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**Development and evaluation of a system of proxy data assimilation for
paleoclimate reconstruction**

By

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26

Abstract

27 Data assimilation (DA) has been successfully applied in the field of paleoclimatology
28 to reconstruct past climate. However, data reconstructed from proxies have been
29 assimilated, as opposed to the actual proxy values. This banned to fully utilize the
30 information recorded in the proxies.

31 This study examined the feasibility of proxy DA for paleoclimate reconstruction.
32 Isotopic proxies ($\delta^{18}\text{O}$ in ice cores, corals, and tree-ring cellulose) were assimilated into
33 models: an isotope enabled general circulation model (GCM) and forward proxy models,
34 using offline data assimilation.

35 First, we examined the feasibility using an observation system simulation experiment
36 (OSSE). The analysis showed a significant improvement compared with the first guess in
37 the reproducibility of isotope ratios in the proxies, as well as the temperature and
38 precipitation fields, when only the isotopic information was assimilated. The
39 reconstruction skill for temperature and precipitation was especially high at low latitudes.
40 This is due to the fact that isotopic proxies are strongly influenced by temperature and/or
41 precipitation at low latitudes, which, in turn, are modulated by the El Niño-Southern
42 Oscillation (ENSO) on interannual timescales.

43 Subsequently, the proxy DA was conducted with real proxy data. The reconstruction
44 skill was decreased compared to the OSSE. In particular, the decrease was significant
45 over the Indian Ocean, eastern Pacific, and the Atlantic Ocean where the reproducibility
46 of the proxy model was lower. By changing the experimental design in a stepwise manner,
47 the decreased skill was suggested to be attributable to the misrepresentation of the
48 atmospheric and proxy models and/or the quality of the observations. Although there
49 remains a lot to improve proxy DA, the result adequately showed that proxy DA is
50 feasible enough to reconstruct past climate.

51

52 1. Introduction

53 Knowledge of past conditions is crucial for understanding long-term climate
54 variability. Historically, two approaches have been used to reconstruct paleoclimate; one
55 based on the empirical evidence contained in proxy data, and the other based on
56 simulation with physically-based climate models. Recently, an alternative approach
57 combining proxy data and climate simulations using a data assimilation (DA) technique
58 has emerged. DA has long been used for forecasting weather and is a well-established
59 method. However, the DA algorithms used for weather forecasts cannot be directly
60 applied to paleoclimate due to the different temporal resolution, spatial extent, and type
61 of information contained within observation data (Widmann et al., 2010). The temporal
62 resolution and spatial distribution of proxy data are significantly lower (seasonal at best)
63 and sparser than the present-day observations used for weather forecasts, and the
64 information we can get does not measure the direct states of climate (e.g., temperature,
65 wind, pressure, etc.), but represents proxies of those states (e.g., tree-ring width, isotopic
66 composition in ice sheets, etc.). Thus, DA applied to paleoclimate is only loosely linked
67 to the methods used in the more mature field of weather forecasting, and it has been
68 developed almost independently from them.

69 Several DA methods have been proposed for paleoclimate reconstruction (von Storch

70 et al., 2000; van der Schrier et al., 2005; Dirren and Hakim, 2005; Goosse et al., 2006;
71 Bhend et al., 2012; Dubinkina and Goosse, 2013; Steiger et al., 2014), and paleoclimate
72 studies using DA have successfully determined the mechanisms behind climate changes
73 (Crespin et al., 2009; Goosse et al., 2010; 2012; Mathiot et al., 2013). In previous studies,
74 the variables used for assimilation have been data reconstructed from proxies (e.g.,
75 surface air temperature) because observation operators or forward models for proxies
76 have not been readily available. Hereafter, the DA method that assimilates reconstructed
77 data from proxies is referred to as reconstructed DA. Recently, proxy modelers have
78 developed and evaluated several forward models (e.g., Dee et al., 2015 and references
79 therein). Thanks to that, currently a few studies have started attempting to assimilate
80 proxy data directly (Acevedo et al., 2016; Dee et al., 2016).

81 The main advantage of proxy DA over reconstructed DA is the richness of information
82 used for assimilation. In previous studies, only a single reconstructed field was
83 assimilated. However, proxies are influenced by multiple variables. Hence, the
84 assimilation of a single variable does not use the full information recorded in the proxies.

85 The reconstruction method itself also limits the amount of information. The most
86 commonly-used climate reconstruction is an empirical and statistical method that relies
87 on the relationships between climate variables and proxies observed in present-day

88 observations. These relationships are then applied to the past climate proxies to
89 reconstruct climate prior to the instrumental period. Most of the studies using this
90 approach assume that the relationship is linear. However, this assumption imposes
91 considerable limitations in which specific climate proxies can be used, and proxies that
92 do not satisfy the assumption have generally been omitted (e.g., PAGES 2k Consortium,
93 2013). Because information on paleoclimate is scarce, it is desirable to use as much
94 information as possible.

95 Furthermore, the reconstruction method also limits the quality of information
96 provided. The method also assumes stationarity of the relationship between the climate
97 and the proxies. However, this assumption has been shown to be invalid for some cases
98 (e.g., Schmidt et al. 2007; LeGrande and Schmidt, 2009). In the case of reconstructed DA,
99 the assimilation of such questionable reconstructed data would provide unrealistic results.
100 In the case of proxy DA; however, the skill of the assimilation is expected to be unchanged,
101 provided the model can correctly simulate the non-stationarity.

102 The concept of proxy data assimilation is not new, and has been proposed in previous
103 studies (Hughes and Ammann, 2009; Evans et al., 2013; Yoshimura et al., 2014; Dee et
104 al., 2015). Yoshimura et al. (2014) demonstrated that the assimilation of the stable water
105 isotope ratios of vapor improves the analysis for current weather forecasting. They

106 performed an observation system simulation experiment (OSSE) assuming that isotopic
107 observations from satellites were available every six hours. Because the isotope ratio of
108 water is one of the most frequently used climate proxies, this represents a significant first
109 step toward improving the performance of proxy data assimilation in terms of identifying
110 suitable variables for assimilation. However, it is not yet clear whether it is feasible to
111 constrain climate only using isotopic proxies whose temporal resolution and spatial
112 coverage are much longer and sparser than those of the specific study.

113 This study examined the feasibility of isotopic proxy DA for the paleoclimate
114 reconstruction on the interannual timescale. Because the study represents one of the first
115 attempts to assimilate isotopic variables on this timescale, we adopted the framework of
116 an OSSE, as in previous climate data assimilations (Annan and Hargreaves, 2012; Bhend
117 et al., 2012; Steiger et al., 2014; Acevedo et al., 2016b; Dee et al., 2016). After the
118 evaluation of proxy DA in the idealized way, we conducted the study with “real” proxy
119 DA. We investigated which factors decreased or increased the skill of the proxy DA. As
120 a measure of skill, we report the correlation coefficient throughout the manuscript.

121 In this study, we used only oxygen isotopes (^{18}O) as proxies. The isotope ratio is
122 expressed in delta notation ($\delta^{18}\text{O}$) relative to Vienna Standard Mean Ocean Water
123 (VSMOW) throughout the manuscript. If the original data were expressed in delta

124 notation relative to Vienna Pee Dee Belemnite (VPDB), they were converted to the
125 VSMOW scale.

126 This paper is structured as follows. In the following section, the data assimilation
127 algorithm, models, data, and experimental design are presented. Section 3 shows the
128 results of the idealized experiment. Section 4 gives the results of the real proxy DA. The
129 Discussion is presented in Section 5. Finally, we present our conclusions in Section 6.

130

131 **2. Materials and methods**

132 **2.1. Data assimilation algorithm**

133 We used a variant of ensemble Kalman filter (EnKF, see Houtekamer and Zhang, 2016,
134 and references therein); sequential ensemble square root filter (EnSRF; Whitaker and
135 Hamill, 2002). EnSRF updates the ensemble mean and the anomalies from the ensemble
136 mean separately, and processes observations serially one at a time if the observations have
137 independent errors.

138 To assimilate time-averaged data, slight modification was made for the method
139 following Bhend et al. (2012) and Steiger et al. (2014). In the modified EnSRF, the
140 analysis procedure is not cycled to the simulation (Bhend et al., 2012); thus, the
141 background ensembles can be constructed from existing climate model simulations

142 (Huntley and Hakim, 2010; Steiger et al., 2014). As such, we can assimilate data with any
143 temporal resolution coarser than the model outputs. In this study, we focused on annual
144 DA.

145 There are two ways to construct the background ensemble in the approach mentioned
146 above (hereafter offline DA); one using ensemble runs as in weather forecasts (Bhend et
147 al., 2012; Acevedo et al., 2016) and the other using a single run (Steiger et al., 2014; Dee
148 et al., 2016). The latter uses the same background ensemble for every analysis step. To
149 reduce computational cost, we chose the latter way, where the ensemble members are
150 individual years. This simplification was valid because the interannual variability in a
151 single run was inherently indistinguishable from the variability in the annual mean within
152 the ensemble of simulations in which the initial conditions were perturbed, at least for
153 atmospheric variables. Thus, the background ensembles were the same for all the
154 reconstruction years and did not contain any year-specific boundary conditions and
155 forcing information; hence, the background error covariance was constant over time.
156 Therefore, this study did not consider non-stationarity between the proxies and climate.
157 Despite the limitations of the algorithm used in this study, it should be noted that the
158 proxy DA could address non-stationarity if one uses temporally varying background
159 ensemble. We return to this point in Section 5.

160 To control spurious long-distance correlations due to sampling errors, a localization
161 function proposed by Gaspari and Cohn (1999) with a scale of 12,000 km was used. The
162 detailed procedure used for the algorithm is described in Steiger et al. (2014).

163

164

165 **2.2. Models**

166 Isotope ratios recorded in ice cores, corals, and tree-ring cellulose were assimilated.
167 To assimilate these variables, forward models for the variables are required. We used the
168 forward model developed by Liu et al. (2013; 2014) for corals, and Roden et al. (2000)
169 for tree-ring cellulose. We assumed that the isotopic composition of ice cores was the
170 same as that of precipitation at the time of deposition. Note that, in reality, the isotope
171 ratio recorded in ice cores is not always equal to that in precipitation due to post-
172 depositional processes (e.g., Schotterer et al., 2004). Because detailed models that
173 explicitly simulate the impact of all the processes involved in determining the value of
174 the ratio are not yet available, we used the isotope ratio in precipitation for that in ice
175 cores to avoid adding unnecessary noise.

176 The isotopic composition in precipitation was simulated using an atmospheric general
177 circulation model (GCM) into which the isotopic composition of vapor, cloud water, and

178 cloud ice are incorporated as prognostic variables. The model explicitly simulates the
179 isotopic composition with all the details of the fractionation processes combined with
180 atmospheric dynamics and thermodynamics, and hydrological cycles. Hence, the model
181 simulates the isotopic composition consistent with the modeled climate. Although many
182 such models have been developed previously (Joussaume et al., 1984, Jouzel et al., 1987;
183 Hoffmann et al., 1998; Noone and Simmonds, 2002; Schmidt et al., 2005; Lee et al., 2007;
184 Yoshimura et al., 2008; Risi et al., 2010; Werner et al., 2011), we used a newly-developed
185 model (Okazaki et al., in prep.) based on the atmospheric component of MIROC5
186 (Watanabe et al. 2010). The spatial resolution was set to T42 (approximately 280 km)
187 with 40 vertical layers.

188 The variability in $\delta^{18}\text{O}$ recorded in coral skeleton aragonite ($\delta^{18}\text{O}_{\text{coral}}$) depends on the
189 calcification temperature and local $\delta^{18}\text{O}$ in sea water ($\delta^{18}\text{O}_{\text{sw}}$) at the time of growth
190 (Epstein and Mayeda, 1953). Previous studies have modeled $\delta^{18}\text{O}_{\text{coral}}$ as the linear
191 combination of sea surface temperature (SST) and $\delta^{18}\text{O}_{\text{sw}}$ (e.g., Julliet-Leclerc and
192 Schmidt, 2001; Brown et al., 2006; Thompson et al., 2011), as follows:

$$193 \quad \delta^{18}\text{O}_{\text{coral}} = \delta^{18}\text{O}_{\text{sw}} + a\text{SST} \quad (1)$$

194 where a is a constant which represents the slope between $\delta^{18}\text{O}_{\text{coral}}$ and SST. In this study,
195 the constant was uniformly set to $-0.22\text{‰}/^{\circ}\text{C}$ for all the corals, following Thompson et al.

196 (2011), and we used a model developed by Liu et al. (2013; 2014) to predict $\delta^{18}\text{O}_{\text{sw}}$. The
197 model is an isotopic mass balance model that considers evaporation, precipitation, and
198 mixing with deeper ocean water. The coral model uses the monthly output of the isotope-
199 enabled GCM as its input, except for the isotope ratio of deeper ocean water, which was
200 obtained from observation-based gridded data compiled by LeGrande and Schmidt et al.
201 (2006). After the model calculates the monthly $\delta^{18}\text{O}_{\text{coral}}$, it is arithmetically averaged to
202 provide the annual $\delta^{18}\text{O}_{\text{coral}}$.

203 The isotope ratio in tree-ring cellulose ($\delta^{18}\text{O}_{\text{tree}}$) was calculated using a model
204 developed by Roden et al. (2000). In this model, $\delta^{18}\text{O}_{\text{tree}}$ is determined by the isotopic
205 composition of the source water used by trees for photosynthesis, and evaporative
206 enrichment on leaves via transpiration. In this study, the value of the isotopic composition
207 in the source water was arbitrarily assumed to be the moving average, traced three-months
208 backward, of the isotopic composition in precipitation at the site. Again, the model used
209 the monthly output of the isotope-enabled GCM as its input. After performing the tree-
210 ring model calculation, the monthly output was weighted using climatological net primary
211 production (NPP) to calculate the annual average. The NPP data were obtained from the
212 US National Aeronautics and Space Administration (NASA) Earth Observation website
213 (<http://neo.sci.gsfc.nasa.gov>).

214 Because the isotopic compositions of the proxies were simulated using the output of
215 the isotope-enabled GCM, their horizontal resolution was the same as that of the GCM.

216

217 **2.3. Experimental design**

218 **2.3.1. Control experiment**

219 The first experiment served as a control (CTRL) experiment, and used the framework
220 of an OSSE. In the experiment, the “simulation” and the “truth” (nature run) were
221 simulated by the same models, with the same forcing, but with different initial conditions.

222 Because the proxy models were driven by the output of the GCM, the modeled proxies
223 were consistent with the modeled climate from the GCM. Thus, here we describe the
224 experimental design for the GCM. The GCM was driven by observed SST and sea-ice
225 data (HadISST; Rayner et al., 2003), and historical anthropogenic (carbon dioxide,
226 methane, and ozone) and natural (total solar irradiance) forcing factors. The simulation
227 covered the period of 1871–2007 (137 years).

228 Although the simulation period included recent times covered by observational data,
229 we assumed that the only variable that could be obtained was the annual mean of $\delta^{18}\text{O}$ in
230 the proxies. We based this assumption on the fact that we wished to perform the DA for a
231 period in which no direct measurements were available, and there were only climate
232 proxies covering the period. Therefore, the temporal resolutions of the “observations” and

233 “simulations” were also annual, considering the typical temporal resolution of the proxies.

234 Observations were generated by adding Gaussian noise to the truth. The spatial
235 distribution of the observations mimicked that of the proxies. The spatial distributions of
236 each proxy for various periods are mapped in Figure 1. As can be seen from the figure,
237 the distributions and the number of proxies varied with time. However, for the sake of
238 simplicity, the distributions of the proxies were assumed to be constant over time in the
239 CTRL experiment (Figure 1 a). The size of the observation errors will be discussed in
240 Section 2.4.

241 The state vector consisted of five variables; surface air temperature and amount of
242 precipitation, as well as the isotopic composition in precipitation, coral, and tree-ring
243 cellulose. The first three variables were obtained from the isotope-enabled GCM, and the
244 other two variables were obtained from the proxy models driven by the output of the
245 GCM.

246

247 **2.3.2. Real proxy data assimilation**

248 The second (REAL) experiment assimilated proxy data sampled in the real world. To
249 mimic realistic conditions, SST and sea-ice concentration data to be used as model forcing
250 were modified from observational to modeled data. In reality, there were no direct

251 observations available for the target period of the proxy DA. Therefore, to reliably
252 evaluate the feasibility of proxy DA, the first estimate should be constructed using
253 modeled SST, as opposed to observed SST. We used SST data from the historical run of
254 the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2007) from
255 the atmosphere-ocean coupled version of MIROC5 (Watanabe et al., 2010) obtained from
256 the CMIP5 data server (<https://pcmdi.llnl.gov/search/cmip5/>).

257 Because the experiment was not an OSSE, nature run was not necessary.

258

259 **2.3.3. Sensitivity experiments**

260 Four sensitivity experiments were conducted to test the robustness of the results of
261 the proxy DA. In the first sensitivity experiment (CGCM), the simulation run was
262 constructed from the simulation forced by the modeled SST and sea ice as in the REAL
263 experiment. The other settings for the simulation run were the same as those in the CTRL
264 experiment. The nature run was the same as that of the CTRL experiment. Thus, this
265 experiment investigated how the reconstruction skill of the results was decreased by using
266 the simulated SST compared to the CTRL.

267 In the second sensitivity experiment (VOBS), the experimental design was the same
268 as that in the CGCM, except for the number of proxies that were assimilated. In the

269 CGCM experiment, the distribution and number of proxies were set to be constant over
270 time, as in the CTRL experiment. In the VOBS experiment, the distribution and number
271 of proxies varied with time. Thus, this experiment investigated how the reconstruction
272 skill was decreased by changing the number of proxies compared to the CGCM.

273 In the third sensitivity experiment (T2-Assim), reconstructed surface temperature (T_r)
274 was assimilated. The purpose of the experiment was to compare the skill of the
275 reconstructed DA with that of the proxy DA. The experimental design was the same as
276 that in the CTRL experiment, except for the variables that were assimilated. The
277 reconstructed temperature was generated with a linear regression model of $T_r = a +$
278 $b \times \delta^{18}O$ where a and b are coefficients and $\delta^{18}O$ is the observed isotope ratio. The
279 coefficients are calibrated with the observed isotope ratio and the true temperature in the
280 CTRL for the period of 1871 to 1950 (80 years). If the correlation between the isotope
281 ratio and the temperature during the calibration period was not statistically significant (p
282 < 0.10), the data was discarded following Mann et al. (2008). This screening process
283 reduced the available data from 94 to 81 grid points.

284 The final sensitivity (M08) experiment was used to examine the sensitivity to the
285 observation network. The experimental design was the same as for the CTRL, except for
286 the spatial distribution of the proxy. The proxy network used in the experiment was the

287 same as that of Mann et al. (2008). We assumed that isotopic information was available
288 for all the sites, even when this was not the case. For example, even if only tree-ring width
289 data were available at some of the sites in Mann et al. (2008), in this experiment we
290 assumed that isotopic data recorded in tree-ring cellulose were available at the site. The
291 number of grids containing observations were 94 and 250 for the CTRL experiment and
292 M08 respectively. The T2-Assim and the M08 were compared with CTRL.

293 The experimental designs are summarized in Table 1.

294

295 **2.4. Observation data**

296 We used paleoclimate data archived at the National Oceanic and Atmospheric
297 Administration (NOAA; <https://www.ncdc.noaa.gov/data-access/paleoclimatology-data>)
298 and data used in the PAGES 2k Consortium (2013). Additionally, 22 tree-ring cellulose
299 and 7 ice core data sets were collected separately from published papers. We only used
300 oxygen isotopic data (^{18}O) whose temporal resolution was higher than annual; proxies
301 whose resolution was lower than annual were excluded. The full list of proxies used in
302 this study is given in the Appendix. Following Crespin et al. (2009) and Goosse et al.
303 (2010), all proxy records were first normalized, and then averaged onto a T42 grid box to
304 eliminate model bias and produce a regional grid box composite. To compare the results

305 from each experiment effectively, the assimilated variables were all normalized in both
306 the simulation and nature runs, and in the observations in all the experiments.

307 Errors were added to the truth in a normalized manner to provide the observation for
308 all the experiment other than REAL. The normalized error was uniformly set to 0.50 for
309 all the proxies. This was based on the measurement error of $\delta^{18}\text{O}$ in ice cores being
310 reported to range from 0.05 to 0.2‰ (e.g., Rhodes et al., 2012; Takeuchi et al., 2014), and
311 the corresponding normalized error (measurement error divided by standard deviation of
312 proxy) then ranges from 0.03 to 0.1, with an average of 0.06. Similarly, the measurement
313 error of $\delta^{18}\text{O}$ in coral ranges from 0.03 to 0.11‰ (e.g., Asami et al., 2004; Goodkin et al.,
314 2008), and the corresponding normalized error ranges from 0.24 to 1.1, with an average
315 of 0.53. The measurement error of $\delta^{18}\text{O}$ in tree-ring cellulose ranges from 0.1 to 0.3‰
316 (e.g., Managave et al, 2011; Young et al, 2015), and the corresponding normalized error
317 ranges from 0.08 to 0.55, with an average of 0.28. In practice, due to the error of
318 representativeness and that in observation operator, it is common to increase the
319 observation errors to ensure that the analysis functions effectively (Yoshimura et al.,
320 2014). Furthermore, the measurement errors were not always available; therefore, a
321 uniform value of 0.5 was used for all the proxies. The corresponding signal-to-noise ratio
322 (SNR) is 2.0. The errors are assumed to be independent for all the experiments.

323

324 **3. Results from the OSSE**

325 The time series of the first estimation, the analysis, and the real values for $\delta^{18}\text{O}$ in
326 corals are compared as an example in Figure 2 at a location where observational data were
327 available (1°N , 157°W). Because the first estimate was the same for all reconstruction
328 years, it is drawn as horizontal lines. After the assimilation, the analysis agreed well with
329 the real values ($R = 0.96$, $p < 0.001$). This confirmed that the assimilation performed well.
330 We then examined how accurately the other variables were reconstructed by assimilating
331 isotopic information. Figure 2 also shows the time series of surface air temperature and
332 precipitation for the same site. There was a clear agreement between the analysis and the
333 truth for both variables ($R = 0.92$ and 0.88 respectively for temperature and precipitation).
334 This indicated that temperature and precipitation were effectively reconstructed by
335 assimilating isotopic variables at this site. This was because the isotope ratio in corals has
336 a signature not only from temperature as given in Eq. 1, but also precipitation (Liu et al.,
337 2013); the correlation with $\delta^{18}\text{O}_{\text{coral}}$ was -0.88 ($p < 0.001$) for both temperature and
338 precipitation, respectively. This example shows that the isotopic proxy records more than
339 one variable.

340 Figure 3 maps the correlation coefficients between the analysis and the truth for the

341 isotope ratio, temperature, and precipitation for 1970–1999. Because the first estimate
342 was constant over time, the temporal correlation between the first estimate and the real
343 value was zero everywhere. Thus, a positive correlation indicated that the DA improved
344 the simulation.

345 The correlation for $\delta^{18}\text{O}$ in precipitation were high at the observation sites, regardless
346 of the proxy type. This was because $\delta^{18}\text{O}$ in both corals and trees is affected by the isotopic
347 composition in precipitated water derived from sea water or soil water. The correlation
348 for $\delta^{18}\text{O}$ in tree-ring cellulose were also high at the observation sites. On the other hand,
349 the high correlation for $\delta^{18}\text{O}$ in corals were not limited around the observation sites but
350 were generally high at low- to mid-latitudes. Similarly, the correlation was high at low-
351 to mid-latitudes for surface temperature. The correlation was also statistically significant
352 ($p < 0.05$) around the observation sites in high latitude. In contrast, closely correlated
353 areas were restricted to low-latitude for precipitation.

354 How can the spatial distribution of the correlation pattern be explained; i.e., what do
355 the proxies represent? To investigate this question, empirical orthogonal function (EOF)
356 analysis was conducted for the simulated $\delta^{18}\text{O}$ in precipitation, corals, and tree-ring
357 cellulose. Only grids that contained observations were included in the analysis. The
358 variables were centered around their means before the analysis. The data covered the

359 period 1871–2007. The EOF patterns and temporal correlations between surface
360 temperature and the characteristic evolution of EOF, or the principal components (PCs)
361 of the first mode of each proxy are shown in Figure 4.

362 The first mode of $\delta^{18}\text{O}$ in ice core explains 14.3% of the total variance and it is the
363 only significant mode according to the Rule of Thumb (North et al., 1982) (the first and
364 the second mode were indistinguishable). The maximum loadings were in Greenland and
365 Antarctica where temperature increase has been observed for the past hundred years (e.g.
366 Hartmann et al., 2013). Indeed, the PC1 shows the significant trend and is correlated with
367 global mean surface temperature ($R=0.44$, $p < 0.001$). Therefore, it is legitimate to regard
368 ice core data as a proxy of global temperature as revealed from observation (Schneider
369 and Noone, 2007).

370 The first modes of $\delta^{18}\text{O}$ in corals, and tree-ring cellulose represent ENSO. The
371 explained variance of the first modes of $\delta^{18}\text{O}$ in corals, and tree-ring cellulose was 44.2,
372 and 19.0%, respectively. The maximum loadings occurred in the central Pacific for corals,
373 and Tibet for tree-ring cellulose. The temporal correlation between the PC1s and NINO3
374 index were 0.95, and 0.37 for corals and tree-ring cellulose, respectively. Because the
375 isotopic composition in corals is influenced by sea temperature, it is expected that the
376 $\delta^{18}\text{O}$ in corals from the central Pacific records the ENSO signature. Interestingly, the

377 analysis revealed that the $\delta^{18}\text{O}$ in tree-ring cellulose was also influenced by ENSO; hence,
378 this proxy contributes to the reconstruction of temperature and precipitation over the
379 tropical Pacific. Indeed, many previous studies have reported the link between $\delta^{18}\text{O}$ in
380 tree-ring cellulose and ENSO (Sano et al. 2012; Xu et al. 2011; 2013; 2015). Xu et al.
381 (2011) inferred the link is caused by the association between ENSO and Indian monsoon
382 rainfall (e.g. Rasmusson and Carpenter, 1983). The positive phase of ENSO results in a
383 decrease in summer monsoon rainfall in India, which leads to dry conditions in summer.
384 The decrease in precipitation leads to isotopically-enriched precipitation, and the dry
385 conditions enhance the enrichment of water in leaves. Correspondingly, the $\delta^{18}\text{O}$ in tree-
386 ring cellulose becomes heavier than normal in the positive phase of ENSO. Due to the
387 relationships between the coral and tree-ring cellulose data and ENSO, the correlation
388 coefficient between the analysis and the truth for the NINO3 index was as high as 0.95 (p
389 < 0.001).

390 Although EOF analysis did not reveal any other significant correlation between PCs
391 and climate indices, climate indices for the North Atlantic Oscillation and Southern
392 Annular Mode calculated using the reconstructed data were significantly correlated with
393 the truth (0.59 and 0.46, respectively).

394

395 **4. Real proxy data assimilation**

396 Based on the results of the idealized experiment described in the previous section, we
397 performed a “real” proxy DA, in which sampled and measured data in the real world were
398 assimilated.

399 The temporal correlation between the analysis and observations for temperature and
400 precipitation are shown in Figure 5 (d, h). The observations were obtained from
401 HadCRUT3 (Brohan et al., 2006) for temperature, and GHCN-Monthly Version 3
402 (Peterson and Vose, 1997) for precipitation.

403 Although the real proxy DA had reasonable skill, it was inferior relative to the CTRL
404 experiment. We investigated the cause of the decreased skill using the outputs of the
405 sensitivity experiments. The design of the experiments was changed in a stepwise fashion
406 to more realistic conditions of proxy data assimilation from the idealized conditions. The
407 correlations between the analysis and the truth, or the observation, for the experiments
408 are shown in Figure 5. The truths for the CGCM and VOBS experiments were the same
409 as those for the CTRL experiment. The global mean correlation coefficients for
410 temperature, precipitation, and NINO3 in the experiments are summarized in Figure 6.
411 Note that the correlation was averaged in the same domain for all the experiments to take
412 into account the differences in representativeness.

413 In the CGCM experiment, the temporal correlations between the analysis and the truth
414 were similar to those in the CTRL experiment for both temperature and precipitation
415 (Figure 5 b, f). This indicates that ENSO and its impacts were well represented in the
416 modeled SST used to construct the “simulation”. Watanabe et al. (2010) reported similar
417 modeled SST and observational values for the amplitude of ENSO measured by the
418 NINO3 index, and the spatial patterns of the temperature and precipitation fields
419 regressed on the NINO3 time series (see Figures 13 and 14 in their report).

420 Because the number of proxies for assimilation differed from that in the CGCM
421 experiment, it was not straightforward to compare the results of the REAL experiment
422 with those of the CGCM experiment. To enable an effective comparison of the results,
423 the same number of proxies were assimilated in the VOBS experiment as in the REAL
424 experiment and the same settings were used as in the CGCM experiment for the other
425 variables. Consequently, the performance of the assimilation of the VOBS experiment
426 was similar to that of the CGCM experiment for 1970–1999.

427 When the REAL and VOBS experiments were compared, the correlation coefficients
428 for temperature were significantly decreased over the Indian Ocean, eastern Pacific, and
429 Atlantic Ocean. These areas corresponded to areas of low reproducibility in the coral
430 model (Liu et al, 2014). The effects of sea current and river flow in these areas, which

431 were not included in the coral model, were deemed to be considerable. Although we
432 cannot attribute all the decreased skill to the coral model, the reproducibility of $\delta^{18}\text{O}$ in
433 corals in these areas requires improvement to enhance the performance of the assimilation.

434

435 **5. Discussion**

436 **5.1. Comparison with the reconstructed temperature assimilation**

437 Hughes and Ammann (2009) recommended assimilating measured proxy data, as
438 opposed to reconstructed data derived from the proxy data. This subsection compares the
439 results from the CTRL and T2-Assim experiments.

440 Figure 7 shows the spatial distribution of the correlation coefficients for temperature
441 and precipitation between the truth and the analysis for each experiment. As a whole, the
442 reconstruction skill was slightly degraded in T2-Assim compared with CTRL with the
443 global mean correlation coefficients for temperature (precipitation) of 0.50 (0.30), 0.45
444 (0.23), for CTRL and T2-Assim, respectively. On the other hand, the skill of proxy DA
445 was not always better than that of T2-Assim (e.g. temperature in tropical Atlantic Ocean).
446 Those pros and cons can be explained by the difference in the observation error and the
447 structure of Kalman gain. Figure 8 shows the SNR of the T_r ranging from 0.22 to 1.6 with
448 the average of 0.65. Accordingly, the observation error is larger than that of CTRL

449 everywhere, and this resulted in the reduction of the reconstruction skill. On the other
450 hand, the better skill in T2-Assim should be owing to the difference in Kalman gain. The
451 Kalman gain determines analysis increments by spreading the information in observations
452 through the covariance between the prior and the prior-estimated observations. We found
453 that the correlations between the prior (temperature) and the prior-estimated observation
454 (temperature and $\delta^{18}\text{O}$ for T2-Assim and CTRL, respectively) were consistently higher in
455 T2-Assim than in CTRL (not shown) as Dee et al. (2016) showed. Thus, the information
456 in the observations were more effectively spread to the analysis in T2-Assim, and this
457 resulted in the improved skill. Note that the screening process hardly hampered the
458 reconstruction skill, because even if the reconstructed temperature was fully used (i.e. not
459 screened), the skill was almost the same as T2-Assim.

460 Conducting similar experiments, Dee et al. (2016) also concluded that the
461 reconstruction skill was almost the same among proxy DA and reconstructed DA if the
462 relation between the reconstructed variable and the proxy is linear. As isotope-enabled
463 GCMs (Schmidt et al. 2007; LeGrande and Schmidt. 2009) and observations and models
464 for tree-rings width (D'Arrigo et al. 2008; Evans et al. 2014; Dee et al., 2016) have
465 demonstrated, however, the relations between the proxies and climate are non-linear and
466 non-stationary as well. Thus, it is difficult to expect that the skill of reconstructed DA will

467 be the same as that of proxy DA if we have the well-defined forward proxy models
468 (Hughes and Ammann, 2009). Although the current models are far from perfect as
469 implicated in Sect. 4.2, the assimilation of proxy data will offer a useful tool for the
470 reconstruction of paleoclimate, in which the relationship between the proxies and climate
471 constructed with the present-day conditions does not apply.

472

473 **5.2. Sensitivity to the distribution of the proxies**

474 The skill of the proxy DA was relatively low over Eurasia and North America, even
475 in the idealized experiment. It was unclear whether this was because of limitations in the
476 proxy data assimilation or the scant distribution of the proxies. This subsection
477 investigates the reasons for the relatively low reproducibility in these areas by comparing
478 the results of the CTRL and M08 experiments, focusing on North America. The number
479 of grids for which proxy data were available over North America was 11 and 126 for the
480 CTRL and M08, respectively.

481 The results for North America are shown in Figure 9. The figure shows the temporal
482 correlation coefficients between the analysis and the truth for surface air temperature and
483 precipitation. The correlation coefficients were calculated for 1970–1999. The skill was
484 high in the area in which the proxies were densely distributed for both variables. The

485 values of the coefficients averaged over the United States (30–50°N, 80–120°W) were
486 0.69 and 0.58 for temperature and precipitation, respectively. Compared to the
487 coefficients of 0.23 and 0.21, respectively, in the CTRL experiment, the skill was
488 enhanced for both variables. This implies that the performance of the reconstruction was
489 strongly dependent on the distribution of the proxy data. Taking into consideration that
490 proxy DA can assimilate not only proxy data but also reconstructed data, proxy DA can
491 take advantage of the use of increasingly large amounts of data. Although it is beyond the
492 scope of this study, the combined use of these data is expected to improve the performance
493 of proxy DA.

494

495 **6. Conclusion and summary**

496 The feasibility of using proxy DA for paleoclimate reconstruction was examined in
497 both idealized and real conditions experiments. The idealized (CTRL) experiment had
498 high skill at low latitudes due to the dependency of coral data on temperature and
499 precipitation in these regions, and the correlation between ENSO and $\delta^{18}\text{O}$ in corals in
500 Pacific and tree-ring cellulose in Tibet. Encouraged by the results, real proxy DA was
501 performed, where the simulation run was constructed from the simulation forced by the
502 modeled SST, and the real (observed) proxy data were assimilated into the simulation

503 (REAL experiment). The skill of the reconstruction decreased compared to CTRL.

504 To investigate the reason for the relatively low skill in REAL compared to CTRL, we
505 performed additional experiments; CGCM and VOBS. The imperfect SST used to drive
506 the CGCM experiment resulted in a slight reduction of the skill compared to the CTRL
507 experiment with perfect SST. This was because ENSO, which is the most important mode
508 for the reconstruction, was well represented in the modeled SST. The result is encouraging
509 because to apply the DA system to reconstruct ages where no instrumental observation is
510 available, we must rely on SST simulated by coupled GCM. Similarly, assimilating the
511 unfixed number of the observation only slightly decreased the reconstruction skill as
512 shown in the comparison between CGCM and VOBS.

513 From the suite of experiments, more than half of the difference between CTRL and
514 REAL remained unexplained. This remaining difference can have a lot of origins: e.g.
515 errors in the isotope incorporated atmospheric GCM, the proxy models, the proxy data
516 and so on. The errors in the models include such as model biases and missing or overly
517 simplified model components. For instance, the coral model does not take into account
518 the impact of ocean current or river runoff in this study. Furthermore, post-depositional
519 processes for simulating isotope ratio in ice core were not included at all. Those processes
520 should be included to enable more efficient utilization of all the data. The errors in proxy

521 data include such as misrepresentation of the targeted temporal and/or spatial scales. It is
522 also possible that the data were highly distorted by non-climatic factors. Thus, a thorough
523 quality control, similar to the procedures used in weather forecasting, should be
524 conducted before assimilation (e.g. Appendix B of Compo et al., 2011). At this stage, it
525 is difficult to show the relative contributions of each factor to the degraded skill in REAL,
526 it is necessary to estimate the impact of structural errors in models as done in Dee et al.
527 (2016).

528 Although the skill of proxy DA is dependent on the reproducibility of the models and
529 the number and quality of the observations, the results suggest that it is feasible to
530 constrain climate using only proxies. Especially, ENSO and ENSO-related variations in
531 temperature and precipitation should be reliably reconstructed even with the current
532 proxy DA system and proxy network used in this study because the correlation coefficient
533 between the analysis and the observations was as high as 0.83 in the REAL experiment.
534 Although the reconstruction of ENSO is dependent on data from corals, and the time span
535 covered by corals is relatively short (a few hundred years), ENSO can still be reliably
536 reconstructed due to its global impact, as was demonstrated in the relationship between
537 isotopes in tree-ring cellulose from Tibet.

538 Moreover, we expect that the reproducibility will increase as more proxy data become

539 available because it was heavily dependent on the spatial distribution. Given that proxy
540 DA can assimilate both proxy data and data reconstructed from proxy, and that the
541 reconstruction skill in reconstructed DA is partly superior to proxy DA, the combined use
542 of the two types of data is beneficial for the performance. In that case, care must be taken
543 not to assimilate dependent information (e.g. proxy data and reconstructed data from the
544 same proxy).

545 The DA algorithm used in this study did not consider non-stationarity among proxies
546 and climate variables because the Kalman gain was constant over time. To address non-
547 stationarity, the Kalman gain for a specific reconstruction year should be constructed for
548 several tens of years before and after that year. Nevertheless, EnKF can only capture
549 linear relationships between observations and the modeled state. The use of other
550 algorithms, such as particle filter (e.g. van Leeuwen, 2009), or four-dimensional
551 variational assimilation (e.g. Rabier et al., 2000), should be investigated in future studies
552 for scenarios where non-linearity is not negligible. Thus, it is important in future studies
553 to investigate non-stationarity and non-linearity among proxies and climate variables to
554 identify suitable algorithms for proxy DA.

555

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562

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777 past changes in summer rainfall, *Clim. Dyn.*, 45, 3609-3622, 2015.

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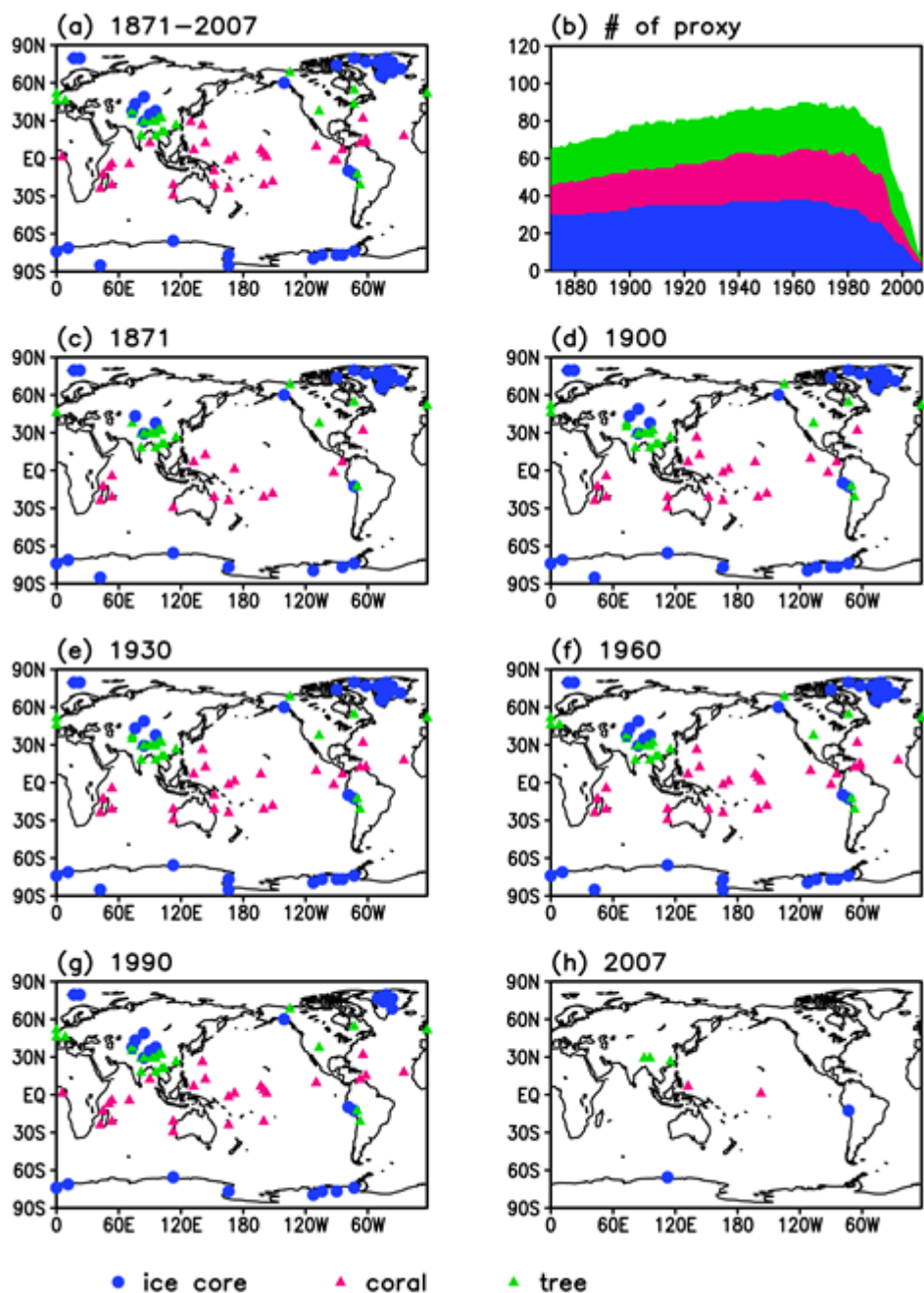
Tables

781 **Table 1.** Experimental designs. The observation network used in the CTRL experiment is
 782 denoted as Orig.

	SST data to drive simulation run	SST data to drive truth run	Assimilated variable	Observation network	Missing data
CTRL	HadISST	HadISST	Simulated $\delta^{18}\text{O}$	Orig	w/o missing
CGCM	Modeled SST	HadISST	Simulated $\delta^{18}\text{O}$	Orig	w/o missing
VOBS	Modeled SST	HadISST	Simulated $\delta^{18}\text{O}$	Orig	w/ missing
REAL	Modeled SST	-	Observed $\delta^{18}\text{O}$	Orig	w/ missing
T2-Assim	HadISST	HadISST	Reconstructed T2 from simulated $\delta^{18}\text{O}$	Orig	w/o missing
M08	HadISST	HadISST	Simulated $\delta^{18}\text{O}$	M08	w/o missing

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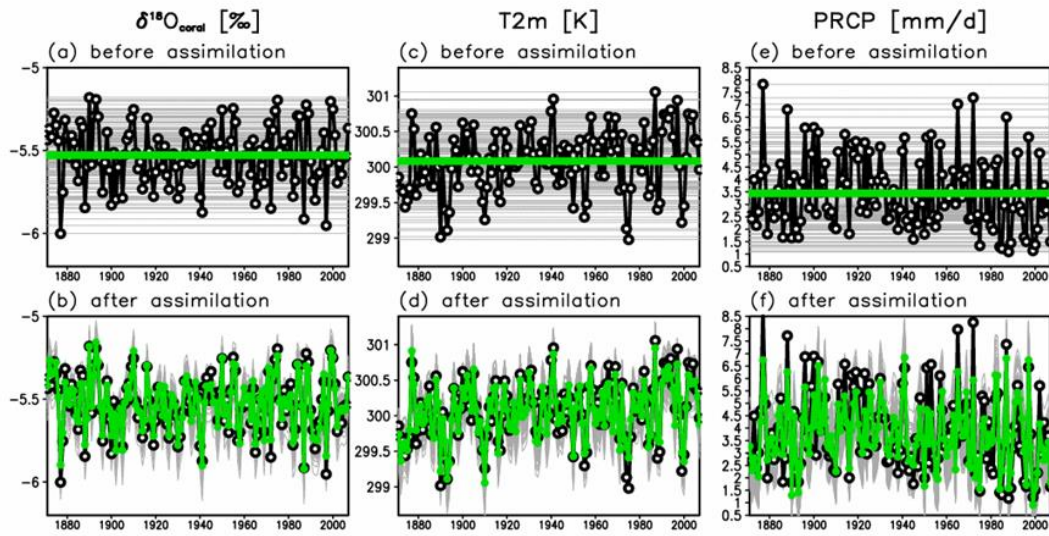


786

787 **Figure 1**

788 Spatial distribution of proxies ($\delta^{18}\text{O}$ in ice cores, corals, and tree-ring cellulose, denoted
 789 by blue, pink, and green, respectively). (a) Proxies spanning at least one year during
 790 1871–2000 are mapped (b) The number of proxies is depicted as a function of time. (c–

791 h) The spatial distributions of the proxies are mapped for (c) 1871, (d) 1900, (e) 1930, (f)
792 1960, (g) 1990, and (h) 2007.
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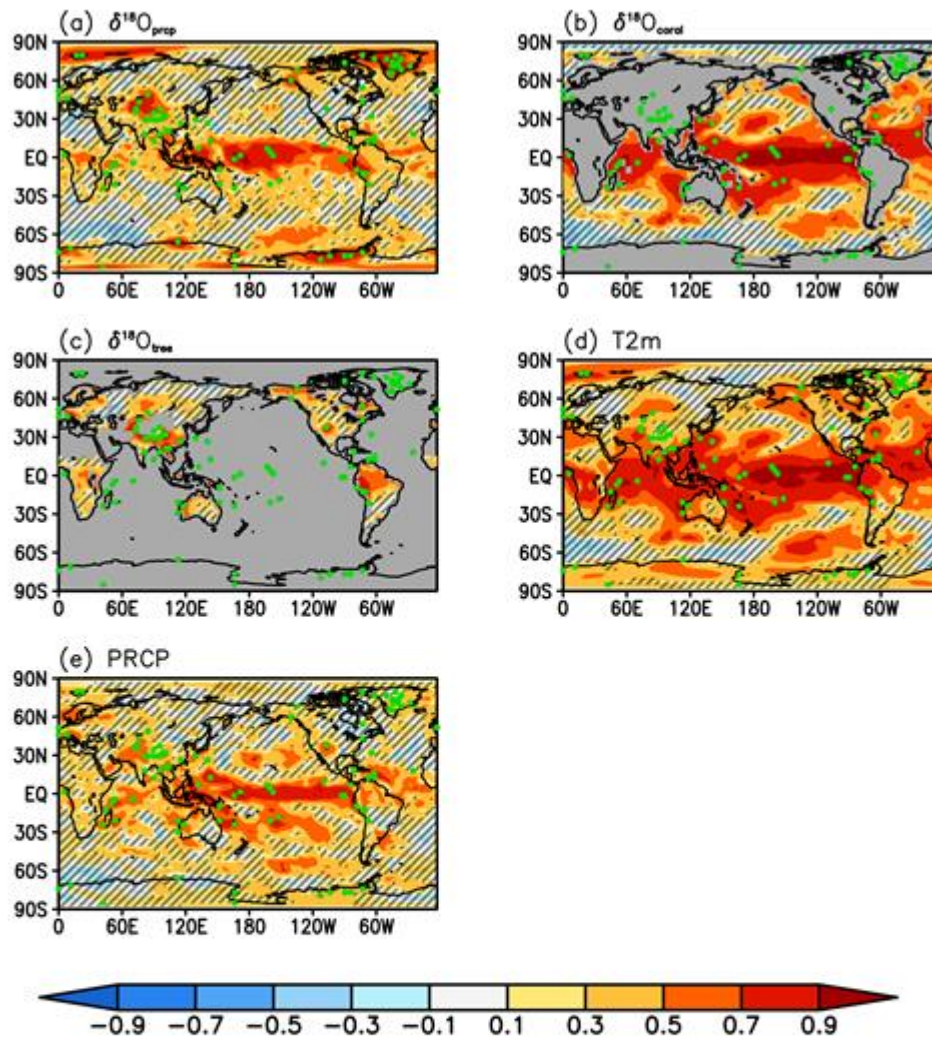


794

795 **Figure 2**

796 Annual mean $\delta^{18}\text{O}$ in corals at a location where observational data were available (1°N ,
 797 157°W) for (a) background and (b) analysis. The black line indicates the truth, gray lines
 798 indicate ensemble members, and green line indicates the ensemble mean.

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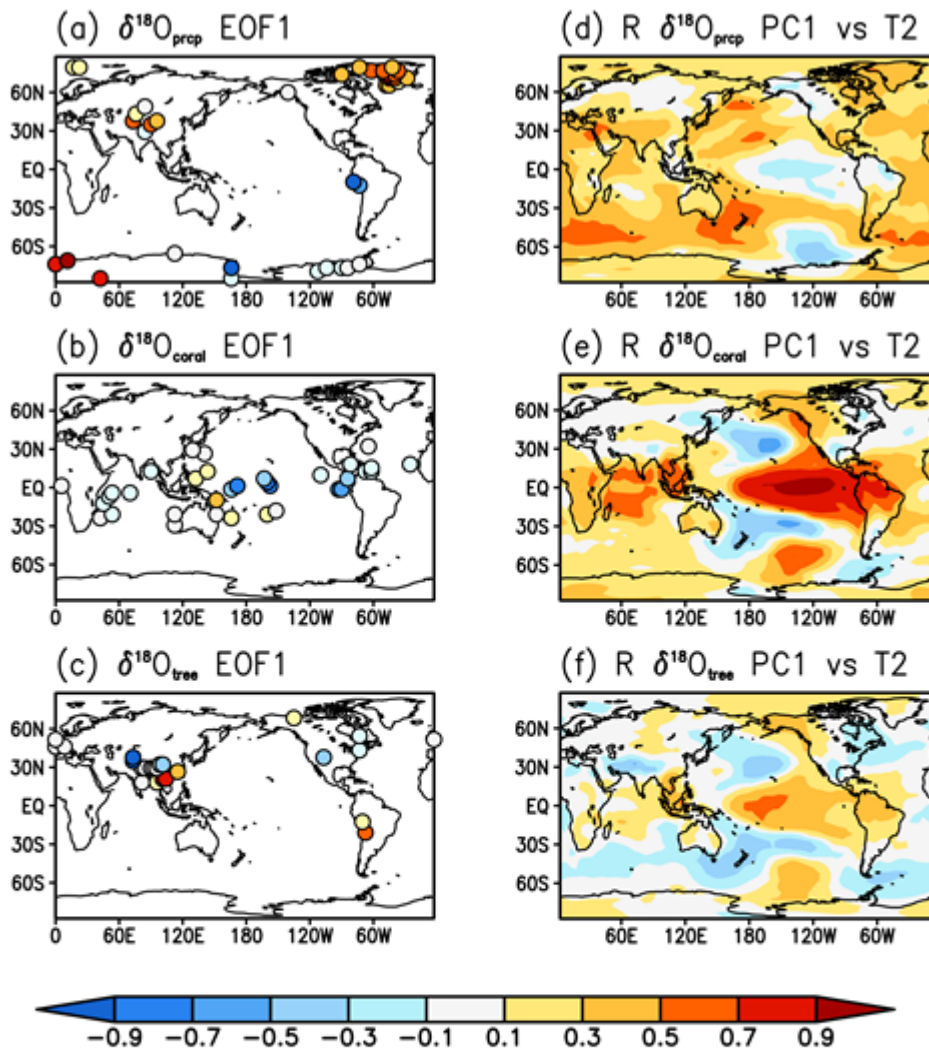


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801 **Figure 3**

802 Temporal correlation between the analysis and the truth. The green dot represents the
 803 location of the proxy sampling site. The hatched area indicates where the correlation is
 804 not statistically significant ($p > 0.05$).

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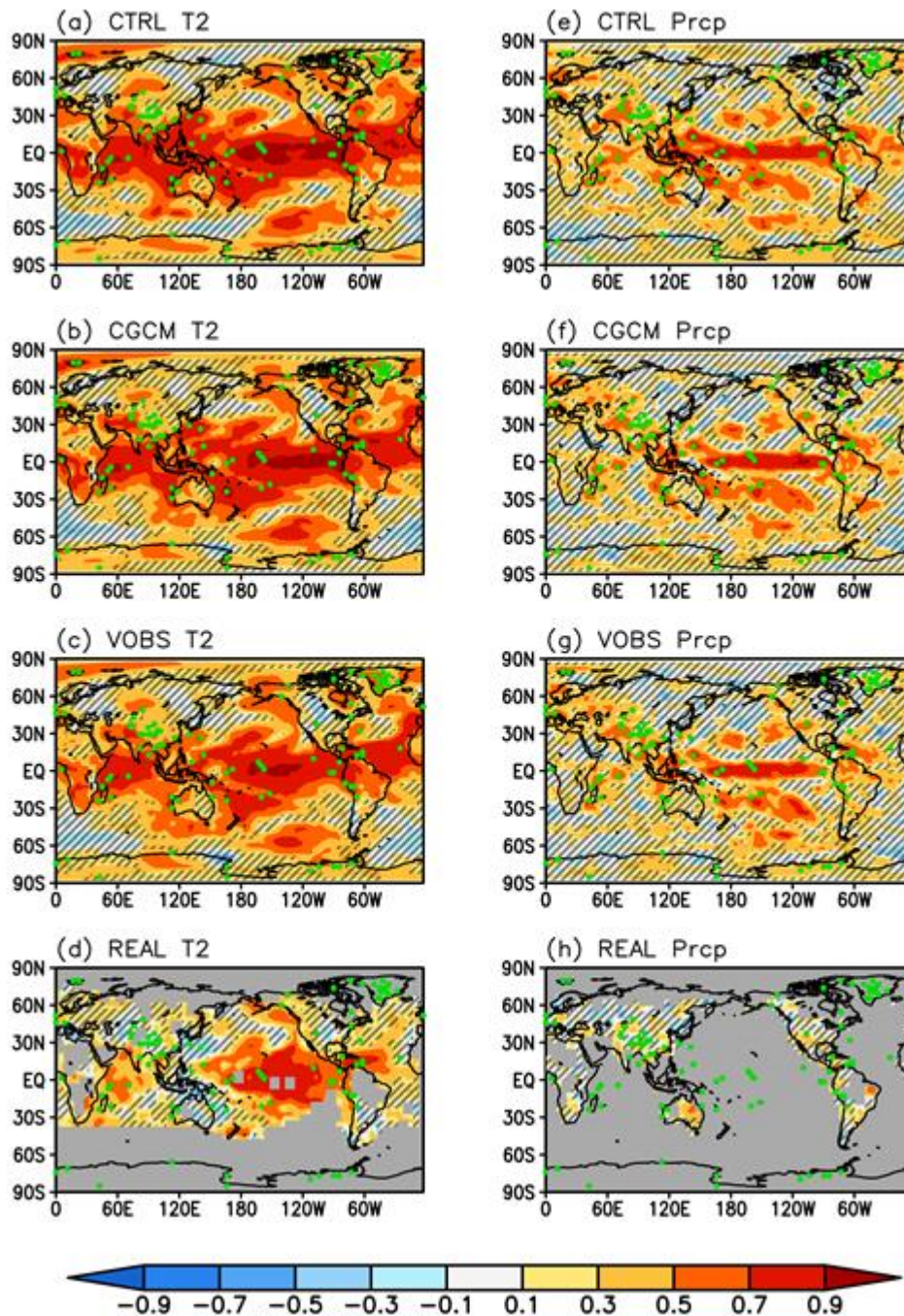


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807 **Figure 4**

808 First mode of EOF and the correlation between PC1 and temperature for (a and d) ice
 809 cores, (b and e) corals, and (c and f) tree-ring cellulose.

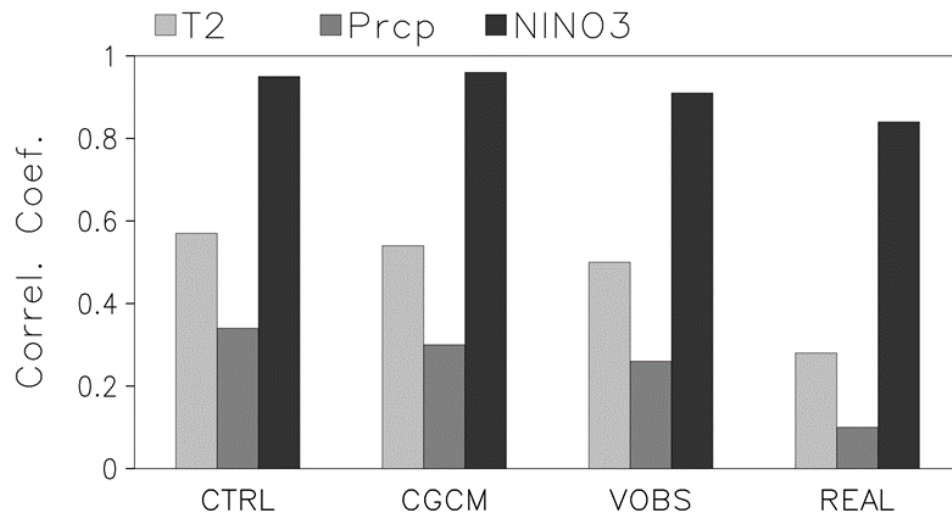
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Figure 5

Temporal correlation between the analysis and the truth for (a–d) temperature and (e–h) precipitation, for each experiment. The green dot represents the location of the proxy sampling site. The hatched area indicates where the correlation is not statistically significant ($p > 0.05$).

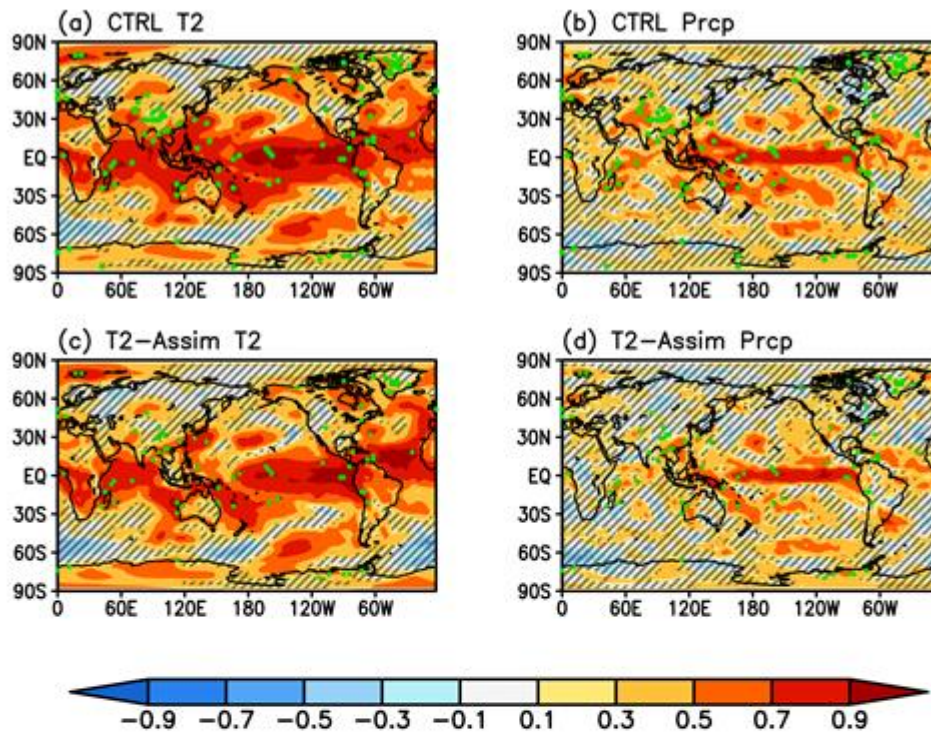


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819 **Figure 6**

820 Temporal correlation between the analysis and the truth for each experiment for 1970–
 821 1999. The values for temperature and precipitation are the global mean of the temporal
 822 correlations.

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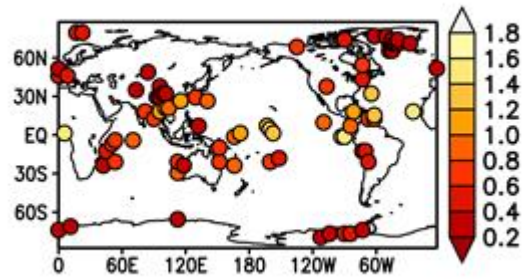


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825 **Figure 7**

826 Temporal correlations between the analysis and the truth for (a, c) temperature and (b, d)
 827 precipitation, for (a, b) CTRL and (b, d) T2-Assim. The green dot represents the location
 828 of the proxy sampling site. The hatched area means that the correlation is not statistically
 829 significant ($p > 0.05$).

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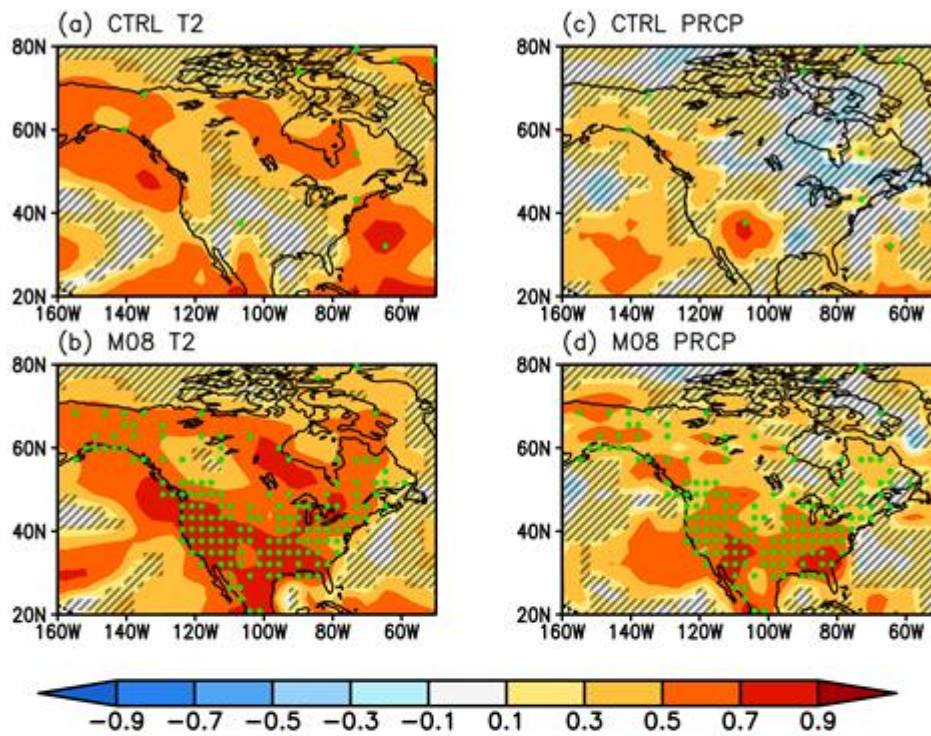


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832 **Figure 8**

833 Signal to noise ratio (SNR) of the reconstructed temperature from the observation used
834 in CTRL.

835



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837 **Figure 9**

838 Temporal correlations in North America between the analysis and the truth for (a, b)
 839 temperature, and (c, d) precipitation, for experiments using different proxy networks. The
 840 green dot represents the location of the proxy sampling site. The hatched area indicates
 841 where the correlation is not statistically significant ($p > 0.05$).

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