilde{\omega}$ and the specific volume $\tilde{\alpha}$ are uncorrelated.

126

127

2.2.2 Advection

128

Horizontal advection and vertical eddy advection are prescribed directly from the GCM as

129

130

$$\frac{ds}{dt} = \frac{c_p}{T} (\langle J_{\text{hadv}} \rangle + \langle J_{\text{veddy}} \rangle) + (s_v - s_d) (\langle S_{\text{hadv}} \rangle + \langle S_{\text{veddy}} \rangle), \quad (3)$$

131

132

$$\frac{dq_t}{dt} = \langle S_{\text{hadv}} \rangle + \langle S_{\text{veddy}} \rangle, \quad (4)$$

133

where c_p is the isobaric specific heat capacity of air; T is temperature; and s_d and s_v are specific entropies of dry air and water vapor, respectively. The terms S_{hadv} and J_{hadv} represent horizontal advection of specific humidity and temperature, and S_{veddy} and J_{veddy} represent vertical eddy advection of specific humidity and temperature. All four advection terms are derived from the GCM. The cfsites output includes total advective ten-

137

138 dependencies of specific humidity (S_{adv}) and temperature (J_{adv}). We obtain the horizontal ad-
 139 vective tendencies from the total advective tendencies as the residuals

$$140 \quad S_{\text{hadv}} = S_{\text{adv}} + \tilde{w} \frac{\partial \tilde{q}_t}{\partial z}, \quad (5)$$

141 and

$$142 \quad J_{\text{hadv}} = J_{\text{adv}} + \tilde{w} \frac{\partial \tilde{T}}{\partial z} + \tilde{w} \frac{g}{c_p}. \quad (6)$$

143 The vertical eddy advective tendencies are derived as

$$144 \quad S_{\text{veddy}} = - \left\langle \tilde{w} \frac{\partial \tilde{q}_t}{\partial z} \right\rangle + \langle \tilde{w} \rangle \frac{\partial \langle \tilde{q}_t \rangle}{\partial z}, \quad (7)$$

145 and

$$146 \quad J_{\text{veddy}} = - \left\langle \tilde{w} \frac{\partial \tilde{T}}{\partial z} \right\rangle + \langle \tilde{w} \rangle \frac{\partial \langle \tilde{T} \rangle}{\partial z}. \quad (8)$$

147 **2.2.3 Relaxation**

148 Unlike in Shen et al. (2020), the large-scale momentum forcing is not applied. In-
 149 stead, the horizontal winds are relaxed to the GCM profiles on a timescale of 6 h. Free-
 150 tropospheric temperatures T and humidities q_t are relaxed to GCM profiles to prevent
 151 drifting from realistic conditions. The relaxation timescale varies with height as

$$152 \quad \Gamma_r(z) = \frac{1}{\tau_r} \times \begin{cases} 0 & z < z_i, \\ 0.5 \left(1 - \cos \left(\pi \frac{z - z_i}{z_r - z_i} \right) \right) & z_i \leq z \leq z_r, \\ 1 & z > z_r. \end{cases} \quad (9)$$

153 Relaxation forcing is commonly used when driving LES or single column models with
 154 GCMs or reanalysis, and the timescale is usually a few hours (e.g. Randall & Cripe, 1999;
 155 Neggers et al., 2012; Zhang et al., 2012). In this study, we set $\tau_r = 24$ h, and $z_r = 3500$ m
 156 and $z_i = 3000$ m.

157 **3 Results**

158 **3.1 LES simulated low clouds**

159 Figure 2 shows the cloud cover, cloud liquid water path (LWP), cloud base and cloud
 160 top at different sites in the LES driven by HadGEM2-A. The LES sample a wide range
 161 of cloud regimes. Near the coasts of Peru (sites 2–4) and California (sites 17–18), the
 162 simulations produce stratocumulus with cloud cover near 100%. The cloud cover decreases
 163 rapidly when moving away from the coast and is about 20–30% in shallow cumulus re-
 164 gions over the open ocean. The transition from stratocumulus to shallow cumulus is also
 165 seen in the decrease in LWP and the increase in cloud top height from the coast to the
 166 open ocean.

167 The cloud properties at different locations have distinct seasonal variations. In the
 168 stratocumulus regions off the coasts, cloud cover and LWP are higher in July and Oc-
 169 tober in both hemispheres. In the shallow cumulus regions over the Southeast Pacific,
 170 cloud cover and LWP peak in July and show low values in January and April. The cloud
 171 base is highest in July and lowest in January, while the cloud top is generally higher in
 172 January than in July, suggesting some seasonal variation in the thickness of clouds. In
 173 the shallow cumulus regions over the Northeast Pacific, cloud cover and LWP show high
 174 values in April and low values in July. The cloud base is highest in April and lowest in
 175 July, and the seasonal variation in the cloud top generally follows that in the cloud base
 176 height.

177 The cloud properties in the LES driven by CNRM-CM5 are shown in Figure 3. Un-
 178 like the LES driven by HadGEM2-A, this LES does not simulate a stratus cloud layer
 179 near the coast of Peru. In the shallow cumulus regions, the cloud fraction and LWP in
 180 some seasons are higher than that in the LES driven by HadGEM2-A, which largely re-
 181 sults from differences at the cloud top. The differences between the two host GCMs will
 182 be discussed further in Section 3.2.

183 Figures 4 and 5 show the vertical profiles of large-scale forcings and cloud prop-
 184 erties of two sites over the Northeast Pacific in HadGEM2-A in July, representing the
 185 cloud regimes of stratocumulus (site 17) and shallow cumulus (site 23). The large-scale
 186 subsidence is stronger at site 17 than at site 23. There is horizontal advective cooling
 187 and drying in the boundary layer at both sites, and their tendencies are stronger at site
 188 17. The advective tendencies are consistent with the lower-level winds, which are northerly
 189 near the coast (site 17) and northeasterly away from the coast (site 23).

190 Figure 6 shows the timeseries of cloud cover and LWP at sites 17 and 23. The LES
 191 reach quasi-steady states in 1–2 days at both sites, although the relatively small domain
 192 size leads to high-frequency oscillations especially for shallow cumulus. The LES sim-
 193 ulate stratocumulus under strong subsidence and advective cooling and drying at site
 194 17, with a cloud top at around 1000 m and a cloud fraction close to 100% (Figure 4g).
 195 The stratocumulus layer is slightly decoupled from the subcloud mixed layer, as seen in
 196 the vertical profiles of total water specific humidity, liquid potential temperature, and
 197 vertical velocity variance below the inversion (Figures 4d–4f). This decoupling may be
 198 due to the strong advective cooling at the bottom of the cloud layer (Figure 4b). At site
 199 23, the LES simulates a shallow cumulus layer with a cloud base at around 500 m and
 200 a cloud top at around 1600 m. The cloud fraction and the corresponding vertical veloc-
 201 ity variance have two peaks (Figures 5d and 5h): just above the lifted condensation level
 202 and just below the inversion. The anvil resulting from the detrainment of cumulus up-
 203 drafts is ubiquitous in the LES simulations of shallow cumulus sites.

204 3.2 Comparison to GCM and sensitivity to large-scale forcing

205 We compare the LES-simulated cloud profiles with those in the host GCM, HadGEM2-
 206 A (Figures 4g, 4h, 5g, and 5h). At site 17 in July, the GCM produces a lower but deeper
 207 stratocumulus layer. The cloud base in the GCM is very close to the surface and lower
 208 than that in the LES by about 400 m, while the cloud top heights are similar between
 209 the GCM and the LES. The maximum cloud fraction and cloud liquid water in the GCM
 210 are much smaller than in the LES, and LWP in the GCM is about 40% smaller. At site
 211 23, the GCM produces a higher and deeper shallow cumulus layer. The cloud base in
 212 the GCM is slightly lower than in the LES, while the cloud top in the GCM is about 500 m
 213 higher. The cloud fraction and cloud liquid water in the GCM are much larger. The GCM
 214 only produces one peak in cloud fraction in the middle of the shallow cumulus layer, as
 215 opposed to the two peaks at the bottom and the top of the cloud layer in the LES.

216 Figure 7a compares LWP at all sites simulated by HadGEM2-A and LES. The spread
 217 of LWP at different sites is much smaller in the LES than in the GCM, and there is no
 218 correlation between the LES and the GCM. In the shallow cumulus regions, LWP is sys-
 219 tematically larger in the GCM, mostly resulting from a deeper cloud layer. The differ-
 220 ence can be as large as 60 g m^{-2} at several sites (e.g., over the North Pacific). In the
 221 stratocumulus regions, the LWP differences between the GCM and the LES are smaller,
 222 although the maximum cloud fraction in the stratocumulus layer in the GCM is always
 223 much smaller than in the LES. This is because the cloud layer is usually much thicker
 224 in the GCM (e.g., Figures 4g and 4h).

225 The large-scale forcing used to drive the LES is dependent on the host GCM. Fig-
 226 ure 8 shows the vertical profiles of large-scale forcings and cloud properties in the LES
 227 driven by the two GCMs, HadGEM2-A and CNRM-CM5, at sites 17 and 23 in July. At

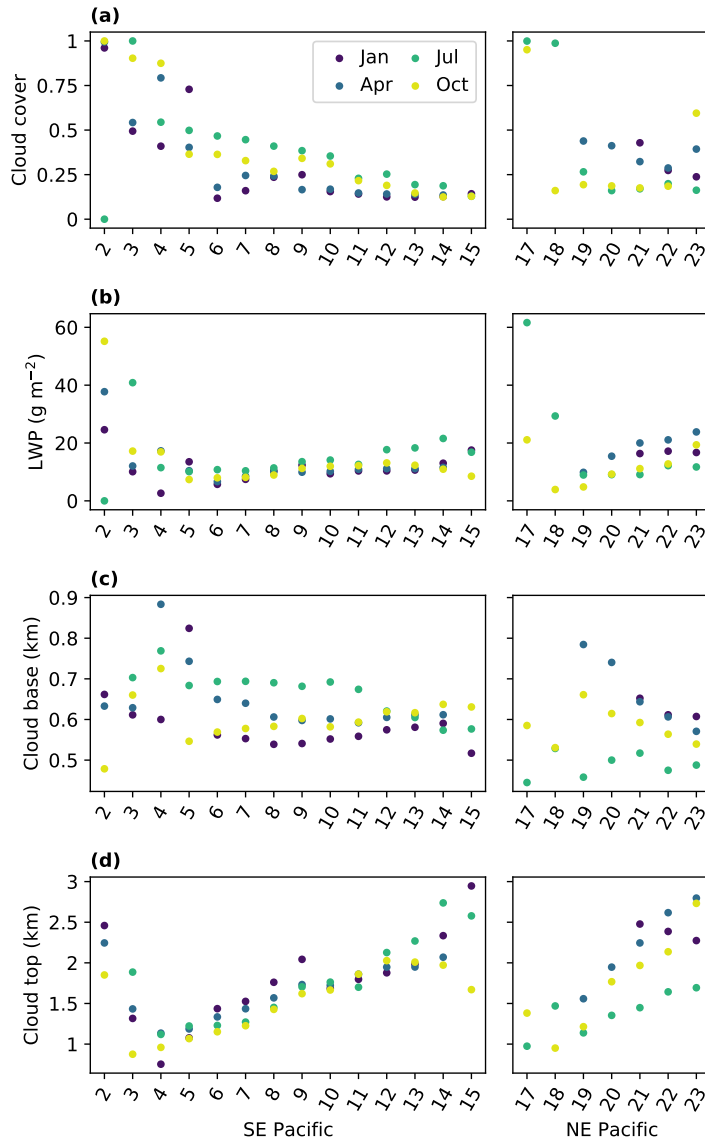


Figure 2: (a) Cloud cover, (b) cloud liquid water path (LWP), (c) cloud base height, and (d) cloud top height at different sites in the LES driven by HadGEM2-A in different seasons. Missing points indicate the cloud top height is higher than 3000 m.

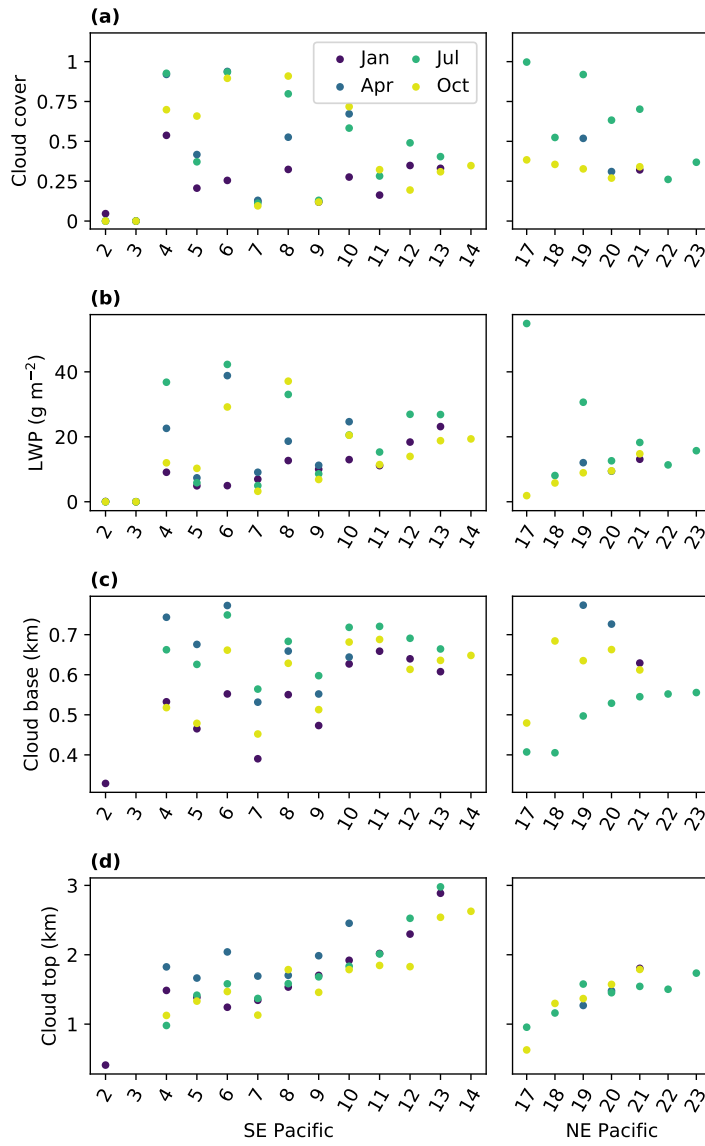


Figure 3: Same as Figure 2 but for LES driven by CNRM-CM5.

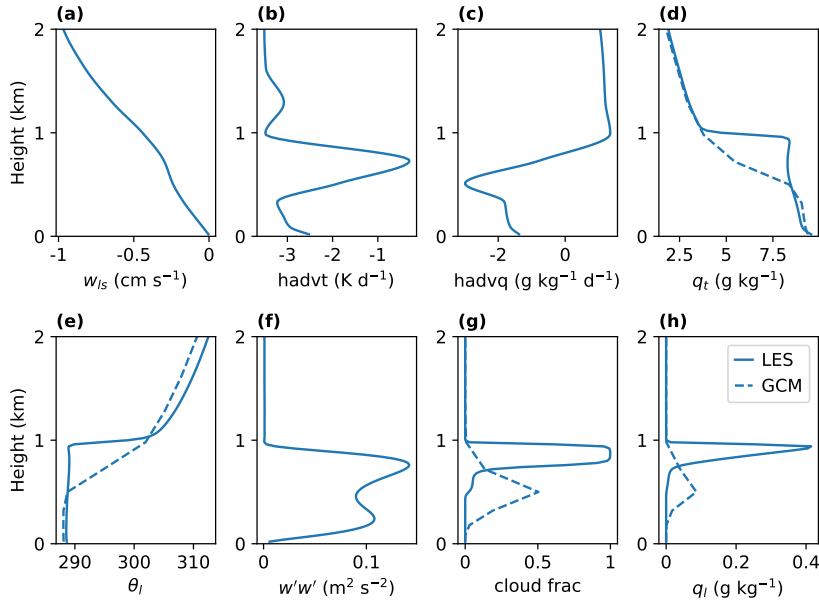


Figure 4: Vertical profiles of (a) large-scale vertical velocity, (b) horizontal advection of temperature, (c) horizontal advection of specific humidity, (d) total water specific humidity, (e) liquid potential temperature, (f) vertical velocity variance, (g) cloud fraction, and (h) cloud liquid water specific humidity in the LES driven by HadGEM2-A at site 17 in July. The dashed lines represent the GCM profiles.

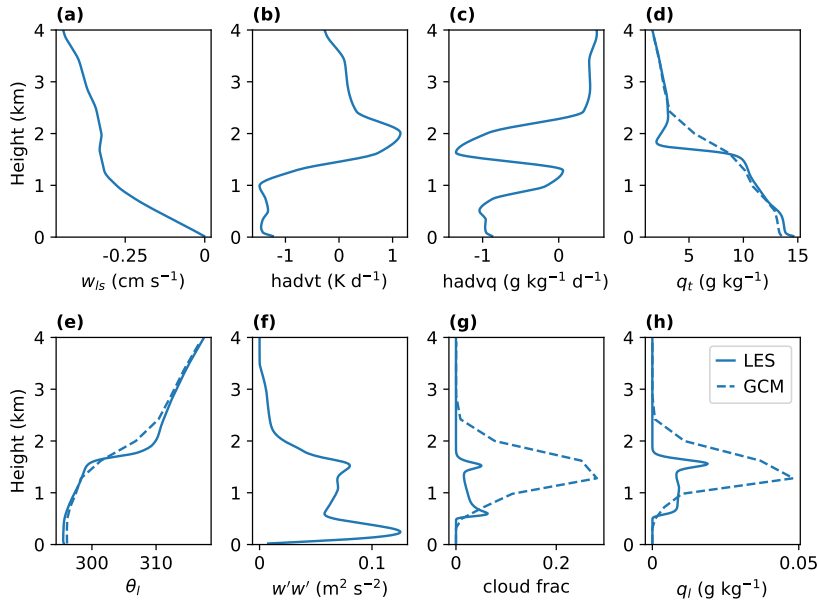


Figure 5: Same as Figure 4, but for site 23 in July.

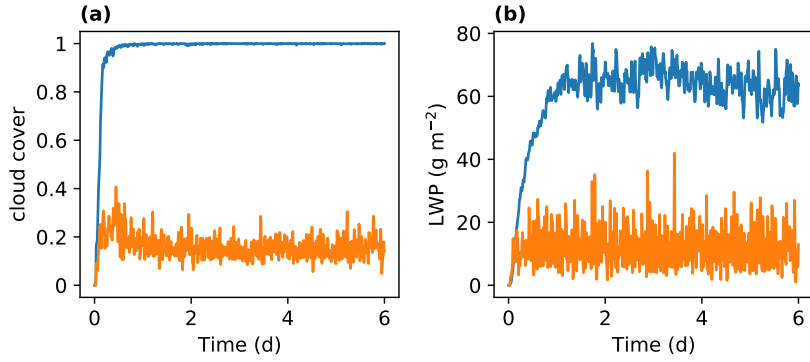


Figure 6: Time series of (a) cloud cover and (b) liquid water path in the LES driven by HadGEM2-A. Blue and orange lines represent sites 17 and 23 in July, respectively.

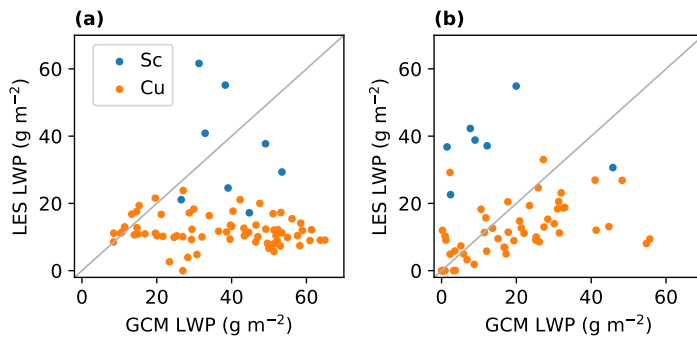


Figure 7: Scatter plot of LWP in the LES and GCM at different sites. Blue and orange dots represent stratocumulus (Sc) and shallow cumulus (Cu) in the LES, respectively. The host GCMs are (a) HadGEM2-A and (b) CNRM-CM5.

228 site 17, the subsidence and horizontal advection of temperature and moisture are gen-
 229 erally similar between the two GCMs. The vertical profiles of cloud fraction and cloud
 230 liquid water in the LES driven by forcing from the two GCMs are almost identical. While
 231 there are some differences in the GCM-simulated cloud profiles, the cloud layers in both
 232 GCMs are thicker than that in the LES, and the maximum cloud fraction and cloud liq-
 233 uid water are smaller. The difference in the large-scale forcing at site 23 is larger. Com-
 234 pared to HadGEM2-A, CNRM-CM5 has a weaker subsidence and a stronger boundary
 235 layer cooling and drying. The LES driven by forcings from the two GCMs yields sim-
 236 ilar vertical profiles of shallow cumulus in general, except that the cloud fraction at the
 237 cloud top is larger in the LES driven by CNRM-CM5. However, the differences between
 238 the GCMs are much larger. Compared to HadGEM2-A, the shallow cumulus layer in CNRM-
 239 CM5 has a lower cloud top and much smaller cloud fraction and cloud liquid water.

240 Figure 9 compares the differences in the GCM- and LES-simulated LWP at all sites
 241 in different seasons. The magnitudes of the differences between the LES are smaller than
 242 15 g m^{-2} for most cases. The difference between the GCMs are much larger. In general,
 243 LWP in CNRM-CM5 is smaller than in HadGEM2-A, and the magnitudes of the differ-
 244 ences are as large as 40 to 50 g m^{-2} at several sites. The magnitudes of the differences
 245 averaged over all cases in the LES and the GCMs are 0.5 and 23.9 g m^{-2} , respectively.
 246 As a result of the smaller LWP, CNRM-CM5 is slightly closer to LES compared to HadGEM2-
 247 A, although there is still not much correlation between the GCM and LES simulated LWP
 248 (Figure 7b).

249 The differences between the LES and the GCM should be interpreted with caution.
 250 One caveat is that the LES is forced by long-time mean forcing, while in the GCM the
 251 large-scale forcing varies with time. Using time-varying forcing in the LES is computa-
 252 tionally expensive as it requires much longer simulations to achieve steady states. For
 253 a more systematic comparison with the LES data presented in this paper, one should
 254 use a single column model with the same parameterizations as in the GCM and with the
 255 same time-mean forcing used to drive the LES. Nevertheless, the fact that the LES forced
 256 by large-scale forcings from the two GCMs agree with each other while the GCMs sim-
 257 ulate very different clouds still suggest biases in the GCM parameterizations.

258 3.3 Low cloud response to climate change

259 One advantage of the forcing framework is that it can be applied to generate LES
 260 of changed climates. While previous studies have used LES to simulate cloud responses
 261 to idealized climate perturbations (e.g. Blossey et al., 2013; Bretherton et al., 2013; Blossey
 262 et al., 2016; Tan et al., 2017; Radtke et al., 2021), driving LES with a GCM allows more
 263 realistic representation of changes in large-scale forcings. In this study, we run a set of
 264 simulations with large-scale forcings from the AMIP4K experiment, where SST is uni-
 265 formly increased by 4 K.

266 Figure 10 shows the change in large-scale forcings and cloud properties in the control
 267 and warmer climates at site 17 and site 23 in July in LES driven by HadGEM2-A.
 268 At site 17, the large-scale subsidence in the free troposphere is about 20%, or $5\% \text{ K}^{-1}$,
 269 weaker in the warmer climate. The horizontal advective cooling weakens in the subcloud
 270 layer and near the top of the cloud, but strengthens in the lower part of the cloud layer;
 271 the change in the advective drying is small. Consistent with weakened subsidence, the
 272 cloud top rises slightly in the warmer climate. The cloud base rises more than the cloud
 273 top, resulting in a slight thinning of the stratocumulus layer and a decrease in LWP by
 274 13%. The thinning of the cloud layer is likely related to the deepened specific humid-
 275 ity jump at the inversion under warming, which results in more efficient entrainment dry-
 276 ing at the cloud top (e.g. Bretherton et al., 2013; Bretherton & Blossey, 2014). At site
 277 23, the weakening of the large-scale subsidence is not uniform with height. Above the
 278 cloud top, the subsidence weakens by about 8%, or $2\% \text{ K}^{-1}$. The change in the advective

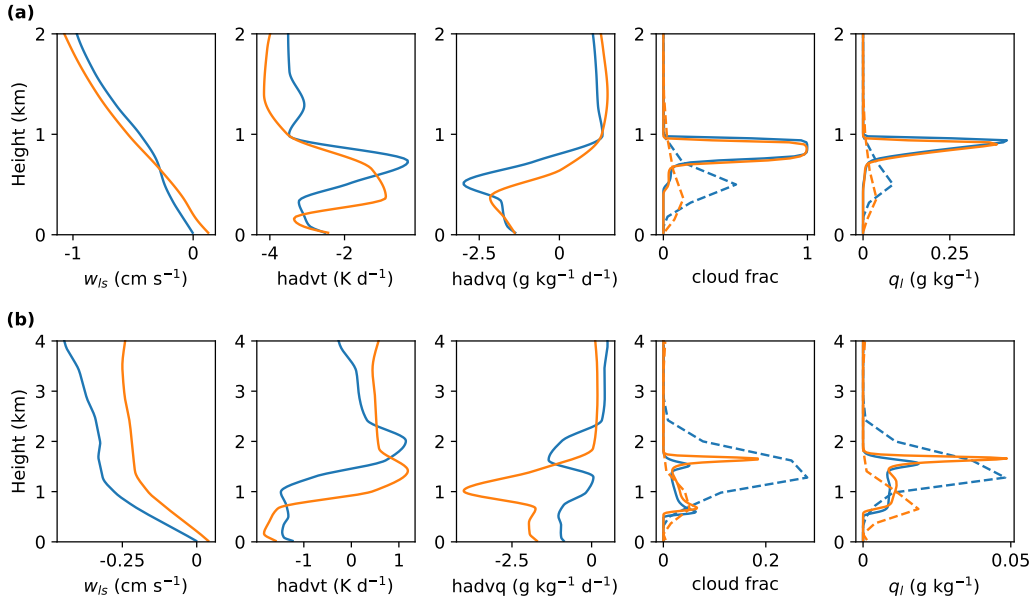


Figure 8: Vertical profiles of large-scale vertical velocity, horizontal advection of temperature, horizontal advection of specific humidity, cloud fraction, and cloud liquid water specific humidity for (a) site 17 and (b) site 23 in July. Blue and orange lines represent LES driven by the large-scale forcing from HadGEM2-A and CNRM-CM5, respectively. Dashed lines represent the host GCMs.

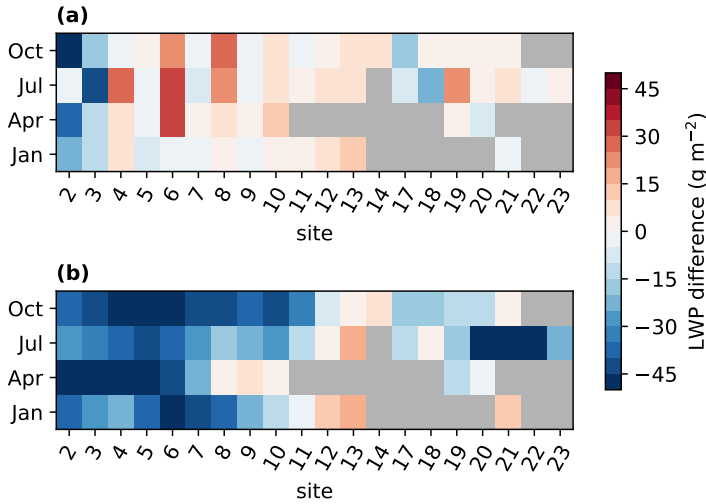


Figure 9: LWP differences at different sites between (a) LES driven by large-scale forcing from HadGEM2-A and CNRM-CM5 and (b) HadGEM2-A and CNRM-CM5. The differences are shown as CNRM-CM5 minus HadGEM2-A. Gray colors indicate the cloud top in at least one of the LES simulations is higher than 3000 m. In the GCMs, LWP is calculated as the vertical integral of cloud liquid water from the surface to 3000 m.

279 tive tendency of temperature in the boundary layer is small, while the magnitude of the
 280 horizontal advective drying increases in the subcloud layer and near the cloud top. Over-
 281 all the shallow cumulus layer does not change much under warming. There is a slight
 282 decrease in cloud fraction near the cloud base. The cloud top rises slightly, and there is
 283 an increase in the anvil cloud fraction and cloud liquid water. However, given the large
 284 variability in the anvil cloud fraction in the control climate, the change may not be statistically significant.
 285

286 Figure 11 shows the changes in cloud properties at all sites in different seasons. Near
 287 the coasts, the changes in cloud cover and LWP in response to warming are sometimes
 288 large, which is usually associated with a change in cloud regimes. However, in shallow
 289 cumulus regions, cloud cover and LWP generally do not change or decrease slightly under
 290 warming, leading to a small positive shortwave cloud feedback (a small decrease in
 291 the magnitude of the shortwave radiative effect). The LES forced by CNRM-CM5
 292 in general also simulate slightly weaker shortwave cloud radiative effects under warm-
 293 ing (Figure 12). The magnitude of the cloud response is stronger at several sites in the
 294 shallow cumulus regions, which is mostly due to the change in the anvil cloud fraction
 295 and cloud liquid water.

296 Figure 13 compares the LES- and GCM-simulated shortwave cloud feedback averaged
 297 over all seasons for the two GCMs. The shortwave cloud feedback is mostly positive
 298 in both the LES and the GCM, except at a few sites in CNRM-CM5. While near the coast
 299 the feedback magnitude can be as large as $6 \text{ W m}^{-2} \text{ K}^{-1}$ in the LES driven
 300 by HadGEM2-A, over the shallow cumulus regions the magnitude is generally smaller
 301 than $1 \text{ W m}^{-2} \text{ K}^{-1}$. This is consistent with estimates of shallow cumulus feedback in
 302 previous LES studies (Bretherton, 2015; Nuijens & Siebesma, 2019) and with observa-
 303 tionally constrained low cloud feedbacks in recent studies (Cesana & Del Genio, 2021;
 304 Myers et al., 2021). However, the shallow cumulus feedback in HadGEM2-A is around
 305 $2\text{--}4 \text{ W m}^{-2} \text{ K}^{-1}$, much stronger than that in the LES. In CNRM-CM5, the shortwave
 306 cloud feedback is weaker and closer to that in the LES (Figure 13b).

307 We emphasize again that the difference in the cloud feedback between the LES and
 308 GCM should be interpreted with caution. Besides the difference in time-mean and time-
 309 varying large-scale forcings as mentioned in Section 3.2, the shortwave cloud feedback
 310 in the GCM includes contributions from mid-level and high-level clouds, which are not
 311 present in the LES. The difference may also be smaller for other GCMs, as the low-cloud
 312 feedback in HadGEM2-A is stronger than in most other GCMs. The climate change sim-
 313 ulations provide not only an opportunity to investigate mechanisms governing cloud feed-
 314 backs in LES under more realistic changes in large-scale forcings. They are also a valu-
 315 able dataset for evaluating and calibrating GCM parameterizations, as previous stud-
 316 ies have shown it is difficult to guarantee that data-driven parameterizations trained on
 317 the current climate remain accurate in a warmer climate (O’Gorman & Dwyer, 2018).

318 4 Conclusions and Discussion

319 In this study, we have generated a library of LES spanning a range of low-cloud
 320 regimes at multiple locations over the East Pacific, by driving LES with large-scale forc-
 321 ings from CMIP5 GCMs. The LES can simulate the transition from stratocumulus off
 322 the coasts to shallow cumulus away from the coasts. The LES results are not very sen-
 323 sitive to the host GCM used to derive the forcings; the differences between clouds sim-
 324 ulated by LES driven by different host GCMs are much smaller than the differences be-
 325 tween the GCM-simulated clouds. The mismatch between the LES and GCMs may sug-
 326 gest biases in GCM turbulence, convection, and cloud parameterizations. We also used
 327 the GCM-driven LES to simulate clouds under climate change with a 4 K increase in SST.
 328 In the LES, there is generally a small decrease in cloud cover and LWP in the warmer
 329 climate, which results in a weak positive shortwave cloud feedback.

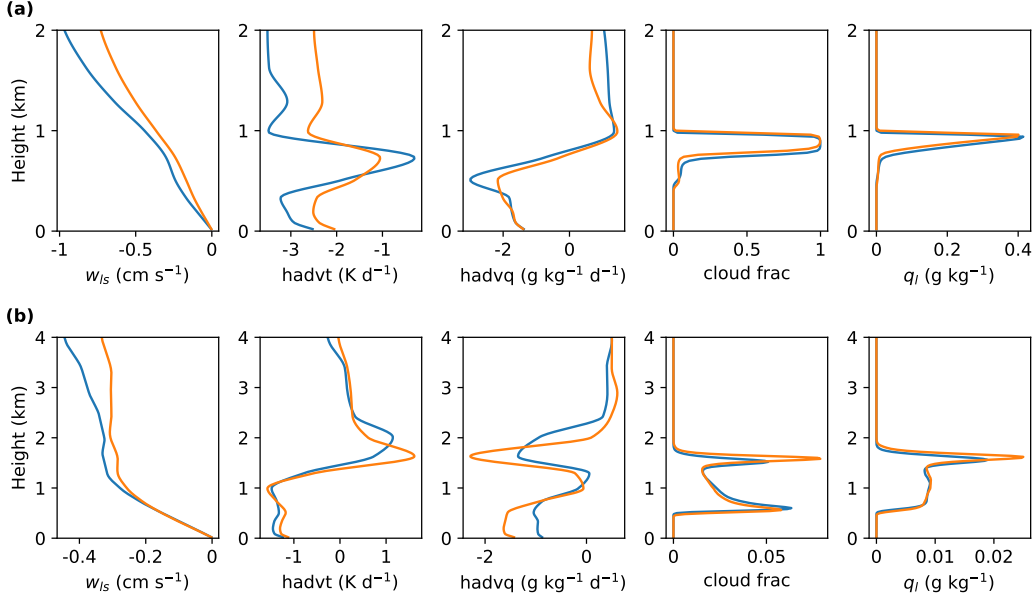


Figure 10: Vertical profiles of large-scale vertical velocity, horizontal advection of temperature, horizontal advection of specific humidity, cloud fraction, and cloud liquid water specific humidity for (a) site 17 and (b) site 23 in July. Blue and orange lines represent LES driven by the large-scale forcing from the AMIP and AMIP4K experiments in HadGEM2-A, respectively.

330 The LES library, including LES of changed climates, provides an opportunity to
 331 systematically train GCM parameterizations. Although the LES may not correctly re-
 332 produce clouds in response to time-varying large-scale forcings, the objective is to ex-
 333 panded the dataset available for calibrating single column models. To this end, the LES
 334 results should be compared with single-column models driven by the same time-mean
 335 large-scale forcings, and ideally with the same parameterizations for other physical pro-
 336 cesses such as radiation and microphysics. The convective parameterization schemes can
 337 be calibrated by minimizing mismatches between the LES and single-column models, for
 338 example, with Bayesian methods (Cleary et al., 2021). The experimental design allows
 339 an iterative workflow, where GCM parameterizations can learn from LES results, and
 340 LES can be run with new large-scale forcings from the GCM with improved parameter-
 341 izations. While this study focused on low clouds over the East Pacific, driving LES with
 342 large-scale forcings from GCMs can be done anywhere on the globe. Optimal experimen-
 343 tal design approaches can be used to select the locations to generate LES that are most
 344 informative about parameterizations (Schneider, Lan, et al., 2017).

345 The LES of changed climates can also be used to investigate mechanisms of cloud
 346 feedbacks under realistic changes in large-scale forcings. This will be explored in more
 347 detail in future work.

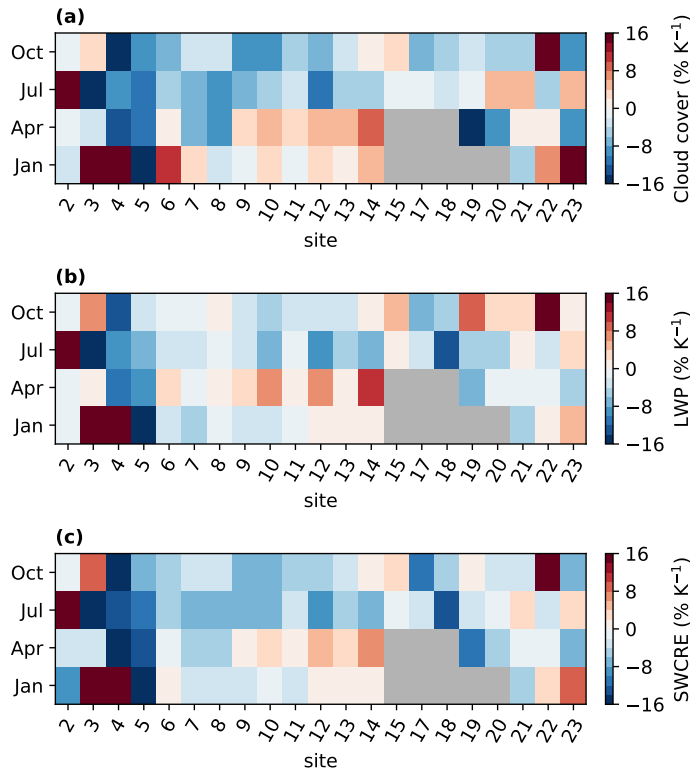


Figure 11: Percentage changes in (a) cloud cover, (b) LWP, and (c) shortwave cloud radiative effect resulting from a 4K increase in SST in the LES driven by HadGEM2-A. Gray colors indicate the cloud top in the LES in the current or warmer climate is higher than 3000 m.

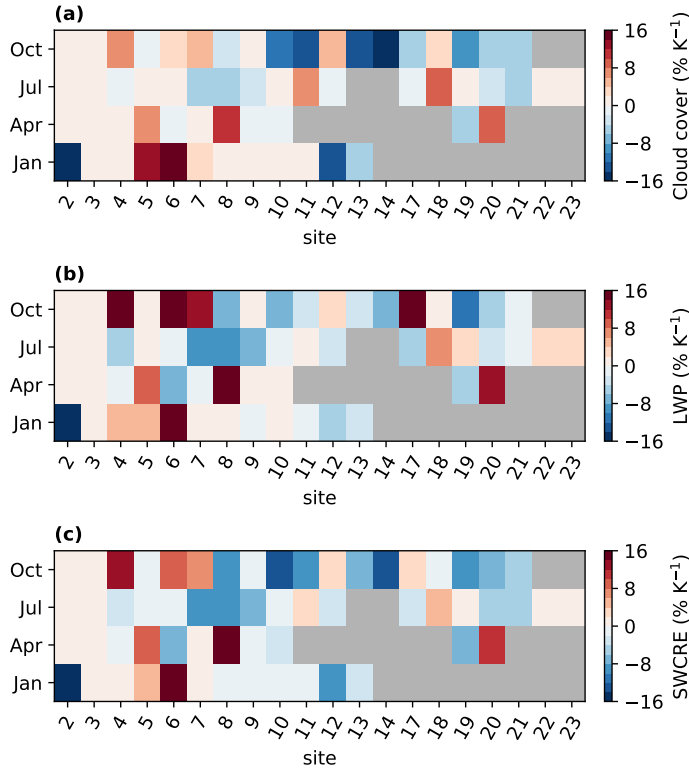


Figure 12: Same as Figure 11 but for LES driven by CNRM-CM5.

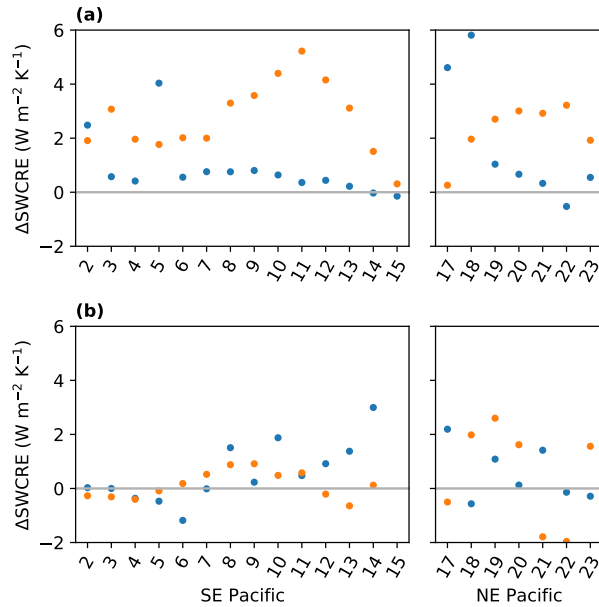


Figure 13: LES (blue) and GCM (orange) simulated shortwave cloud feedback under a 4 K increase in SST. The host GCMs are (a) HadGEM2-A and (b) CNRM-CM5. The results are averaged over all seasons.

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