

21

22

Abstract

23

24

25

26

27

28

29

30

31

32

33

While the ability of land surface conditions to influence the atmosphere has been demonstrated in various modeling and observational studies, the precise mechanisms by which land-atmosphere feedback occurs are still largely unknown – particularly the mechanisms that allow land moisture state in one region to affect atmospheric conditions in another. Such remote impacts are examined here in the context of atmospheric general circulation model (AGCM) simulations, leading to the identification of one potential mechanism: the phase-locking and amplification of a planetary wave through the imposition of a spatial pattern of soil moisture at the land surface. This mechanism, shown here to be relevant in the AGCM, apparently also operates in nature, as suggested by supporting evidence found in reanalysis data.

34 **1. Introduction**

35 Numerous studies with atmospheric general circulation models (AGCMs) have
36 demonstrated the ability of soil moisture variations to affect the overlying atmosphere (e.g.,
37 Shukla and Mintz 1982, Delworth and Manabe 1989, Koster et al. 2000, Douville et al. 2001,
38 Guo et al. 2012). Observations-based studies are also suggestive of such impacts (e.g., Betts and
39 Ball 1995, Findell and Eltahir 1997, Koster et al. 2003, 2011, Taylor et al. 2011). The impacts
40 are often discussed in the context of “land-atmosphere feedback” because the affected
41 atmospheric variables (e.g., air temperature, precipitation) are often the ones that helped produce
42 the soil moisture variations in the first place.

43 The impacts identified in the literature are generally at the local scale. A wetter-than-
44 average soil might change the relative magnitudes of the surface turbulent fluxes, which in turn
45 might induce changes in the overlying boundary layer, perhaps leading to conditions more
46 conducive to moist convection (Betts et al., 1994). A higher evaporation rate from a wetter-than-
47 average soil would also reduce surface temperature through evaporative cooling, which in turn
48 could reduce the temperature of the overlying air (e.g., Seneviratne et al. 2010).

49 The ability of soil moisture, however, to have a *remote* impact on the atmosphere – an
50 impact, for example, on air temperatures a thousand kilometers away – is still largely
51 undetermined, addressed by only a handful of studies (e.g., van den Dool et al. 2003). Taylor et
52 al. (2011) examine mechanisms for remote impacts at the mesoscale (tens to hundreds of
53 kilometers). At even larger scales, the mechanisms must involve changes in the large scale
54 circulation. How this would work is still largely unexplored.

55 We examine this question here. We use an AGCM to explore one potential mechanism
56 for remote soil moisture impacts on meteorological fields, a mechanism involving the phase-
57 locking of a planetary wave over a specific soil moisture pattern. We start in section 2 with a
58 diagnostic analysis of AGCM simulations. This analysis provides the information needed to
59 design specialty simulations (section 3) that confirm the operation of the mechanism within the
60 model. Supporting evidence that the mechanism operates in nature as well – i.e., evidence that it
61 is not simply a model construct – is extracted from reanalysis data in section 4.

62

63 **2. Analysis of Atmospheric Model Simulations**

64 The modeling system utilized throughout this study is the GEOS-5 system of the National
65 Aeronautics and Space Administration Global Modeling and Assimilation Office
66 (NASA/GMAO). All simulations examined use only the coupled atmospheric and land model
67 components of the system, prescribing sea surface temperatures (SSTs) from observations using
68 AMIP-style (Atmospheric Model Intercomparison Study; Gates et al. 1992) protocols. The
69 atmospheric model is described in some detail by Rienecker et al. (2008) and Molod et al.
70 (2012), and the land surface model is the Catchment model of Koster et al. (2000).

71 The present section focuses on the analysis of an archived ensemble of ten simulations
72 covering the period 1871-2011 [Schubert et al. 2014]. Monthly data from these simulations are
73 available at a resolution of $1.25^{\circ} \times 1^{\circ}$. We focus here on monthly averages of root zone soil
74 moisture (WRZ), 2-meter air temperature (T2M), and meridional wind velocity at 250 mb
75 (V250) taken from the last 35 years of each simulation. Focusing on this latter period, which
76 still provides a full 350 years of data for analysis, allows for more consistency with the MERRA

77 reanalysis period (section 4) and, more importantly, reduces the impact of the long-term
 78 temperature trend on our results.

79 For convenience, the monthly data were aggregated to a resolution of $2.5^\circ \times 2^\circ$. Soil
 80 moisture values were then converted to standard normal deviates:

$$81 \quad Z_{WRZ}(i,j,m,n) = [WRZ(i,j,m,n) - M_{WRZ}(i,j,m)] / \sigma_{WRZ}(i,j,m), \quad (1)$$

82 where i and j are the longitudinal and latitudinal indices of the grid cell, m is the month, n is the
 83 year, M_{WRZ} is mean of WRZ over all years, and σ_{WRZ} is its standard deviation. The T2M and
 84 V250 data were converted to simple anomalies:

$$85 \quad T2M(i,j,m,n)' = T2M(i,j,m,n) - M_{T2M}(i,j,m), \text{ and} \quad (2)$$

$$86 \quad V250(i,j,m,n)' = V250(i,j,m,n) - M_{V250}(i,j,m). \quad (3)$$

87 Our analysis focused on identifying the April soil moisture pattern over CONUS (the
 88 conterminous United States) that is most strongly related to July temperature anomalies in the
 89 U.S. Great Plains and thus may someday (with more research) be useful for prediction. To
 90 simplify and thereby clarify the analysis, we searched for what is arguably the simplest 2-D soil
 91 moisture pattern possible: a “dipole” of soil moisture anomalies, with a positive anomaly in one
 92 location paired with a negative anomaly in another. The search proceeded as follows. For a
 93 given pairing of grid cells (representing the dipole centers), the 350 Aprils were ranked in terms
 94 of dipole strength:

$$95 \quad \text{dipole strength} = -D_1(n) D_2(n) \quad \text{if } D_1(n) > 0 \quad (4)$$

$$96 \quad = 0 \quad \text{if } D_1(n) < 0,$$

97 where $D_1(n)$ is the average value of Z_{WRZ} in April of year n in the 9 grid cells centered on the
98 first chosen dipole point (so as to consider a spatial scale of ~ 600 km) and $D_2(n)$ is the
99 corresponding average for the 9 grid cells centered on the second point. The subset of simulated
100 Apriks with dipole strengths in the top 20% of all values (70 Apriks in all) comprised a composite
101 of years over which the subsequent July T2M spatial fields were averaged. This process was
102 repeated with both orderings of every possible pairing of grid cells in CONUS, and the particular
103 dipole that produced the highest composited July T2M anomaly in the Great Plains was
104 identified.

105 Results are shown in Figure 1. Figure 1a shows the April Z_{WRZ} field for the composited
106 years for the identified dipole, with the centers of this dipole marked as white circles. The
107 associated July T2M' composite for that subset of years is shown in Figure 1b. According to the
108 GCM, when April soil moisture is high in the northwestern U.S. and low in the Great Plains, the
109 subsequent July temperature anomaly in the Great Plains tends to be positive, by more than 2°K
110 in some places. Supplemental composites using the same sampling of years but different
111 ensemble members do not show the same signal; the July temperature signal shown is not
112 explained by the particular SSTs of the composited years.

113 The dipole pattern in Figure 1a and its impact on Great Plains temperature is the main
114 finding of this part of the analysis, and yet two additional points are worth making. First, an
115 analogous compositing based on a monopole of April soil moisture (not shown) does not lead to
116 such large temperature anomalies; the dipole provides the larger temperature signal. Second, the
117 composited July V250 anomaly field (Figure 1c) shows a distinct wave pattern, with a positive
118 lobe of V250 anomalies in the western half of the continent and a negative lobe in the eastern
119 half. Together these findings motivate the GCM experiments discussed in the next section.

120

121 **3. Focused Experiments**

122 A hypothesis consistent with Figure 1 is that the soil moisture pattern seen in Figure 1a
123 persists into the summer and, during July, affects the surface turbulent fluxes and (perhaps)
124 precipitation in such a way as to promote the wave pattern seen in Figure 1c – perhaps by
125 inducing a travelling planetary wave in the troposphere to phase-lock over the continent. The
126 wave, in turn, might then exacerbate the surface Great Plains heating, completing a positive
127 feedback loop. Both segments of this loop (the land affecting the atmosphere, and the
128 atmosphere affecting the land) are now addressed in specialized AGCM experiments.

129

130 a. Experiment 1: The Land-Atmosphere Component of the Feedback Loop

131 To examine how land conditions may affect dynamical patterns in the atmosphere, we
132 compare two ensembles of GEOS-5 simulations covering April-July of 2012. The control
133 ensemble consists of 192 AMIP-style simulations performed on a $1^\circ \times 1^\circ$ grid, the simulations
134 differing from each other in their atmospheric initial conditions, taken from different years of the
135 MERRA reanalysis (with slight perturbations imposed in each year to increase the ensemble
136 size). The experiment ensemble is identical to the control except for the imposition of a soil
137 moisture dipole pattern: during April in these simulations, any precipitation simulated over a
138 northwestern region of the U.S. (the blue box in Figure 2a) was artificially increased five-fold
139 before being applied to the land surface (with the increase deposited as liquid), and precipitation
140 simulated over the Great Plains (the red box in Figure 2a) was zeroed. Precipitation was not
141 modified during the May-July period.

142 Shown in Figure 2b,c are the resulting differences in key July fields (experiment minus
143 control). The precipitation modifications led to soil moisture anomalies that extended into July,
144 which in turn induced strong July temperature anomalies, including a heating in the U.S. Great
145 Plains (Figure 2b). The imposed soil moisture dipole also had an impact on the atmosphere's
146 general circulation, as manifested in the V250 winds – Figure 2c shows a wavelike pattern in the
147 V250 difference field, similar to that seen in Figure 1c. Indeed, the source of this pattern can
148 only be the imposed dipole, as all other aspects of the two ensembles are identical.

149 Two additional points are worth making about this phase of the analysis. First, the
150 wavelike pattern does not appear until June (not shown) and July, which is consistent with the
151 idea that soil moisture fields influence the atmosphere the most during the warmest months,
152 when evaporation is highest. Second, we performed two supplemental 192-member ensembles
153 (results not shown), one that imposed only the April wetting in the northwestern U.S., and one
154 that imposed only the April drying in the Great Plains. Both ensembles show some warming
155 over the Great Plains. Although the warm anomaly in the latter is much higher, it is still lower
156 than that in Figure 2b – again, the dipole pattern produces a greater warm anomaly than the
157 monopole pattern.

158

159 b. Experiment 2: The Atmosphere-Land Component of the Feedback Loop

160 The other phase of the feedback loop, i.e., the ability of a specific wavelike structure to
161 induce surface warming in the Great Plains, is examined here with two additional sets of
162 ensembles. The control for this comparison is an AMIP-style 32-member ensemble covering the
163 period May 21 – July 31, 2012. The experiment is a 32-member ensemble differing from the

164 control in only one way: upstream of North America, within the box outlined in Figure 3a,
165 atmospheric conditions were forced to agree with conditions captured by the MERRA reanalysis
166 for the period, using a technique called “replay”¹. The motivation for this modification was the
167 known existence of a Rossby-wave pattern over North America during the hot summer of 2012
168 (Wang et al. 2014) and the expectation that the wave was instigated by conditions somewhere in
169 this upstream area (e.g., Schubert et al. 2011). The hope was that with these upstream conditions
170 prescribed, the V250 wave patterns seen in Figures 1c and 2c would be more prevalent in the
171 experiment ensemble than in the control ensemble.

172 This turns out to be the case, especially in June. Figure 3c shows the difference between
173 the average June V250 fields from the experiment and control ensembles. A clear wavelike
174 pattern is seen, with a positive lobe in the west and a negative lobe in the east. Furthermore,
175 surface warming appears in the central U.S. (Figure 3b).

176 Given the experimental design, this warming is a direct consequence of the upstream
177 forcing, presumably through the generation of planetary waves; the warming appears roughly
178 between the positive and negative lobes of the V250 difference field, i.e., at the location of an
179 increase in the upper level high where: (i) subsidence tends to induce cloudless skies and thus
180 increased surface radiative forcing, and (ii) surface winds tend to advect warm air in from the

¹ The GEOS-5 Data Assimilation system was developed so that analysis increments produced during the assimilation cycle are inserted gradually, typically over a 6-hr interval (Bloom et al. 1996). This approach has been generalized so that the model can be “replayed” against an existing analysis (e.g., MERRA), i.e., the analysis increments can be used to guide the evolution of model state in an (otherwise) free-running AGCM toward that of the analysis. This approach has been further generalized so that only certain regions of the atmosphere are constrained to agree with the analysis; this is the approach used here.

181 south. Schubert et al. (2011) found that at monthly time scales, such waves are indeed well
182 correlated with continental surface temperatures during summer, with correlation patterns that
183 are consistent with the waves' largely barotropic structure, with a slight westward tilt with
184 height.

185

186 **4. Supporting Evidence from Reanalysis**

187 It is natural to ask if this mechanism – a soil moisture dipole inducing a planetary wave
188 pattern, which can in turn amplify Great Plains warming – also operates in nature. Because
189 nature does not allow the type of experiments performed in sections 2 and 3, demonstrating this
190 conclusively is impossible. Supporting evidence for the feedback is nevertheless found in
191 MERRA reanalysis data (Rienecker et al. 2011). Focusing on monthly averages, we processed
192 the 35 April root zone soil moisture fields in this dataset (covering 1979-2013) into standard
193 normal deviates and converted the 35 July temperature and V250 fields into anomalies. We then
194 identified the 7 Aprils (20% of the total) with the highest soil moisture dipole strength, where
195 dipole strength is defined as in (4), averaging over the boxes shown in Figure 2a.

196 Figure 4a shows the average April root zone soil moisture field for the 7-yr composite;
197 the dipole is, by construct, apparent in the plot. Figure 4b shows the July T2M anomaly field.
198 Warm July conditions, with an average anomaly of up to 1K or more, are seen in the Great Plains
199 for the subsetted years – the historical anomalies were arguably predictable from the presence of
200 the April soil moisture dipole. Furthermore, the composite July V250 anomaly field for these
201 years shows a pattern very similar to that seen in Figures 1c and 2c, supporting the idea that the
202 soil moisture dipole had an impact on the planetary wave structure.

203 MERRA reanalysis data, while not conclusive, are thus consistent with the feedback
204 mechanism established for the AGCM. Of course, reanalysis data are not pure observations;
205 model machinery is reflected to some extent in the data, and indeed the AGCM underlying
206 MERRA is an updated version of that used in Sections 2 and 3. Nevertheless, the number of
207 observations assimilated into the reanalysis over North America gives us confidence that the July
208 T2M and V250 fields, and even the April WRZ anomalies, in the MERRA dataset are realistic,
209 reflecting what actually happened.

210

211 **5. Summary**

212 Figure 2 shows that in the AGCM, imposing a dipole structure in April soil moisture,
213 with wet conditions in the northwestern U.S. and dry conditions in the Great Plains, promotes a
214 July wave pattern in the atmosphere. Figure 3 shows that instigating such a wave pattern (in this
215 case through a remote mechanism, over Asia) leads to increased 2m air temperatures in the U.S.
216 Great Plains and, to a small extent, cooler temperatures over the Northwest, bolstering the
217 surface temperature signal. While much of the Great Plains temperature anomaly in Figure 2b is
218 presumably a reflection of drier soil moistures there and the associated decrease in evaporative
219 cooling, not all of it is; the induced formation of the wave structure and its ability to feed back on
220 the temperature anomaly constitutes a feedback loop for the model climate, one involving a
221 change in the large-scale circulation. Evidence for the mechanism is seen in the MERRA
222 reanalysis (Figure 4).

223 The dipole identified and utilized in our experiments is, of course, only one of potentially
224 many soil moisture patterns of relevance to land-atmosphere feedback in the climate system.

225 The approach presented here could prove useful in identifying and analyzing additional patterns.

226

227 *Acknowledgements:* Support for this project was provided by the NOAA Modeling, Analysis,
228 Predictions and Projections (MAPP) program, the NASA Energy and Water cycle Study
229 (NEWS) program, and the NASA Modeling, Analysis, and Prediction Program.

230

References

231 Betts, A.K., J.H. Ball, A.C.M. Beljaars, M.J. Miller, and P. Viterbo, 1994: Coupling between
232 land-surface, boundary-layer parameterizations and rainfall on local and regional scales:
233 Lessons from the wet summer of 1993. Preprints, Fifth Conf. on Global Change Studies,
234 74th Annual Meeting, Nashville, TN, Amer. Meteor. Soc.

235 Betts, A. K., and J. H. Ball, 1995: The FIFE surface diurnal cycle climate. *J. Geophys. Res.*,
236 100, 25679-25693.

237 Bloom, S., L. Takacs, A. DaSilva, and D. Ledvina, 1996: Data assimilation using incremental
238 analysis updates. *Mon. Wea. Rev.*, 124, 1256–1271.

239 Delworth, T.L., and S. Manabe, 1989: The influence of soil wetness on near-surface
240 atmospheric variability. *J. Clim.*, 2, 1447-1462.

241 Douville, H., F. Chauvin, and H. Broqua, 2001: Influence of soil moisture on the Asian and
242 African monsoons, Part 1, Mean monsoon and daily precipitation. *J. Clim.*, 14, 2381-
243 2403.

244 Findell, K. L., and E. A. B. Eltahir, 1997: An analysis of the soil moisture-rainfall feedback,
245 based on direct observations from Illinois. *Water Resour. Res.*, 33, 725-735.

246 Gates, W. L., 1992: AMIP: The Atmospheric Model Intercomparison Project. *Bull. Amer.*
247 *Meteor. Soc.*, 73, 1962–1970.

248 Guo, ZC, P. A. Dirmeyer, T. DelSole, and R. D. Koster, 2012: Rebound in atmospheric
249 predictability and the role of the land surface. *J. Climate*, 25, 4744-4749.

250 Koster, R. D., M. J. Suarez, and M. Heiser, 2000: Variance and predictability of precipitation at
251 seasonal-to-interannual timescales. *J. Hydrometeor.*, **1**, 26–46.

252 Koster, R. D., M. J. Suarez, A. Ducharne, M. Stieglitz, and P. Kumar, 2000: A catchment-based
253 approach to modeling land surface processes in a general circulation model: 1. Model
254 structure, *J. Geophys. Res.*, **105**(20), 24,809– 24,822.

255 Koster, R. D., M. J. Suarez, R. W. Higgins, and H. M. Van den Dool, 2003: Observational
256 evidence that soil moisture variations affect precipitation. *Geophys. Res. Lett.*, **30**,
257 doi:10.1029/2002GL016571.

258 Koster, R. D., M. J. Suarez, and M. Heiser, 2000: Variance and predictability of precipitation at
259 seasonal-to-interannual timescales. *J. Hydrometeor.*, **1**, 26–46.

260 Koster, R. D., and Co-Authors, 2011: The second phase of the Global Land-Atmosphere
261 Coupling Experiment, Soil moisture contributions to subseasonal forecast skill. *J.*
262 *Hydromet.*, **12**, 805-822.

263 Molod, A., L. Takacs, M. Suarez, J. Bacmeister, I.-S. Song, and A. Eichmann, 2012: The GEOS-
264 5 Atmospheric General Circulation Model: Mean Climate and Development from
265 MERRA to Fortuna. *NASA Technical Report Series on Global Modeling and Data*
266 *Assimilation, NASA TM—2012-104606*, Vol. **28**, 117 pp

267 Rienecker, M. M., and Coauthors, 2008: The GEOS-5 Data Assimilation System Documentation
268 of versions 5.0.1 and 5.1.0, and 5.2.0. NASA Tech. Rep. Series on Global Modeling and
269 Data Assimilation, NASA/TM-2008-104606, Vol. 27, 92 pp.

270 Rienecker, M. M., and Co-Authors, 2011: MERRA, NASA's Modern-Era Retrospective
271 Analysis for Research and Applications. *J. Climate*, **24**, 3624-3648.

272 Shukla, J., and Y. Mintz, 1982: Influence of land-surface evapotranspiration on the earth's
273 climate. *Science*, **215**, 1498–1501.

274 Schubert, S., H. Wang, and M. Suarez, 2011: Warm Season Subseasonal Variability and Climate
275 Extremes in the Northern Hemisphere: The Role of Stationary Rossby Waves. *J. Climate*, **24**,
276 4773-4792.

277 Schubert, S., H. Wang, R. Koster, M. Suarez, and P. Groisman, 2014: Northern Eurasian Heat Waves
278 and Droughts. *J. Climate*, **27**, 3169-320.

279 Seneviratne, S. I., and Co-Authors, 2010: Investigating soil moisture-climate interactions in a changing
280 climate, A review. *Earth-Sci. Rev.*, **99**, 125-161.

281 Taylor, C. T., A. Gounou, F. Guichard, P. P. Harris, R. J. Ellis, F. Couvreux, and M. De Kauwe, 2011:
282 Frequency of Sahelian storm initiation enhanced over mesoscale soil-moisture patterns. *Nature*
283 *Geosci.*, **4**, 430-433.

284 van den Dool, H., J. Huang, and Y. Fan, 2003: Performance and analysis of the constructed analogue
285 method applied to U.S. soil moisture over 1981-2001. *J. Geophys. Res.*, **108**,
286 10.1029/2002JD003114.

287 Wang, H., S. Schubert, R. Koster, Y.-G. Ham, and M. Suarez, 2014: On the Role of SST Forcing in the
288 2011 and 2012 Extreme U.S. Heat and Drought: A Study in Contrasts. *J. Hydromet.*, in press.

289

290

Figure Captions

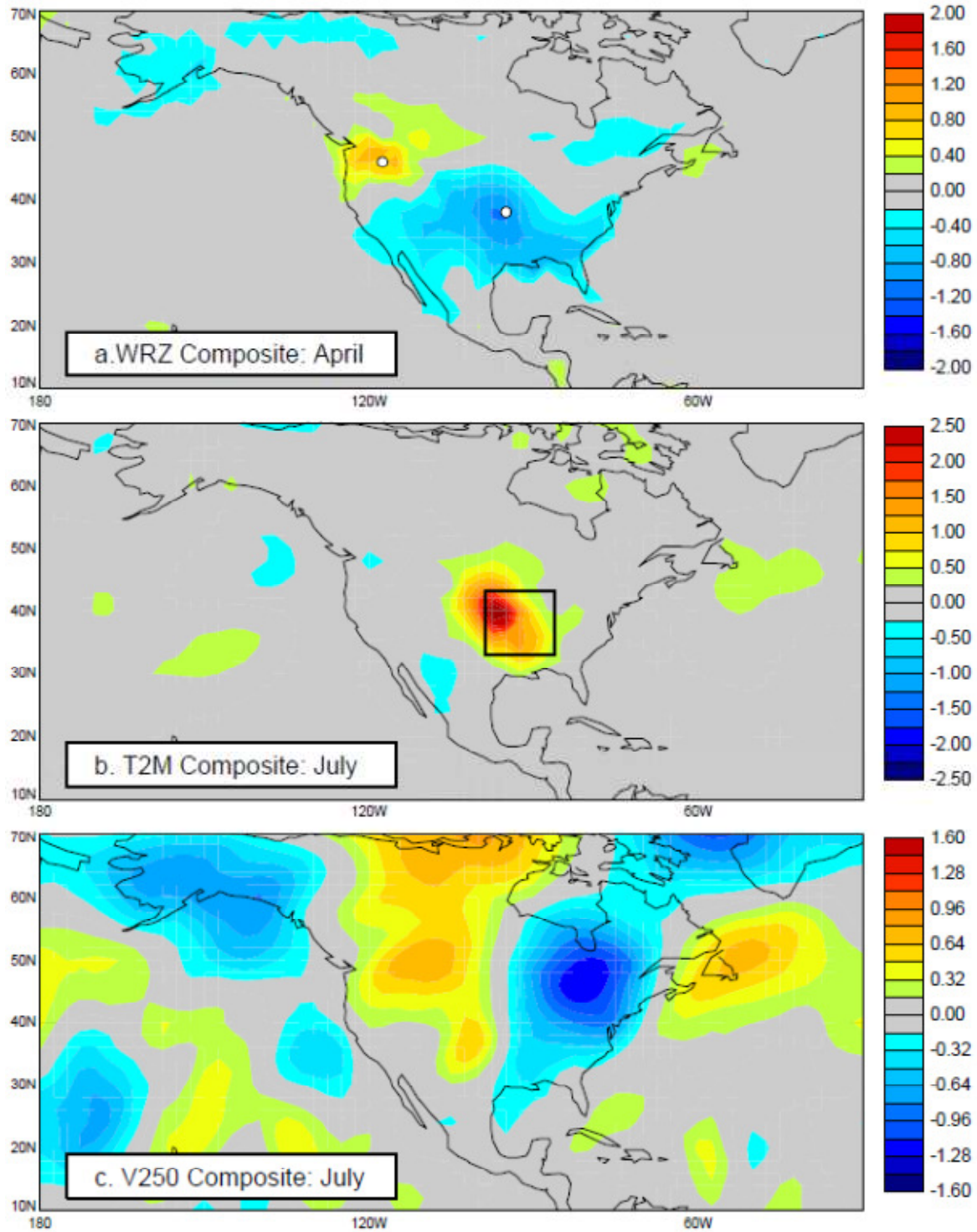
291 Figure 1. a. Composite of the standard normal deviate of April soil moisture over the 20% of
292 simulation years for which the April soil moisture dipole centered on the small white circles is
293 strongest (see text). b. Corresponding composite (i.e., for the same simulation years) of July
294 surface air temperature anomalies. c. Corresponding composite (i.e., for the same simulations
295 years) of July 250 mb meridional wind anomalies.

296 Figure 2. a. Locations where April precipitation is modified in specialized experiments. April
297 precipitation water applied to the land surface is increased five-fold in the blue area, and it is set
298 to zero in the red area. b. Resulting July surface air temperature anomalies. c. Resulting July
299 250 mb meridional wind anomalies.

300 Figure 3. a. Location of the upstream area over which atmospheric states were forced to agree
301 with states from an analysis (and thus were forced to be realistic), using a technique known as
302 ‘replay’. b. Resulting June surface air temperature anomalies. c. Resulting June 250 mb
303 meridional wind anomalies.

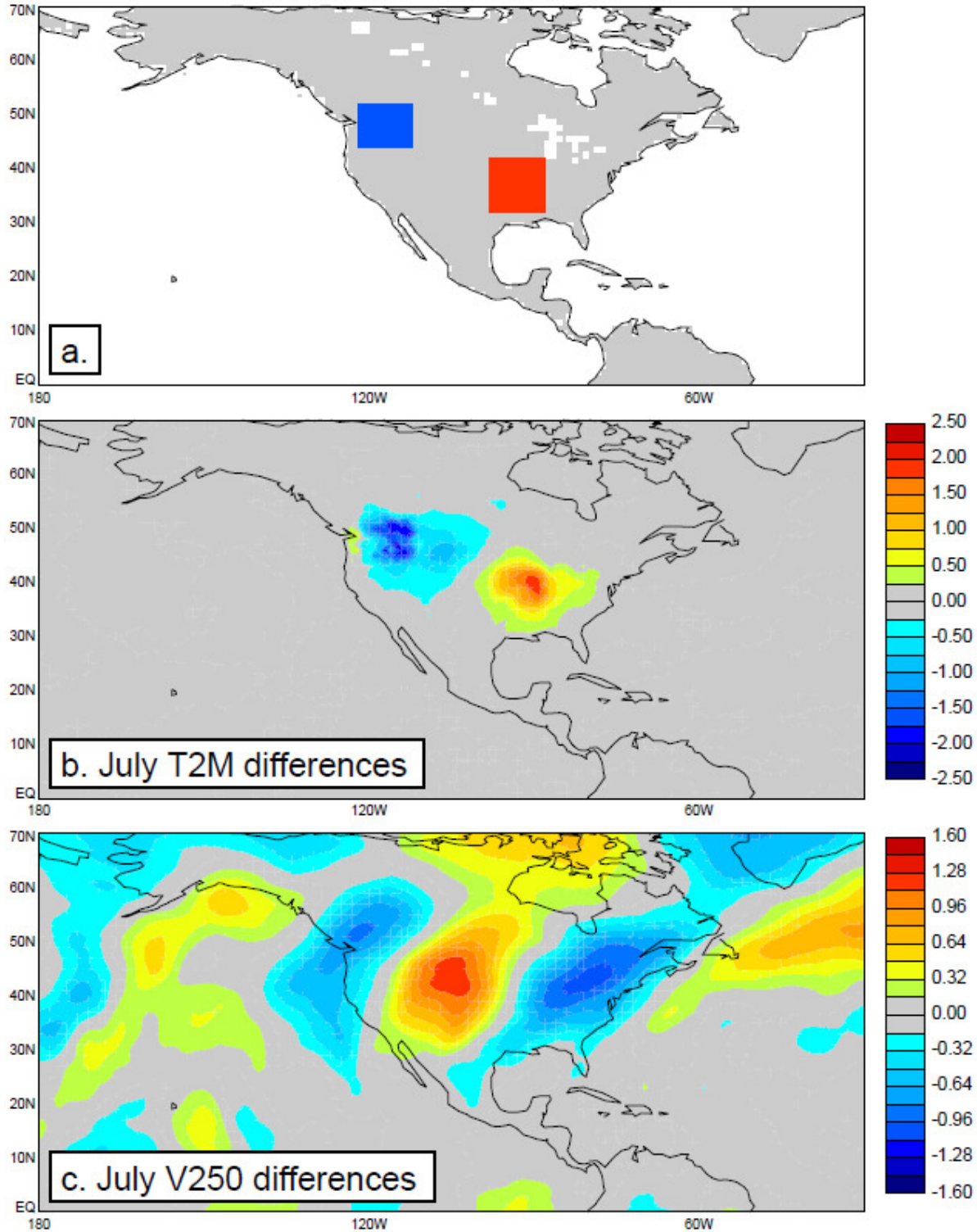
304 Figure 4. a. Standard normal deviate of reanalysis April soil moisture, composited over the 20%
305 of reanalysis years for which the April soil moisture dipole in the outlined areas (same as those
306 in Figure 2a) is strongest (see text). b. Corresponding composite (i.e., for the same reanalysis
307 years) of July surface air temperature anomalies. c. Corresponding composite (i.e., for the same
308 reanalysis years) of July 250 mb meridional wind anomalies.

309



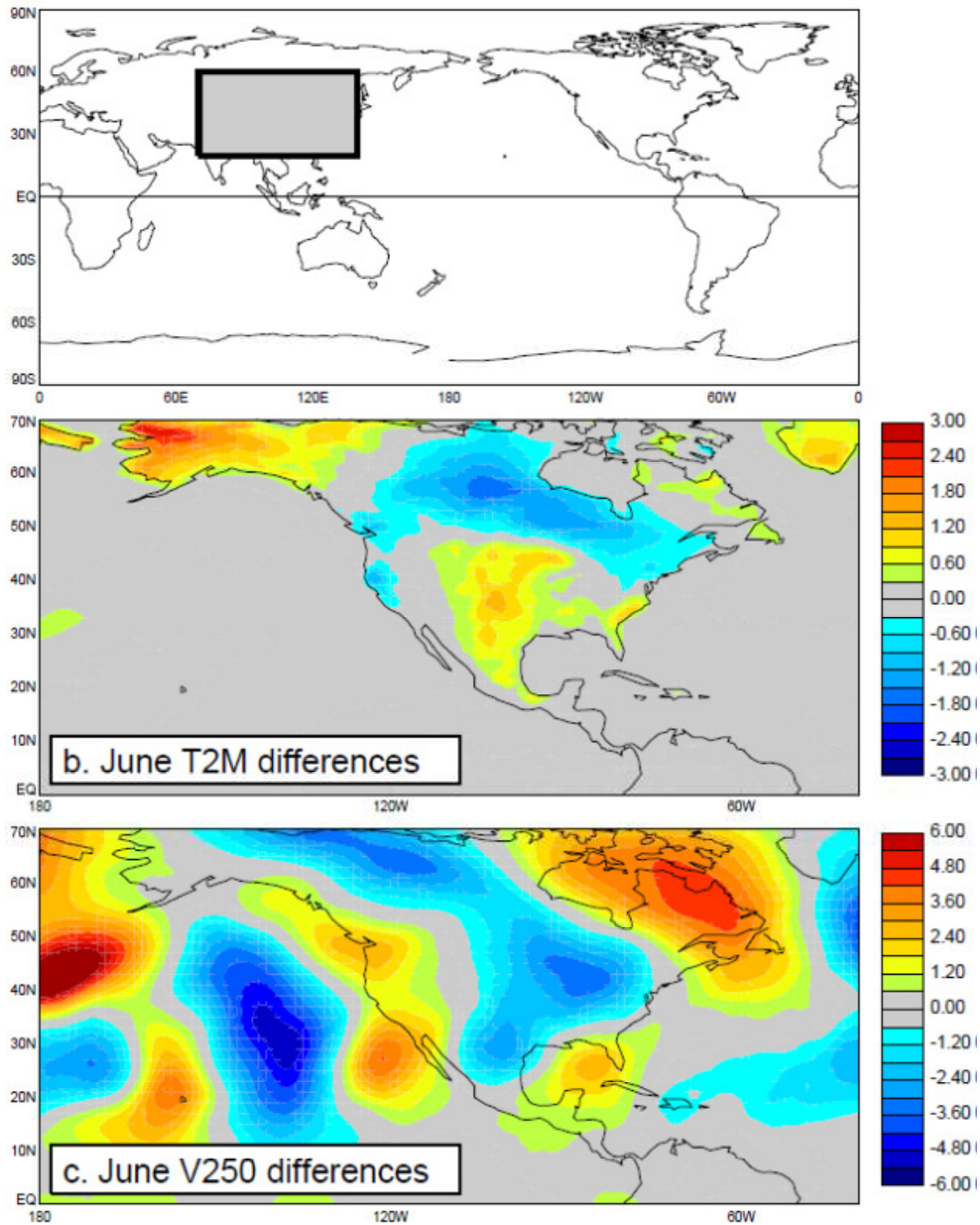
310

311 Figure 1. a. Composite of the standard normal deviate of April soil moisture over the 20% of
 312 simulation years for which the April soil moisture dipole centered on the small white circles is
 313 strongest (see text). b. Corresponding composite (i.e., for the same simulation years) of July
 314 surface air temperature anomalies. c. Corresponding composite (i.e., for the same simulations
 315 years) of July 250 mb meridional wind anomalies.



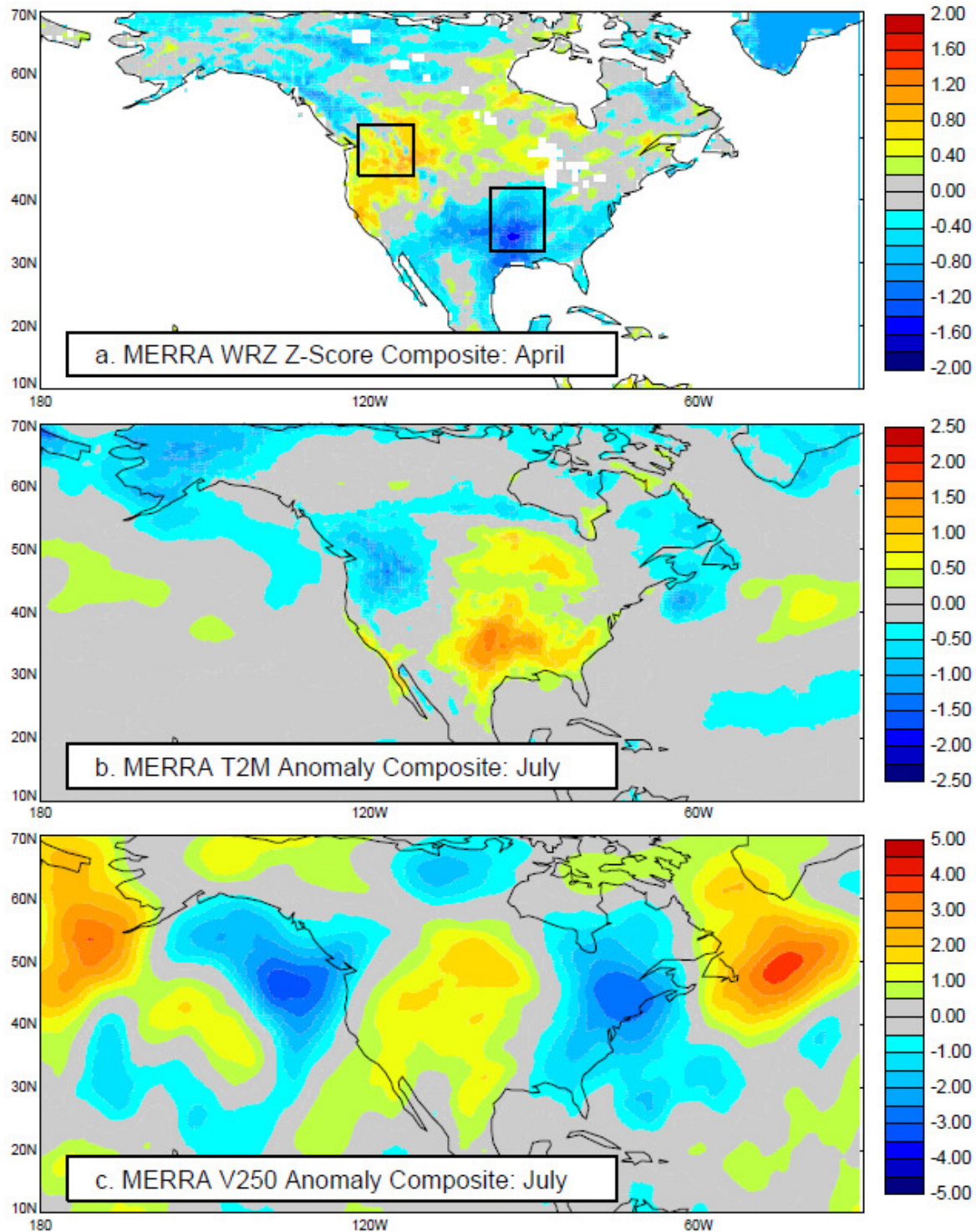
316

317 Figure 2. a. Locations where April precipitation is modified in specialized experiments. April
 318 precipitation water applied to the land surface is increased five-fold in the blue area, and it is set
 319 to zero in the red area. b. Resulting July surface air temperature anomalies. c. Resulting July
 320 250 mb meridional wind anomalies.



321

322 Figure 3. a. Location of the upstream area over which atmospheric states were forced to agree
 323 with states from an analysis (and thus were forced to be realistic), using a technique known as
 324 ‘replay’. b. Resulting June surface air temperature anomalies. c. Resulting June 250 mb
 325 meridional wind anomalies.



326

327 Figure 4. a. Standard normal deviate of reanalysis April soil moisture, composited over the 20%
 328 of reanalysis years for which the April soil moisture dipole in the outlined areas (same as those
 329 in Figure 2a) is strongest (see text). b. Corresponding composite (i.e., for the same reanalysis
 330 years) of July surface air temperature anomalies. c. Corresponding composite (i.e., for the same
 331 reanalysis years) of July 250 mb meridional wind anomalies.