1   Using the anomaly forcing Community Land Model (CLM 4.5) for crop yield projections

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11   Abstract

13   Crop growth in land surface models normally requires high temporal resolution climate data (3-
14   hourly or 6-hourly), but such high temporal resolution climate data are not provided by many
15   climate model simulations due to expensive storage, which limits modeling choice if there is an
16   interest in a particular climate simulation that only saved monthly outputs. The Community Land
17   Surface Model (CLM) has proposed an alternative approach for utilizing monthly climate
18   outputs as forcing data since version 4.5, and it is called the anomaly forcing CLM. However,
19   such an approach has never been validated for crop yield projections. In our work, we created
20   anomaly forcing datasets for three climate scenarios (1.5 °C warming, 2.0 °C warming, and
21   RCP4.5) and validated crop yields against the standard CLM forcing with the same climate
22   scenarios using 3-hourly data. We found that the anomaly forcing CLM could not produce crop
23   yields identical to the standard CLM due to the different submonthly variations, and crop yields
24   were underestimated by 5-8% across the three scenarios (1.5 °C, 2.0 °C, and RCP4.5) for the
25   global average, and 28-41% of cropland showed significantly different yields. However, the
26   anomaly forcing CLM effectively captured the relative changes between scenarios and over time,
27   as well as regional crop yield variations. We recommend that such an approach be used for
28   qualitative analysis of crop yields when only monthly outputs are available. Our approach can be
29   adopted by other land surface models to expand their capabilities for utilizing monthly climate
30   data.

31
32   Key words: Community Land Model; Crop yields; Anomaly forcing
33
34
35   Introduction
36
37   Increasing numbers of future climate scenarios exhibit large uncertainties for crop yield
38   projections. Crop yields may increase or decrease depending on which climate projection is used
39   (Lobell et al., 2008; Rosenzweig et al., 2014; Urban et al., 2012). Ensemble future climate
40   projections, such as CMIP5, showed a large range of future climate projections, even for one
41   emission scenario (Knutti and Sedlacek, 2013). Using all future climate projections is not
42   realistic not only because of the computational expense but also because many of these future
43   climate projections only save monthly climate outputs that are not suitable for crop models that
44   require high temporal resolution forcing data. Some standalone process-based crop models run in
45   daily time steps, and some crop models embedded in land surface models need at least 6-hour
46   climate data as the forcing data to represent diurnal cycles. Only a small portion of the CMIP5

47   (Coupled Model Intercomparison Project 5) simulations (<25%) can be used as the forcing data
48   for crop models, leaving little room for crop modelers to choose a particular climate model
49   projection that is of interest.
50
51   The Community Land Model (CLM) (Oleson et al., 2013) is a state-of-the-art land surface model
52   that simulates biogeophysical (radiation transfer, vegetation-soil-hydrology, surface energy
53   fluxes, etc.) and biogeochemical (soil carbon and nitrogen cycle, vegetation photosynthesis,
54   dynamic vegetation growth, etc.) processes. CLM is the default land model in the Community
55   Earth System Model (CESM) (Hurrell et al., 2013), and it can be run either online coupled with
56   the rest of CESM (atmosphere and ocean) or offline (the land model only, forced with climate
57   datasets) for multiple spatial extents (site, regional, and global) and at different resolutions. The
58   crop model derived from AgroIBIS (Kucharik, 2003) was introduced to CLM4.0 by Levis et al.
59   (2012), and it is responsible for crop growth phenology (temperature determined), carbon
60   allocation algorithms, and crop management (e.g., irrigation). The crop model in CLM runs
61   when the soil biogeochemical component is active, and it was tested with the CLM-CN in
62   version 4.0 and tested with CLM-BGC in version 4.5, where CLM-CN and CLM-BGC are
63   officially supported soil biogeochemical components in CLM4.0 and CLM4.5 respectively.
64   Since their introduction, crop models in the CLM have been developed to represent more crop
65   types and processes, such as soybean nitrogen fixation (Drewniak et al., 2013), ozone impacts on
66   yields (Lombardozzi et al., 2015), winter wheat growth responses to cold hazards (Lu et al.,
67   2017), and maize growth responses to heat stress (Peng et al., 2018). CLM simulates nine crop
68   types, accounting for 54% of global total crop production (other production is represented by the
69   most similar crop type): maize, soybean, spring wheat, winter wheat, cotton, rice, sugarcane,
70   tropical maize, and tropical soybean. In this study, we used CLM version 4.5 (Oleson et al.,
71   2013).
72
73   Since version 4.5, CLM offers a built-in function that indirectly uses monthly climate outputs as
74   the forcing data, and is called the anomaly forcing CLM (Lawrence et al., 2015). Anomaly
75   forcing CLM reconstructs new subdaily forcing data by applying the precalculated future
76   monthly anomaly signals to user-defined historical subdaily forcing data, referred to as the
77   reference data. The future monthly anomaly signals are calculated by the future monthly climate
78   outputs and by use of historical monthly outputs. The choice of reference data is arbitrary. Any
79   existing subdaily forcing data (e.g., CRUNCEP (Viovy, 2018), QIAN (Qian et al., 2006)) for
80   CLM can be used as the reference data. The historical monthly outputs are recommended to be
81   multiyear averaged to represent the historical means and avoid affecting the monthly anomaly
82   signal by rare, extreme events in a particular year. Such an arbitrary choice is because the goal of
83   the original anomaly forcing CLM is not to reconstruct future forcing that is identical to the
84   actual future forcing when the high temporal resolution data were saved. Rather, the original goal
85   of the anomaly forcing CLM is to understand the influences due to the anomaly signal by
86   comparing the simulation with the anomaly forcing CLM to the simulation run with the reference
87   data. The differences between the two simulations are due to the anomaly signals.
88
89   In our study, we modified the anomaly forcing CLM to fit our goals to understand whether we
90   could simply use the anomaly forcing CLM for crop yield projections when only monthly
91   climate data were available. We carefully chose the historical monthly data and the reference
92   data so that the reconstructed future anomaly forcing had nearly identical monthly means as the

93 desired subdaily future forcing, but we used different submonthly variations. We created
94 anomaly forcing datasets for three future scenarios (1.5 °C warming, 2.0 °C warming, and
95 RCP4.5) for 2006-2075 for which both the subdaily and monthly climate outputs were available
96 from three CESM simulations. With the three paired CLM simulations, we validated the
97 anomaly forcing CLM by comparing it to the standard CLM.
98
99 Methods
100
101 The original anomaly forcing CLM has been available since CLM4.5. This approach reconstructs
102 the subdaily (3-hourly or 6-hourly) forcing data by applying the monthly anomaly signal to user
103 selected subdaily reference data; therefore, it indirectly uses the monthly atmospheric outputs as
104 the forcing data for CLM. This approach does not change any of the scientific code in CLM; it
105 only adds code that reads the monthly anomaly signals and automatically applies these to the
106 reference data while the CLM is running. There were two monthly anomaly signals for RCP4.5
107 and RCP8.5 that were generated using the CESM future projections and were ready for use. It is
108 the user's choice to select which subdaily reference (e.g., CRUNCEP or CLMQIAN) and which
109 years to use. By simply modifying user_nl_cpl namelist and adding data streams of the anomaly
110 forcing variables (see the appendix for the detailed usage), the anomaly forcing CLM will
111 automatically read the monthly anomaly signal and apply the signal to each time step of the
112 reference data within a month. When the reference data period is less than the anomaly signal
113 period, the anomaly forcing CLM will cycle the same reference data until the simulation is
114 complete. Because the different selections of reference data can generate different forcings, even
115 with the same monthly anomaly signals, one should not use the simulation from the anomaly
116 forcing CLM to represent the actual simulation. Rather, the original goal of the anomaly forcing
117 CLM is to compare the simulation with the anomaly forcing and simulation with the reference
118 forcing data to understand the effects of the monthly anomaly signals on land surface variables.
119
120 The goal of this work is to test how well crop yield projections from the anomaly forcing CLM
121 compare to the projections from the standard forcing CLM, given that anomaly forcing has the
122 same monthly average as standard forcing. We selected three future scenarios for CESM
123 simulations that saved both monthly outputs and 3-hourly outputs, where the 3-hourly outputs
124 were directly used in the standard forcing CLM, and the monthly outputs were indirectly used in
125 the anomaly forcing CLM. We calculated the anomaly forcing signals using the monthly CESM
126 outputs and the monthly average of reference data, so that when applying the anomaly signals to
127 the reference data, it is expected to generate identical monthly means as does regular forcing.
128 However, due to a limit in calculations of precipitation anomalies (precipitation anomaly ratio
129 less than 5 times) and how the CLM treats snow and rainfall, the anomaly forcing CLM did not
130 show identical snow and rainfall monthly averages and introduced bias in the crop yield
131 simulations (see the results section).
132
133 Table 1. A summary of the original anomaly forcing CLM and the modifications in this work

	Original anomaly forcing CLM	Modifications in this work
3 h/6 h reference data	User choice	6 h Community Atmosphere Model outputs from one historical low warming

		ensemble simulation 1996-2005
Monthly anomaly signals	Existing for RCP4.5 and RCP8.5	• Anomalies between future scenarios and monthly means of reference data • Three future scenarios: 1.5 °C, 2.0 °C, and RCP4.5 • Each scenario had monthly outputs and 3 h outputs
Goals	Climate impact due to anomaly signals when comparing the anomaly run with the reference run	Given that anomaly forcing has the same monthly mean as the standard CLM forcing, can we use it for crop yield projections?

134
135   We randomly chose the 6-hourly reference data (1996-2005) from one of the 11 historical low
136   warming ensemble CESM simulations. Additionally, we selected three CESM future simulations
137   for the 1.5 °C warming, 2.0 °C warming, and RCP4.5 scenarios, where all the three simulations
138   saved both the monthly outputs and the 3-hourly outputs. We then calculated the monthly
139   anomaly signal at each grid cell for each scenario (1.5, 2.0, and RCP45) from 2006-2075. The
140   monthly anomaly signals are differences for temperature, specific humidity, wind, and air
141   pressure and are ratios for solar radiation and precipitation between the monthly outputs of each
142   scenario and the 1996-2005 averaged monthly values of the reference data. The anomaly forcing
143   signal has both spatial and monthly variations. When running the anomaly forcing simulation for
144   2006-2070, CLM repeatedly uses the 10-year reference period and applies the anomaly signal of
145   a month to all subdaily reference forcing in this month. For example, an anomaly forcing
146   simulation for 2006 January uses the 1996 January reference data plus or multiplied by (if the
147   anomaly signal is a ratio) the 2006 January anomaly signal. If the 2006 January temperature
148   anomaly is 1 K for a grid cell, then all 1996 January reference data will be increased by 1 K for
149   the grid cell.
150
151   The monthly anomaly signal is calculated at each grid cell (i,j). For temperature, pressure, wind,
152   and humidity, the anomaly signal is the difference between the future monthly data and the
153   historical monthly average (equation 1). For solar radiation, longwave radiation, and
154   precipitation, the anomaly signal is the ratio between the future monthly data and the historical
155   monthly average (equation 2). We set the maximum ratio for precipitation to 5 to avoid
156   unrealistic extreme precipitation, which also introduced biases in precipitation (discussed in the
157   discussion section).
158
159    $$af_{i,j,m} = fut_{i,j,m} - hist_{i,j,m} \quad (1)$$
160

161 $$af_{i,j,m} = fut_{i,j,m}/hist_{i,j,m} \quad (2)$$

162 Where $af_{i,j,m}$ is anomaly forcing signal at a location i and j in a month m, $fut_{i,j,m}$ is the averaged
163 future value and $hist_{i,j,m}$ is the averaged historical value at a location i and j in a month m.

164

165 We set up global CLM crop simulations (compset CLM45BGCCROP) at 1.9 by 2.5 in latitude
166 and longitude, respectively, using the anomaly forcing CLM and the regular forcing CLM for the
167 1.5 °C warming, 2.0 °C warming, and RCP4.5 scenarios. All simulations used the default
168 nitrogen fertilization rates and a constant CO_2 level of 359.8 ppm. For each scenario, we validate
169 the crop yield in the anomaly forcing CLM to the regular forcing CLM to determine if we can
170 use the anomaly forcing CLM for future crop yield projections. We also studied whether the
171 anomaly forcing CLM has a similar crop growth response to transient CO_2 and nitrogen
172 fertilization. The transient CO_2 and nitrogen fertilization did not add extra computational cost
173 compared to the constant CO_2 and nitrogen fertilization simulation. However, due to our limited
174 computational resources could not afford more experiments, we only tested such responses for
175 the RCP4.5 scenario. The transient CO_2 levels in the RCP45 scenario gradually increased from
176 379 ppm in 2006 to 530 ppm in 2070. To test the nitrogen fertilization effects, we simply added a
177 zero nitrogen fertilization simulation here. For the crop yield analysis, we aggregated the
178 individual crop yield into an integrated crop yield by area weighted mean based on the crop area
179 map MAPSMAP (https://www.mapspam.info/) 2005 crop area. The regional crop yield was
180 simply the regional averaged crop yield at 9 regions defined in Ren et al., (2018).

181

182 We adopted the two-sample Kolmogorov-Smirnov test (KS test) to test the statistical
183 significance of differences between the anomaly forcing CLM and the standard CLM for
184 atmospheric forcing data and yield. We used the KS test because some variables at some grid
185 cells did not necessarily follow normal distributions. The KS test is a nonparametric test that
186 detects differences in the empirical probability distributions between two samples, and the two
187 samples do not need to have normal distributions (Justel et al., 1997; Marozzi, 2013). When
188 repeated using the ten-year reference data, we expected that the ten year averaged monthly
189 anomaly forcing would show no significant differences from the regular forcing. Thus, for the
190 atmospheric forcing data, we tested probability distribution differences between anomaly forcing
191 and regular forcing for every ten-year averaged monthly dataset (sample size was 7x12=84). For
192 crop yields, we used the every ten-year averaged annual yields (sample size was 7). We used
193 linear regression coefficent (R^2), bias (equation 3), percentage differences (equation 4) in our
194 evaluations.

195

196 $$bias = CLM_{anomaly\ forcing} - CLM_{standard} \quad (3)$$

197 $$\%differences = 100 * (\frac{CLM_{anomaly\ forcing}}{CLM_{standard}} - 1) \quad (4)$$

198

199

200 Results

201

202 We aimed to generate an anomaly forcing that produced identical monthly averages as its
203 counterpart regular forcing (the desirable 3-hourly forcing data for CLM) but with different
204 submonthly variations. All atmospheric forcing variables achieved this goal except for
205 precipitation and its liquid and ice components, rain and snow. The linear regression coefficients

206   (R^2) between anomaly forcing and standard forcing for the monthly means of incoming solar
207   radiation, bottom layer atmosphere temperatures (sigma vertical coordinate, $\sigma=0.9925$) ,
208   pressures, humidities, and winds all showed R^2 values above 0.99, and there were also no
209   significant differences for these variables for all grid cells. However, for rain and snow, the R^2
210   values were 0.63-0.87 and 0.88-0.96 across the three scenarios, respectively (Figure 1a).
211   Statistically significant differences were also found for rain and snow in many regions in the
212   Northern Hemisphere (Figure 2). We used monthly variances as a measure of the submonthly
213   variations. We calculated the variation for twelve months in each decade, so we have 7 decades
214   and 12 months variance and the sample size is 84 when setting up the regression. R^2 for
215   variances of forcing were low for most variables except for incoming solar radiation (Figure 1b).
216   Such lower R^2 values indicated that anomaly forcing could not represent the submonthly
217   variations as well as the regular forcing.
218

219   There were two error sources for precipitation. First, there was overall average lower
220   precipitation in the anomaly forcing by 0.02 mm/day, 0.03 mm/day, and 0.2 mm/day in the
221   1.5 °C, 2.0 °C, and RCP45 scenarios, respectively. Such slightly lower precipitation was because
222   we set the maximum precipitation anomaly ratio to 5 to avoid unrealistically extreme
223   precipitation levels. Ratio 5 was suggested by NCAR scientists David Lawrence and Sean
224   Swenson, who are core developers of CLM and wrote the initial anomaly forcing code in CLM.
225   Most of unrealistic extreme precipitation ratio are actually due to the nearly zero historical
226   precipitation (the denominator of equation 2). The cap for the precipitation anomaly ratio is use
227   to avoid such situation. Second, the CLM used the temperature in each time step to determine if
228   the given precipitation was rain or snow. Precipitation was rain when temperature was above
229   273.15 K, otherwise it was snow. Therefore, the different submonthly variations in temperature
230   resulted in different submonthly variations for snow and rain. Due to this problem, the lower
231   precipitation did not evenly distribute to the rain and snow bias, for which rain was
232   underestimated by 0.08-0.3 mm/day, and snow was overestimated by 0.06-0.11 mm/day across
233   the three scenarios. The significantly different regions were mainly in the Northern Hemisphere
234   and the Antarctic, and most regions in the Southern Hemisphere did not show significant
235   differences in rain or snow. How the rain and snow biases affected yield projections will be
236   discussed.

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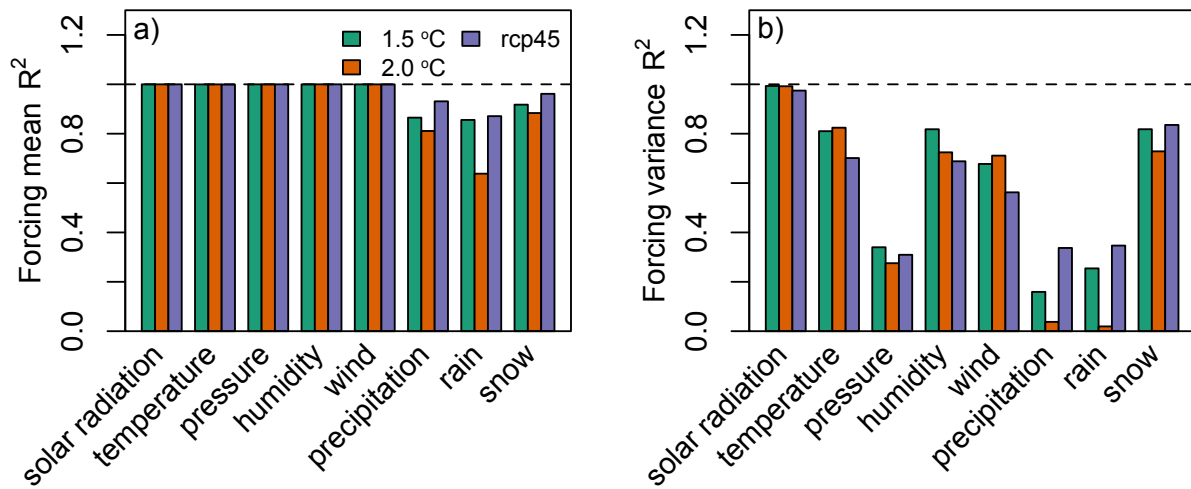
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239 Figure 1. Linear regression coefficients (R^2) between a) decade-averaged monthly mean (sample
240 size =12 months x 7 decades=84) between anomaly forcing and regular forcing and b) every ten
241 year-averaged monthly variance between anomaly forcing and regular forcing.
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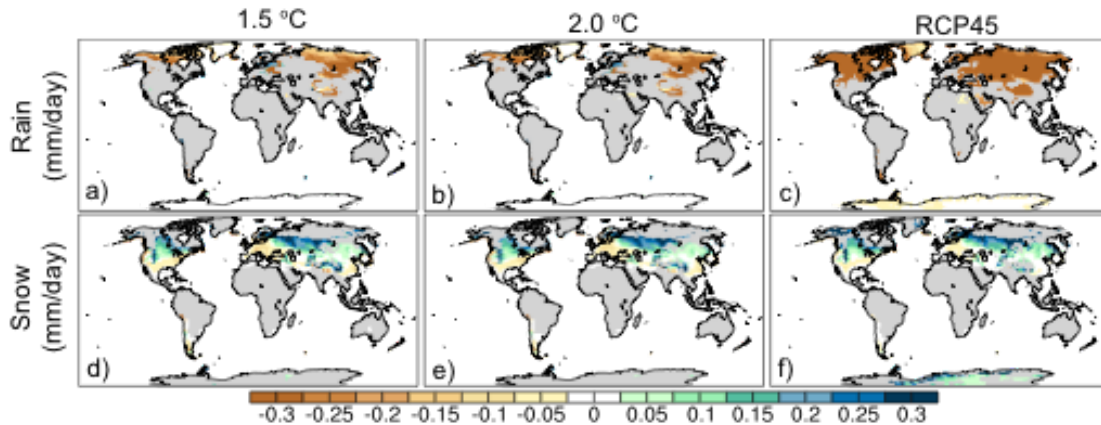
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245 Figure 2. 70-year averaged differences between anomaly forcing and regular forcing for rain (a-
246 c) and snow (d-f) for the 1.5°C, 2.0 °C, and RCP4.5 scenarios. All differences shown here are
247 statistically significant differences tested by the Kolmogorov-Smirnov test with a sample size of
248 84. The gray areas are regions that did not show significant differences.
249
250 When compared to crop yield simulations in the standard CLM, the anomaly forcing CLM
251 underestimated crop yields by 5-8% across the three scenarios for the global average, and 28-
252 41% of cropland showed statistically significant differences in yields. The rainfed crop yield
253 differences across the three scenarios showed largely similar spatial distributions: overestimation
254 in the northern US and Europe and underestimation in the Southern Hemisphere and in East Asia

255 (Figure 3d-f). The overestimated rainfed crop yield (mainly for maize and wheat) in the anomaly
256 forcing CLM is due to higher water availability in these regions, which is a result of higher snow
257 in the anomaly forcing CLM. For irrigated crops, such overestimations in the northern US and
258 Europe disappear (Figure 3g-i) because sufficient irrigation was added to the irrigated soil
259 column in the standard CLM, which removed the plant water stress that was seen for rainfed
260 crops. However, the underestimations in the Southern Hemisphere and East Asia were persistent,
261 because water availability does not cause yield differences for irrigated crops; we suspect such
262 underestimations were caused by the other error in forcing data: the different submonthly
263 variations in the forcing data.
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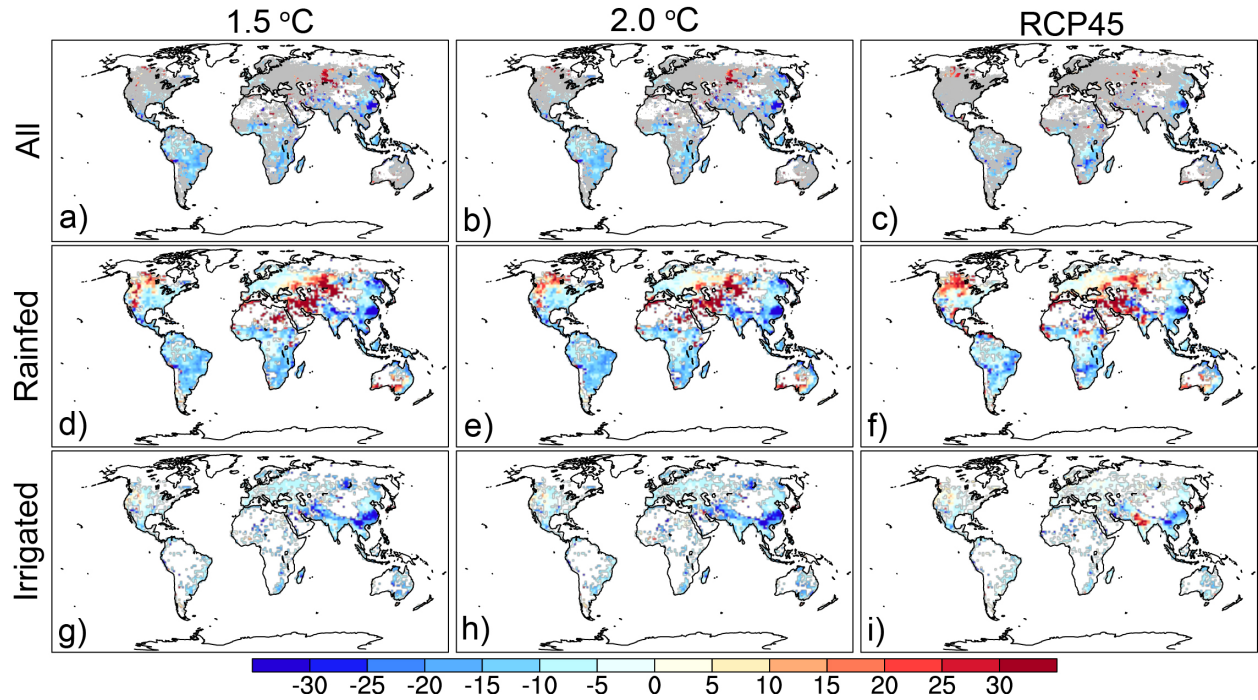
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267 Figure 3. The percentage differences of 70-year integrated yields between the anomaly forcing
268 CLM and the standard CLM for all crops (a-c), rainfed crops (d-f), and irrigated crops (g-i) for
269 the 1.5 °C, 2.0 °C, and RCP45 scenarios. The white regions are where no crops grow based on
270 the historical crop map in 2005 (MAPSPAM 2005; https://www.mapspam.info/). For plots a-c,
271 we showed only the significant differences as determined by the by Kolmogorov-Smirnov test
272 with a sample size of 7. The regions with insignificant differences are masked as gray in a-c. For
273 plots d-i, we did not mask the insignificant differences to show an overall bias.
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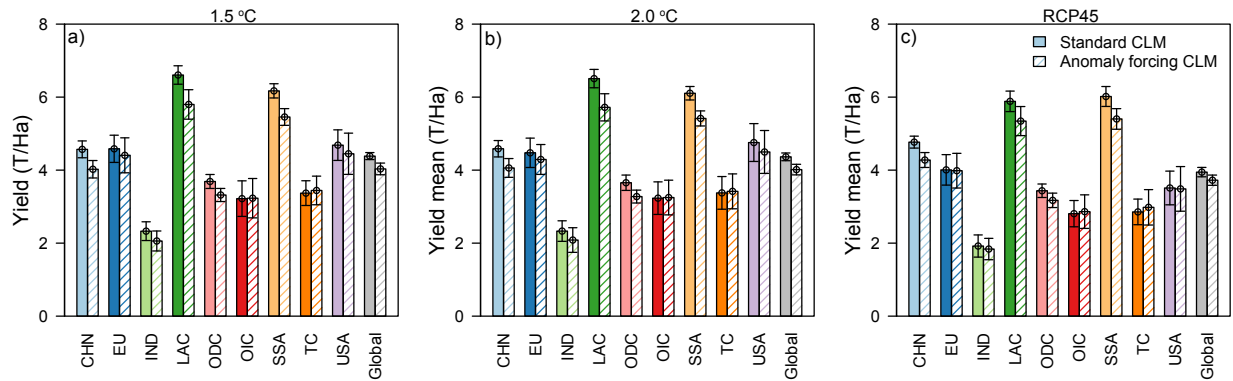

279 Figure 4. Regional comparisons of the 70-year integrated mean yields and yield standard

280 deviations between the anomaly forcing CLM and the standard CLM. The error bars indicate 70-

281 year yield standard deviations. CHN: China; EU: European Union; IND: India; LAC: Latin

282 America; ODC: Other Developing Countries; OIC: Other Industrialized Countries; SSA: Sub-

283 Saharan Africa; TC: Transition Countries; USA: United States

284 The global 70-year averaged yields ± standard deviation in the standard CLM (Ren et al., 2018)

285 and in the anomaly forcing CLM are 4.38 ± 0.09 and 4.03 ± 0.16 t/ha, respectively, in the 1.5 °C

286 scenario, 4.36 ± 0.11 and 4.01 ± 0.14 t/ha, respectively, in the 2.0 °C scenario, 3.95 ±0.13 and

287 3.72 ± 0.14, respectively, in the RCP45 scenario (Figure 4). The anomaly forcing CLM captured

288 the regional yield variations. Latin America (LAC) showed the highest yield while India (IND)

289 showed the lowest yields for both the anomaly forcing CLM and the standard CLM across the

290 three scenarios.

291

292

293 Although the crop yields were underestimated, the anomaly forcing CLM could qualitatively

294 represent the spatial yield differences between two climate scenarios. Comparing 2.0 °C to

295 1.5 °C, there was a 4-8% yield increase in the northern U.S. and a 0-4% yield decrease in (Figure

296 5a) in the southeast U.S. When comparing the RCP45 to the 1.5 °C scenario, crop yields in the

297 U.S. were largely reduced (up to 50%). The anomaly forcing CLM clearly captured these yield

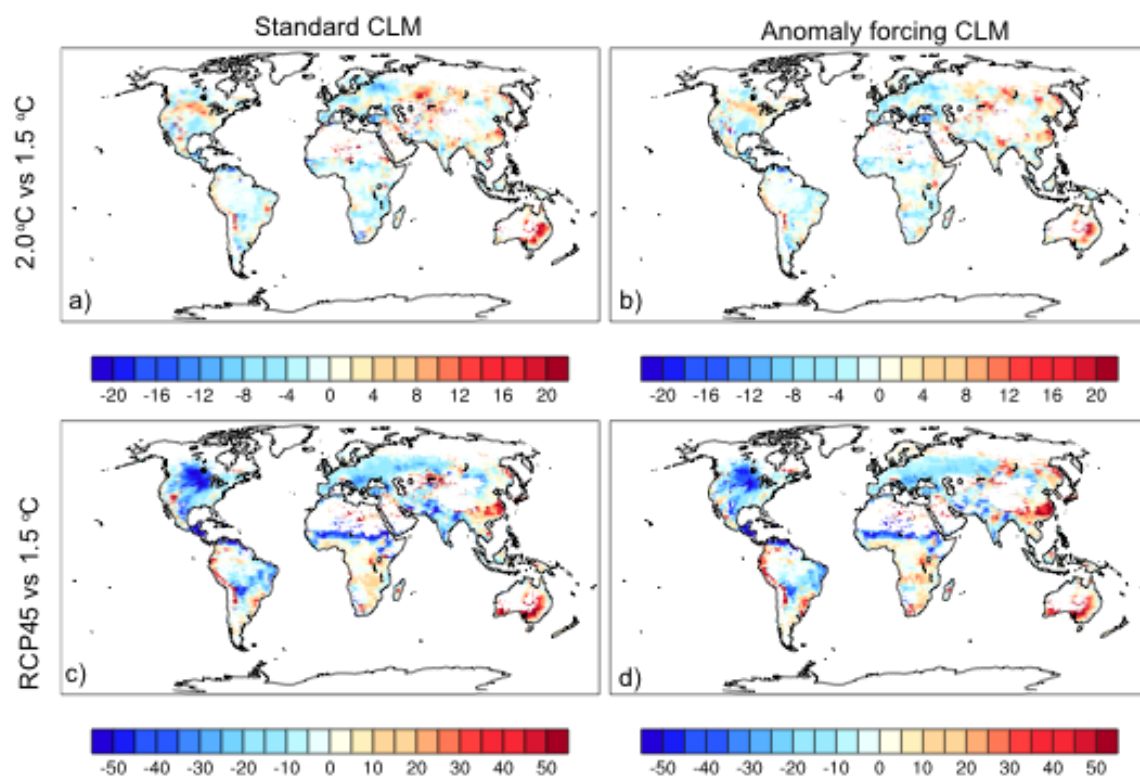
298 differences (Figure 5b and 5d).

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Figure 5. The percentage of 70-year integrated yield differences between 2.0 °C and 1.5 °C (top
panel) RCP45 to 1.5 (bottom panel) in the standard CLM and the anomaly forcing CLM

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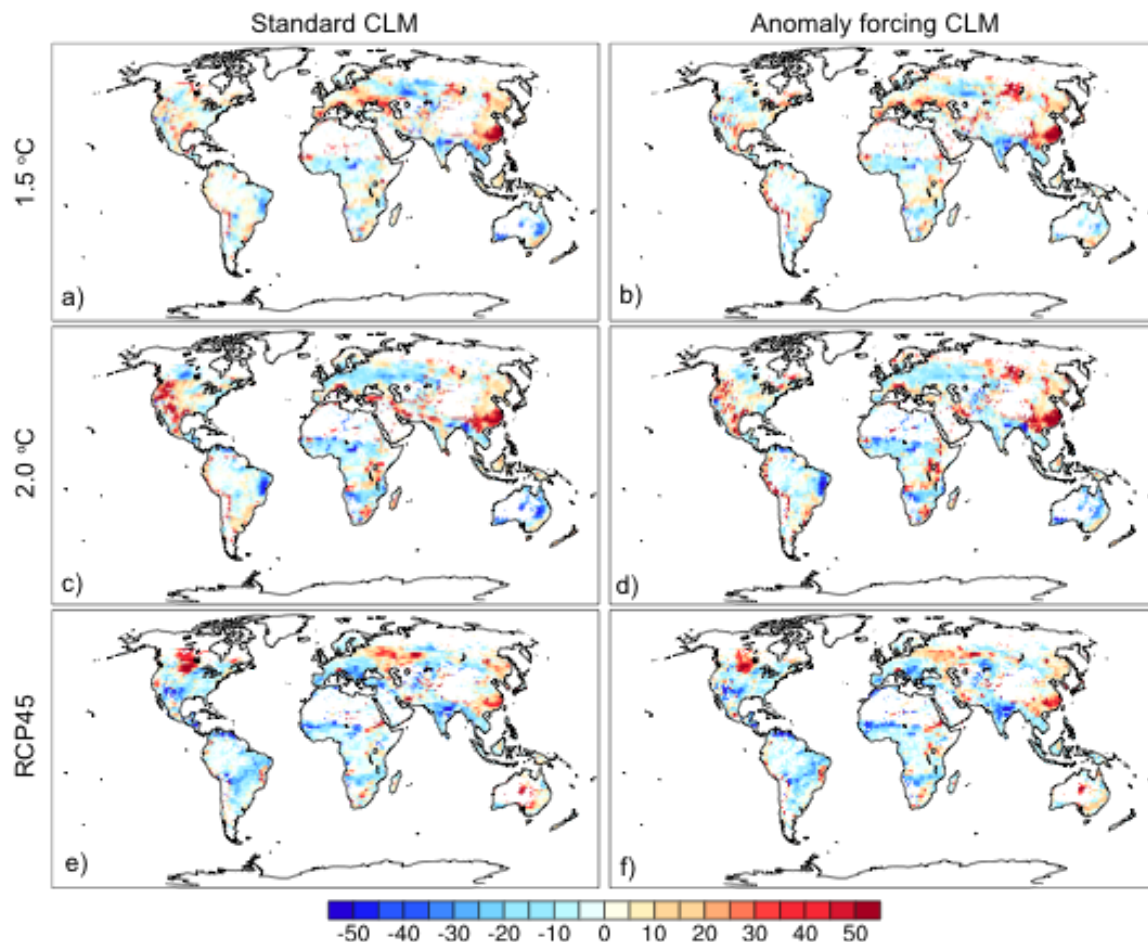
Figure 6. The percentage yield difference from 2006-2015 to 2066-2075 in the standard CLM and anomaly forcing CLM across the three scenarios

The anomaly forcing CLM also captured yield changes over time for each climate scenario. The three scenarios showed some similarities in yield changes from 2006-2015 to 2066-2075. For example, crop yields increased in Southeast China and decreased in Sub-Saharan Africa. There were also yield changes that were unique to each scenario that were also found in the anomaly forcing CLM. For example, crop yields increased in Europe for the 1.5 °C scenario (Figure 6a-b), while they decreased in Europe for the 2.0 °C and RCP45 scenarios (Figure 6c-f), and crop yields declined in the U.S. for the RCP45 scenario (Figure 6e-f) while they increased for the 1.5 °C and 2.0 °C scenarios (Figure 6 a-d).

All simulations in the above evaluations adopted a constant CO_2 level (359.8 ppm) and crop types dependent fixed nitrogen fertilization (25-500 kg N/ ha), so whether the anomaly forcing CLM simulated a similar or different crop growth response to CO_2 or nitrogen fertilization is unknown. Due to limited computational resources, we tested crop responses to transient CO_2 and nitrogen fertilization only for the RCP45 scenario and assumed that the other scenarios would show the same differences as the RCP45 scenario. The transient CO_2 in the RCP45 scenario gradually increased from 379 ppm in 2006 to 530 ppm in 2075. To test the effects of nitrogen

326 fertilization, we simply added a zero nitrogen fertilization simulation. Although all grid cells had
327 the same amounts of CO_2 increase in a given year (no spatial variation), crop yields had spatial
328 variations in response to transient CO_2. Most regions showed a 5-10% yield increase, but some
329 regions showed much higher yield increases, such as northern India, the southern edge of the
330 Sahara, and Australia (Figure 7a). Such crop yield responses to transient CO_2 spatial patterns
331 were also captured by the anomaly forcing CLM (Figure 7b). Similar for the crop yield responses
332 to nitrogen fertilization, the anomaly forcing CLM simulated crop yield increase spatial patterns
333 (Figure 7c-d), in which the Southern Hemisphere and Asia had greater yield increases in
334 response to nitrogen fertilization.
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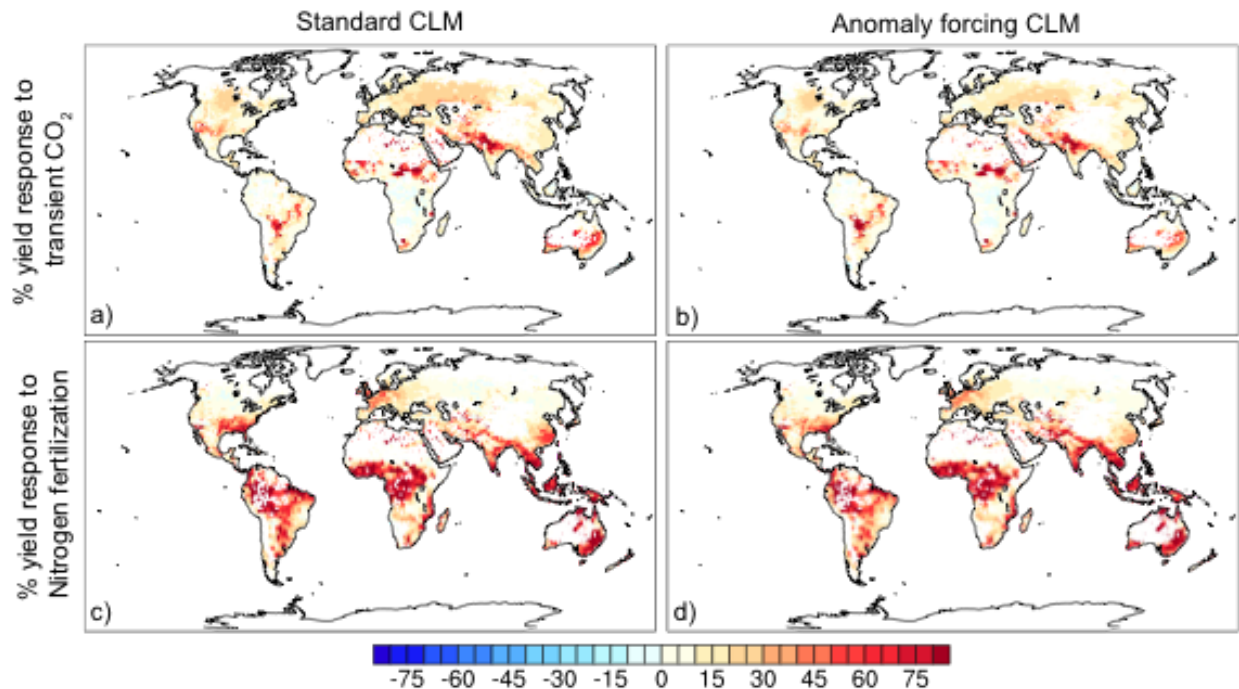
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339   Figure 7. 70-year averaged integrated crop yield response to transient CO_2 and to no nitrogen
340   fertilization in the anomaly forcing CLM (a and b) and in the standard CLM (c and d) for the
341   RCP45 scenario.
342

Discussion

343
344
345 In this work, we created anomaly forcing datasets for three future climate scenarios, and we
346 validated the crop yields in the anomaly forcing CLM by comparison with the crop yields in the
347 standard CLM. The differences between the anomaly forcing CLM and standard CLM were due
348 only to differences in forcing data, for which the standard CLM used regular forcing (three-
349 hourly forcing) and the anomaly forcing CLM used anomaly forcing. We found that the anomaly
350 forcing CLM underestimated crop yields but identified the regional yield variations, as well as
351 yield differences between two climate scenarios and yield changes over time. The anomaly
352 forcing CLM could not generate the exact same crop yields as the standard CLM due to errors in

353 precipitation and in the submonthly variations. However, it could be used for qualitative analysis
354 of relative crop yield changes among different scenarios and over time.
355
356 The overall underestimation of crop yields may be due to differences in phenology that resulted
357 from different submonthly variations. Some of the low yields in the anomaly forcing CLM may
358 be explained by shorter grain fill periods. For example, the lower rice yields in southeast China
359 are due to a 5-10 day shorter grain fill period in the anomaly forcing CLM (Figure S1;a-c); maize
360 and soybean in the Southern Hemisphere also showed a 1-5 day shorter grain fill period that may
361 account for the lower yields (Figure S1; d-i). In addition to the low yields, the anomaly forcing
362 CLM also simulated lower GPP and LAI compared to the standard CLM (Figure S2; a1-b3), and
363 the spatial distributions of GPP and LAI differences were very similar to the yield differences.
364
365 Some regions in the Northern Hemisphere showed higher rainfed crop yields in the anomaly
366 forcing CLM, which is due to higher soil moistures at planting that resulted from higher snow
367 levels in the Northern Hemisphere. Crop growth in CLM is very sensitive to the soil moisture at
368 planting, and higher soil moisture (Figure S2; c1-c3) results in unstressed crop growth and hence
369 produces higher yields. When adequate irrigation is applied, both the anomaly forcing and the
370 standard CLM models have sufficient water for crop growth, and the overestimations
371 disappeared. Therefore, the anomaly forcing may not be appropriate for estimating the actual
372 future irrigation demands but is able to distinguish the relative differences in irrigation demand
373 across different climate scenarios.
374
375 The energy fluxes in the anomaly forcing CLM and in the standard CLM were different due to
376 different crop growth rates and differences in forcing data. The higher snow cover in the
377 Northern Hemisphere creates higher albedo and lowers absorbed solar radiation and hence lower
378 surface energy fluxes. The higher LAI increased the summer latent heat flux up to 5 W.m^{-2}
379 (Figure S3), while the annual latent heat flux showed 5-10 W.m^{-2} (Figure S2; d1-d3) lower
380 values in the anomaly forcing CLM due to the lower net radiation. In the Southern Hemisphere,
381 lower LAI (Figure S2; a1-a3) resulted in lower latent heat fluxes (Figure S2; d1-d3) and higher
382 sensible heat fluxes (Figure S2; e1-e3).
383
384 The regional yield comparisons indicate that the anomaly forcing CLM effectively captured
385 regional yield variations but with slightly lower yield biases. We want to point out that the very
386 high crop yields in Latin America and in Sub-Saharan Africa, and the very low crop yields in
387 India in both the anomaly forcing CLM and the standard CLM approaches are not realistic when
388 compared to the UNFAO yields (http://www.fao.org/statistics/en/). Such biases in the CLM have
389 been discussed by Levis et al. (2018), and the low yields in India are due to incorrect crop
390 phenology when crops entered the grain fill during the dry season. The high yields in Latin
391 American and in Sub-Saharan Africa were due to the nitrogen fertilization amounts based on US
392 levels, which are too high for these regions.
393
394 The crop model in the most recent version of CLM5.0 includes new features as reported in
395 Lombardozzi et al., (2020). For example CLM5.0 uses time-varying spatial distributions of
396 major crop types and has updated fertilization and irrigation schemes. These updates of crop
397 model in CLM5.0 may improve the crop yield simulations for both standard CLM and anomaly
398 forcing CLM compared to crop yield in reality. The anomaly forcing method in CLM5.0 remains

399 unchanged so we speculate the bias due to anomaly forcing may still exist in CLM5.0. For
400 example, CLM5.0 uses the same threshold to differ rain and snow, so the bias due to higher snow
401 cover in the Northern Hemisphere may still exists in CLM5.0. However, how will the magnitude
402 of the bias change is unclear. We suggest that the anomaly forcing of CLM5.0 to be tested if the
403 research interest is in absolute yield or in qualitative difference.

405 Our approach can be adopted by other land surface models to expand their capabilities for
406 utilizing monthly climate data. The source code of the anomaly forcing CLM is available at the
407 repository website Zenodo https://doi.org/10.5281/zenodo.3900671. The path is
408 post4.5crop_slevis/models/lnd/clm/src/cpl/ lnd_import_export.F90 when unzip
409 post4.5crop_slevis_codeforGMD.tar.gz. The Fortran code could be transplanted to other land
410 surface models which use NetCDF format atmospheric forcing.

412 Conclusions

414 The Community Land Surface model offers an alternative way in utilize the monthly climate as
415 the forcing data. Such an approach could expand user choice of forcing data when high temporal
416 resolution climate data are not available. In this work, we created anomaly forcing data for three
417 climate scenarios (1.5 °C warming, 2.0 °C warming, and RCP4.5) and validated crop yield
418 projections in the anomaly forcing CLM against the standard CLM. The anomaly forcing CLM
419 underestimated crop yields by 5-8%, which was largely due to the differences in phenology and
420 photosynthesis that resulted from the different submonthly variations. How CLM treated
421 precipitation as rain or snow also introduced biases in crop yields and in the energy flux
422 simulations. Although the anomaly forcing CLM could not generate crop yields identical to the
423 standard CLM, it could be used for qualitative analysis of crop yield changes across various
424 scenarios over time.

426 Code availability

428 The CLM source code used in our study is available at repository website Zenodo:
429 https://doi.org/10.5281/zenodo.3900671

431 Author contribution

433 Yaqiong Lu designed and performed the simulations. Yaqiong Lu and Xianyu Yang analyzed the
434 results and wrote the manuscript.

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446
447
448 Appendix: a user guide for using anomaly forcing CLM
449
450 Running the anomaly forcing CLM is similar to the standard CLM but with several additional
451 steps. First, the monthly anomaly data are prepared as described in the method section. Then, the
452 user needs to modify user_nl_cpl and user_nl_datm to specify which forcing variables to add to
453 the anomaly signals. There are seven anomaly forcing variables (Table A2), and the user can
454 specify one, or two, or all variables in the two namelists (user_nl_cpl and user_nl_datm). The
455 final step is to add the corresponding anomaly forcing data streams depending on which anomaly
456 forcing variables were specified in user_nl_cpl and user_nl_datm.
457
458
459 1. Modify user_nl_cpl and user_nl_datm
460
461 The user may add part or all of the following text to user_nl_cpl.
462
463 cplflds_custom = 'Sa_prec_af->a2x', 'Sa_prec_af->x2l','Sa_tbot_af->a2x',
464 'Sa_tbot_af->x2l','Sa_pbot_af->a2x', 'Sa_pbot_af->x2l','Sa_shum_af->a2x',
465 'Sa_shum_af->x2l','Sa_u_af->a2x', 'Sa_u_af->x2l','Sa_v_af->a2x',
466 'Sa_v_af->x2l','Sa_swdn_af->a2x', 'Sa_swdn_af->x2l','Sa_lwdn_af->a2x', 'Sa_lwdn_af->x2l'
467
468 Add part or all of the following text into user_nl_datm:
469
470 anomaly_forcing=
471 'Anomaly.Forcing.Precip','Anomaly.Forcing.Temperature','Anomaly.Forcing.Pressure','Anomaly
472 .Forcing.Humidity','Anomaly.Forcing.Uwind','Anomaly.Forcing.Vwind','Anomaly.Forcing.Short
473 wave','Anomaly.Forcing.Longwave'
474
475 Also attach the anomaly forcing data streams in user_nl_datm:
476
477 streams = "datm.streams.txt.CLMCRUNCEP.Solar 1996 1996 2005",
478 "datm.streams.txt.CLMCRUNCEP.Precip 1996 1996 2005",
479   "datm.streams.txt.CLMCRUNCEP.TPQW 1996 1996 2005",
480 "datm.streams.txt.presaero.clim_2000 1 1 1",
481   "datm.streams.txt.Anomaly.Forcing.Precip 2006 2006 2075",
482 "datm.streams.txt.Anomaly.Forcing.Temperature 2006 2006 2075",
483   "datm.streams.txt.Anomaly.Forcing.Pressure 2006 2006 2075",
484 "datm.streams.txt.Anomaly.Forcing.Humidity 2006 2006 2075",
485   "datm.streams.txt.Anomaly.Forcing.Uwind 2006 2006 2075",
486 "datm.streams.txt.Anomaly.Forcing.Vwind 2006 2006 2075",
487   "datm.streams.txt.Anomaly.Forcing.Shortwave 2006 2006 2075",
488 "datm.streams.txt.Anomaly.Forcing.Longwave 2006 2006 2075",
489   "/glade/p/work/yaqiong/inputdata/atm/datm7/co2.1pt5degC.streams.txt 1901 1901 2075"

490
491 mapalgo = 'bilinear', 'bilinear', 'bilinear', 'bilinear', 'bilinear', 'bilinear', 'bilinear', 'bilinear',
492 'bilinear',
493   'bilinear', 'bilinear', 'bilinear','nn'
494 tintalgo = 'coszen', 'nearest', 'linear', 'linear', 'nearest', 'nearest', 'nearest', 'nearest', 'nearest',
495 'nearest',
496   'nearest', 'nearest','linear'
497
498 Any combination or subset of anomaly forcing variables can be used. For example,
499   cplflds_custom = 'Sa_prec_af->a2x', 'Sa_prec_af->x2l' (in user_nl_cpl)
500 anomaly_forcing='Anomaly.Forcing.Precip' (in user_nl_datm)
501 will only adjust precipitation. The reference data and period are defined in env_run.xml.
502
503 2. Add the anomaly forcing data stream
504 The anomaly forcing data stream is where to specify the data path of the monthly anomaly
505 forcing signal and to tell the code which variable to retrieve. A list of all anomaly forcing data
506 stream file names and the variables in the anomaly forcing data and the code are given in Table
507 2. An example of the content in user_datm.streams.txt.Anomaly.Forcing.Humidity is also
508 attached. The user only needs to add the corresponding variable data streams that are defined in
509 user_nl_cpl.
510
511 Table A2. A list of the anomaly forcing data streams and the corresponding variables in the
512 anomaly forcing data and the code

Data stream file names	Vars in data	Vars in code
user_datm.streams.txt.Anomaly.Forcing.Humidity[1]	huss	shum_af
user_datm.streams.txt.Anomaly.Forcing.Precip	pr	prec_af
user_datm.streams.txt.Anomaly.Forcing.Pressure	ps	pbot_af
user_datm.streams.txt.Anomaly.Forcing.Shortwave	rsds	swdn_af
user_datm.streams.txt.Anomaly.Forcing.Temperature	tas	tbot_af
user_datm.streams.txt.Anomaly.Forcing.Uwind	uas	u_af
user_datm.streams.txt.Anomaly.Forcing.Vwind	vas	v_af
user_datm.streams.txt.Anomaly.Forcing.Longwave	rlds	lwdn_af

513 [1]An example of the content in the data stream was given below:
514   <dataSource>
515   GENERIC
516   </dataSource>
517   <domainInfo>
518   <variableNames>
519   time
520   xc   lon
521   yc   lat
522   area
523   mask
524   </variableNames>
525   <filePath>
526   /glade/p/cesmdata/cseg/inputdata/share/domains

```
527        </filePath>
528        <fileNames>
529          domain.lnd.fv0.9x1.25_gx1v6.090309.nc
530        </fileNames>
531      </domainInfo>
532      <fieldInfo>
533        <variableNames>
534          huss  shum_af
535        </variableNames>
536        <filePath>
537          THE ANOMALY FORCING SIGNAL DATA PATH
538        </filePath>
539        <fileNames>
540          THE ANOMALY FORCING SIGNAL DATA NAME
541        </fileNames>
542        <offset>
543          0
544        </offset>
545      </fieldInfo>
546
547
548  Reference:
```

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