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Journal of Geophysical Research: Atmospheres

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Supporting Information for

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Skillful Subseasonal Forecasts of Weekly Tornado and Hail Activity using the Madden-Julian Oscillation

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18 **Introduction**

19 In Text S1, we demonstrate the robustness of our results to the heterogeneities found in
20 the storm reports. In Text S2, we provide the locations of the data repositories used in this study.
21 In the supporting figures, we display Figure 2 with its statistical significance plotted and the
22 plotting function's smoothing turned off (Figure S1); skill scores of forecasts for severe weather
23 variables using a leave-three-years-out cross validation rather than a leave-one-year-out cross
24 validation (Figure S2); composites of severe weather variables based on the RMM index rather
25 than the OMI (Figure S3); skill scores of forecasts for severe weather variables based on the
26 RMM index rather than the OMI (Figure S4); composites of tornado and hail reports rather than
27 events (Figure S5); skill scores of forecasts for tornado and hail reports rather than events
28 (Figure S6); and composites of tornado and hail events for the sub-periods of 1979-1996 and
29 1997-2015 (Figure S7). In Table S1, we provide sample sizes for the number of days in each
30 MJO phase.

31

32 **Text S1. Sensitivity of the results to heterogeneities in the storm reports**

33 There are well-documented, non-meteorological heterogeneities that influence the
34 upward trends seen in the numbers of tornado and severe hail reports in recent years, primarily
35 related to population growth, denser road networks, an increasing number of storm chasers, and
36 changes in reporting criteria (Agee & Childs, 2014; Allen & Tippett, 2015). Because we are
37 primarily concerned with the subseasonal variability of convective severe weather rather than its
38 interannual variability, these heterogeneities in the storm reports are not expected to be
39 excessively deleterious. With respect to the tornado reports, the non-meteorological influence is
40 diminished greatly by restricting our analysis to only tornado reports with intensities of EF1 or

41 greater because they show no discernible annual trend, as opposed to the inclusion of EF0
42 tornadoes which display a discontinuous upward jump in the 1990s associated with the advent of
43 Doppler radar (Agee & Childs, 2014; Tippett et al., 2015). With respect to both tornado and hail
44 reports, Allen and Tippett (2015) suggests three tests to gauge the robustness of an analysis to
45 heterogeneities, all of which we perform in this study. First, reports can be analyzed in the
46 context of events rather than total number of reports. We test the sensitivity of our analysis to
47 using reports instead of events and find little qualitative difference (compare Figures 2 and 5 to
48 Figures S5 and S6, respectively). Second, the analysis can be performed on a subsampling of
49 time periods. In Figures S7, we compare the two sub-periods of 1979–1996 and 1997–2015.
50 While there is little qualitative difference between the two sub-periods in the Plains, there are
51 differences evident in the Southeast. These differences likely explain the higher predictive skill
52 of the empirical prediction model in the Plains versus the Southeast (compare Figures 5d,e to
53 Figures 5i,j). Third, and perhaps most importantly, environmental parameters important to severe
54 weather activity can serve as proxies to the actual storm reports (Allen et al., 2015). We analyze
55 CAPE, SRH, and CSRH2 throughout this study and find their subseasonal behavior to be
56 consistent with that of the tornado and hail events (Figures 2 and 5).

57

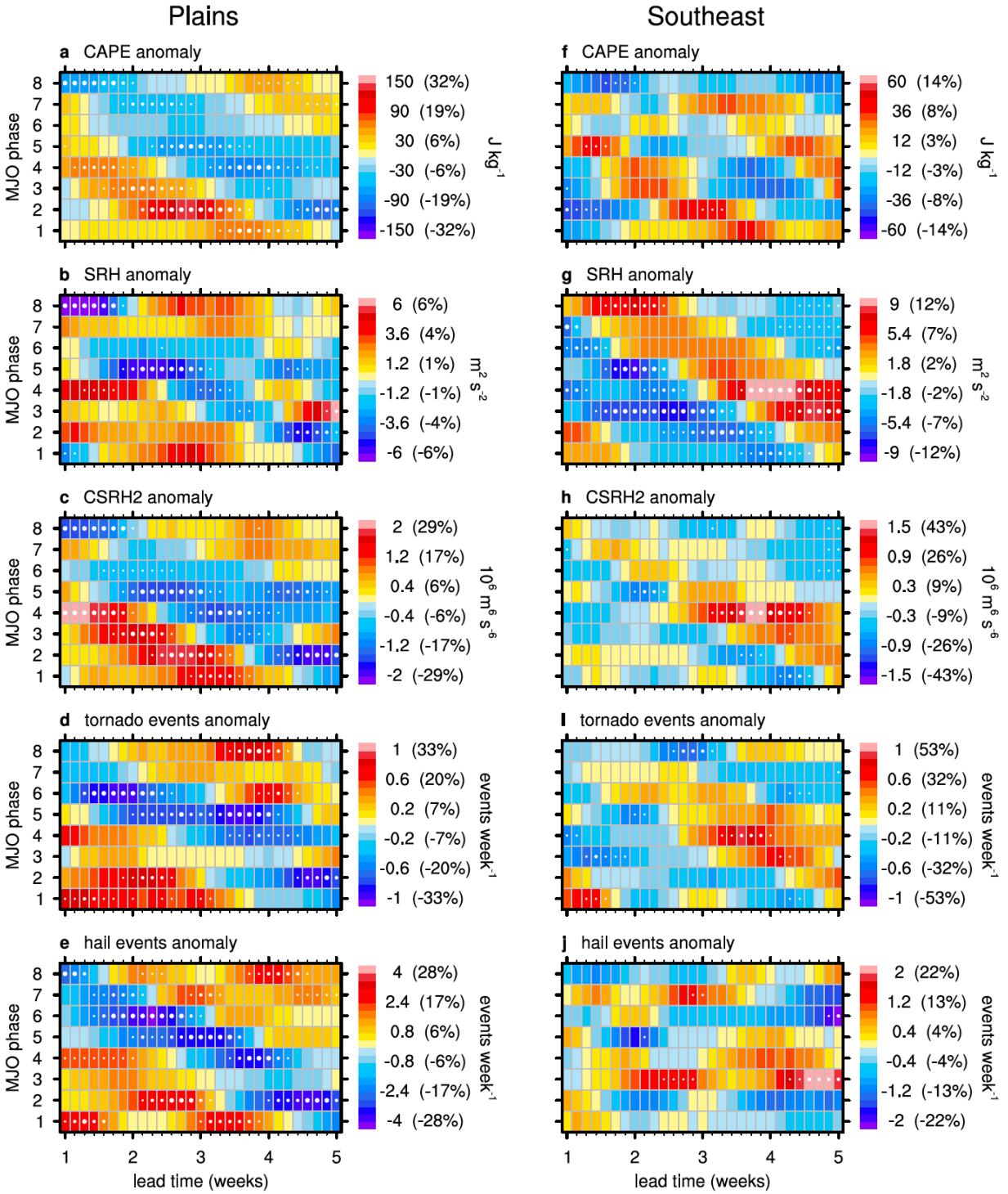
58 **Text S2. Data availability**

59 ERA-Interim data (Dee et al., 2011) were obtained on 8 September 2016 and are
60 available from the ECMWF public data set portal ([http://apps.ecmwf.int/datasets/data/interim-
61 full-daily/levtype=sfc/](http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/)).

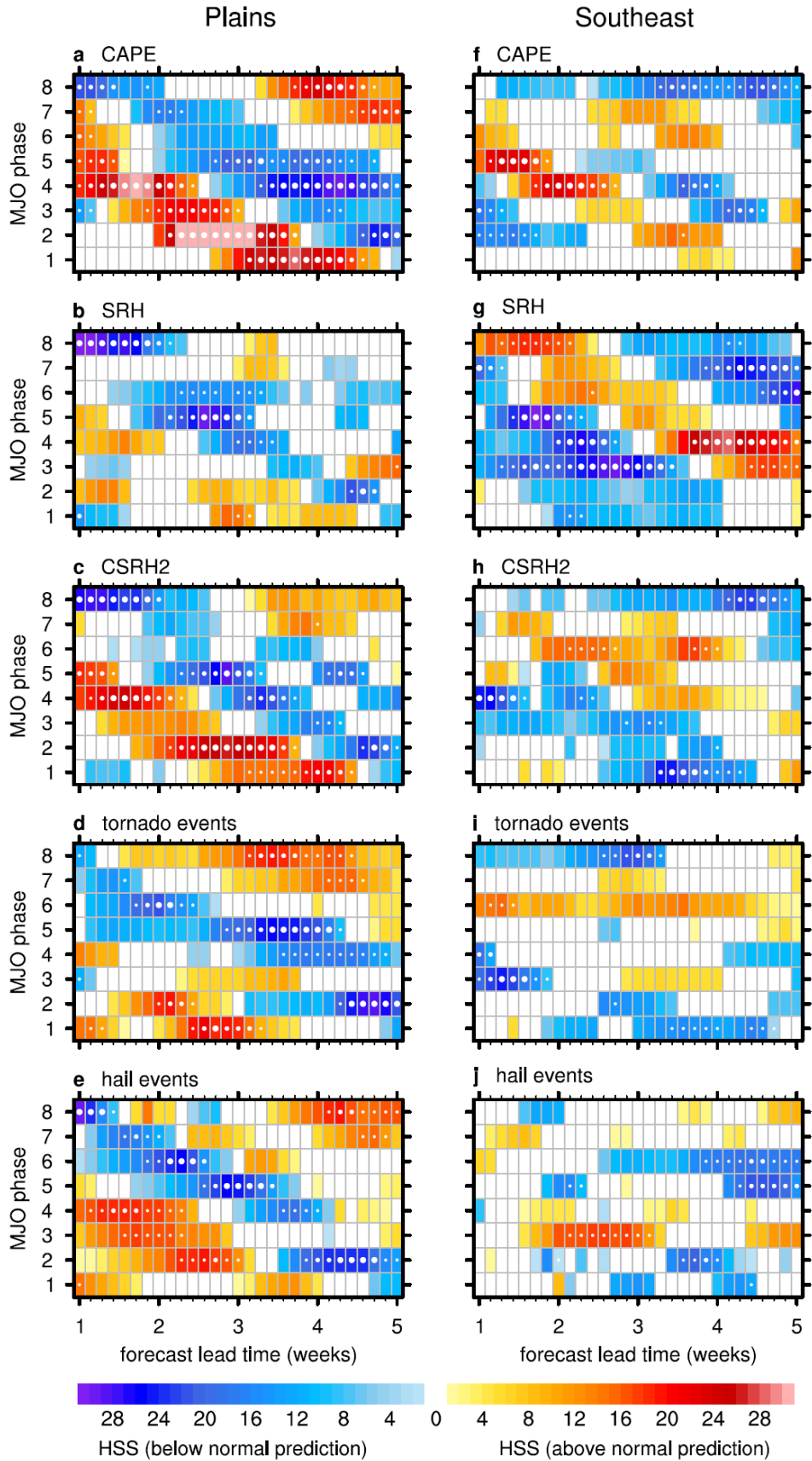
62 Tornado and hail reports data (Schaefer & Edwards, 1999) were obtained on 7 August
63 2017 and are available from the SPC's Severe Weather Database, archived at the National
64 Centers for Environmental Information (<https://www.ncdc.noaa.gov/stormevents/>).

65 The OMI (Kiladis et al., 2014) was obtained on 6 January 2017 and is available from
66 NOAA Earth System Research Laboratory Physical Sciences Division
67 (<https://www.esrl.noaa.gov/psd/mjo/mjoindex/>).

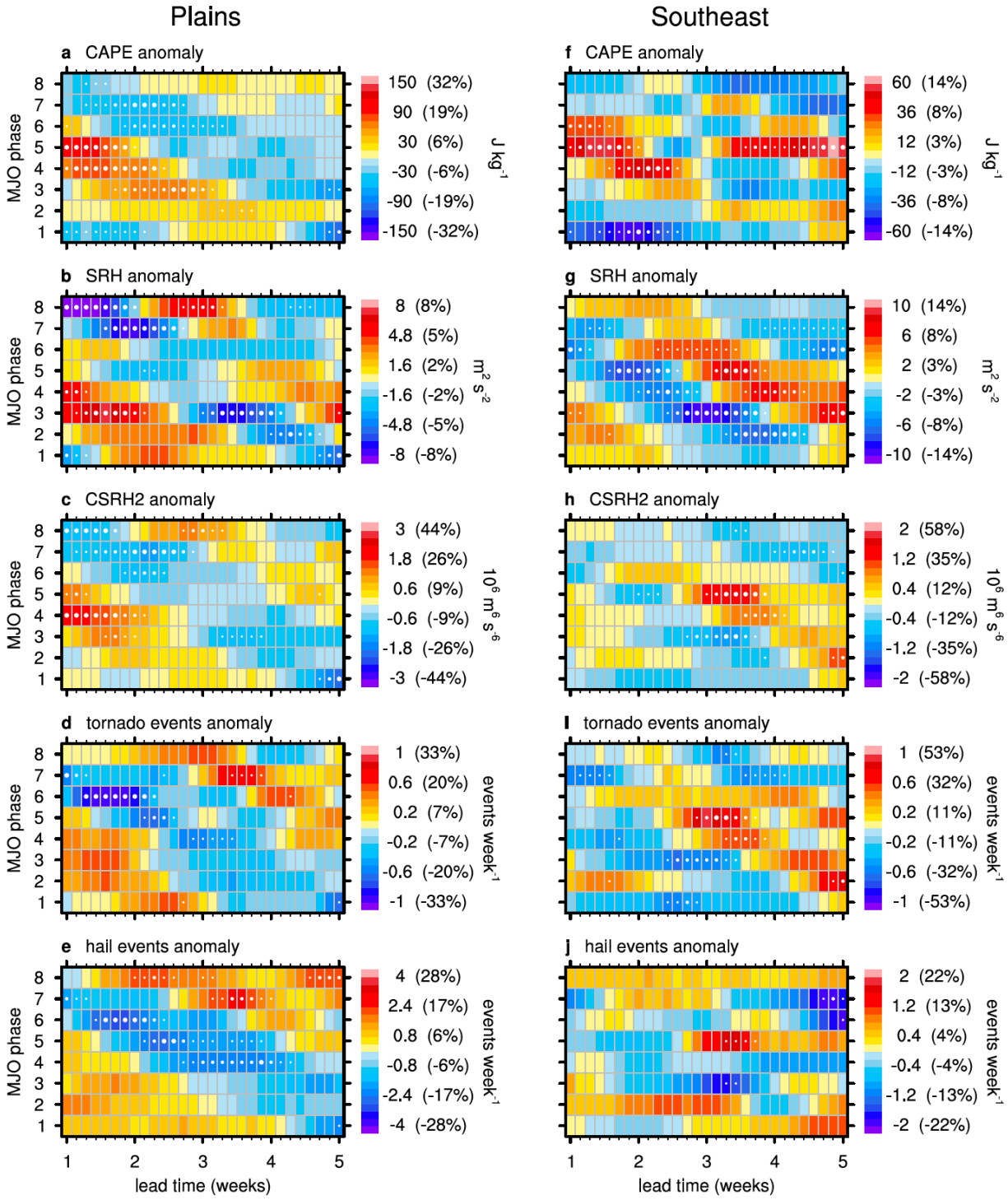
68 The RMM index (Wheeler & Hendon, 2004) was obtained on 11 October 2016 and is
69 available from the Australian Government Bureau of Meteorology
70 (<http://www.bom.gov.au/climate/mjo/>).



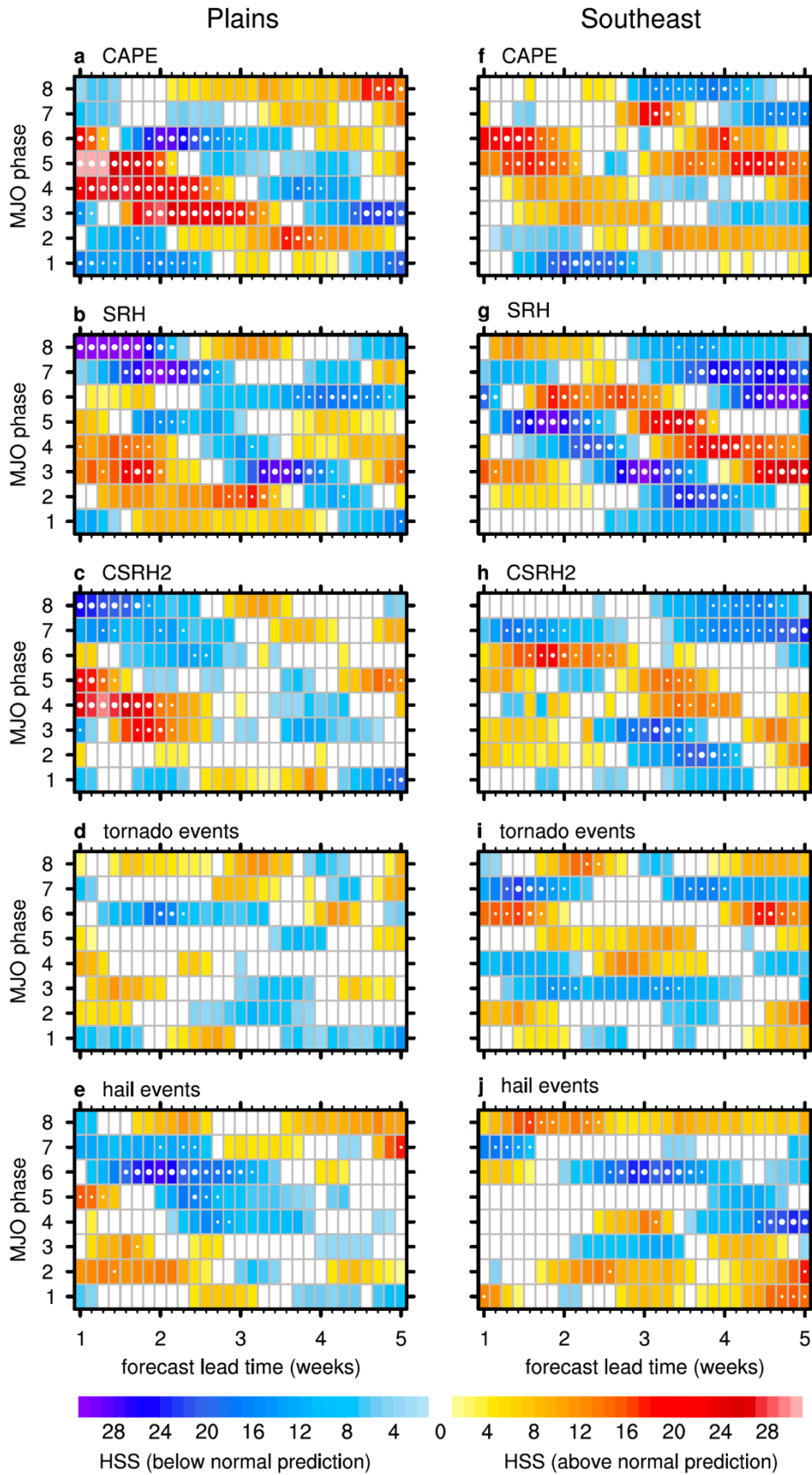
72 **Figure S1.** As in Figure 2 but with its statistical significance plotted and the plotting function's
73 smoothing turned off. Statistical significance is conveyed by small, medium, and large white dots
74 for composites of MJO phase and lead time that are more skillful than 80%, 90%, and 95%,
75 respectively, of 1000 random composites generated by a bootstrapping technique that accounts
76 for autocorrelation (see Section 2.6).



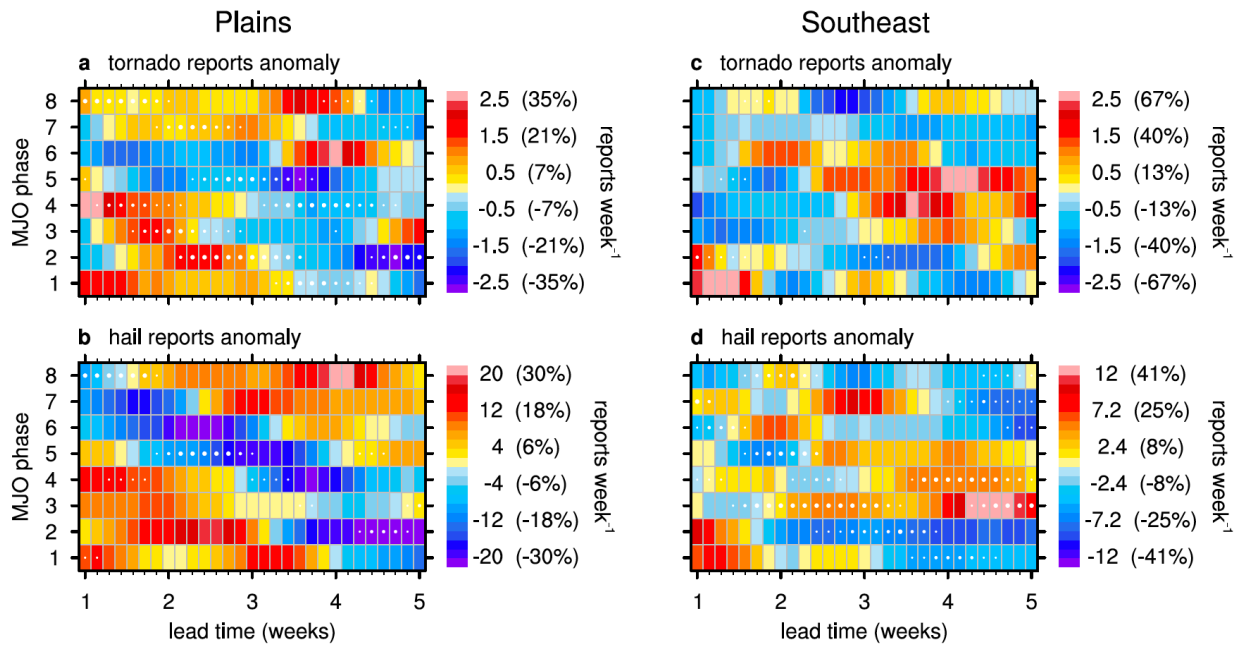
78 **Figure S2.** As in Figure 5, except the Heidke skill scores of the empirical prediction model for
79 leave-three-years-out cross validation rather than leave-one-year-out cross validation are shown
80 for **(a,f)** CAPE, **(b,g)** SRH, **(c,h)** CSRH2, **(d,i)** tornado events, and **(e,j)** hail events for the **(a-e)**
81 Plains and **(f-j)** Southeast. Forecasts are issued for 12 consecutive, non-overlapping three-year
82 periods. These forecasts are generated from each period's respective training period of 34 left-
83 out years. For example, the years 1982–2015 constitute the training period used to generate a
84 forecast for 1979–1981; and the years 1979–2011 and 2015 are used to generate a forecast for
85 2012–2014.



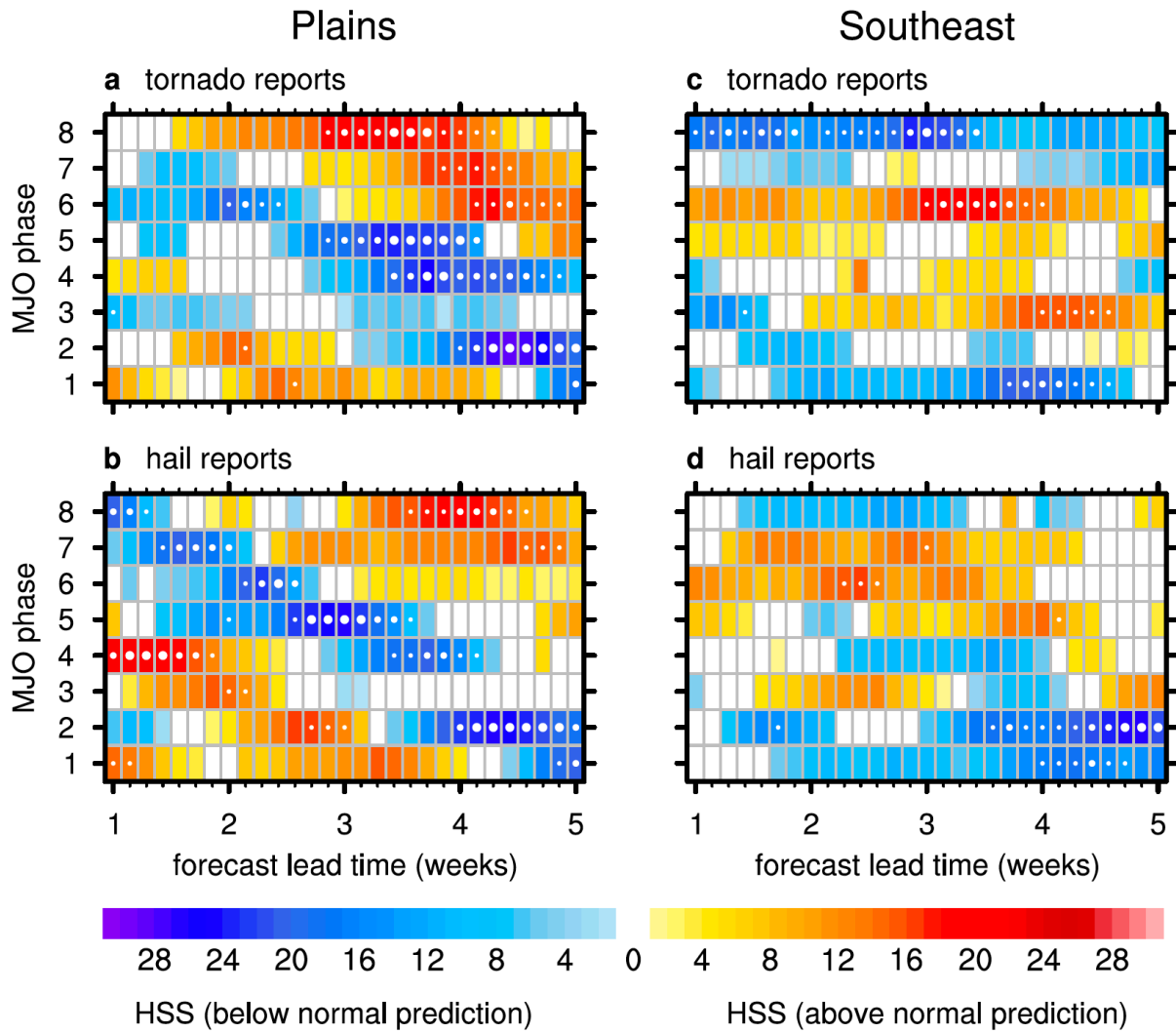
87 **Figure S3.** As in Figure S1, except composites based on the RMM index rather than the OMI are
88 shown for anomalous **(a,f)** CAPE, **(b,g)** SRH, **(c,h)** CSRH2, **(d,i)** tornado events, and **(e,j)** hail
89 events for the **(a-e)** Plains and **(f-j)** Southeast.



91 **Figure S4.** As in Figure 5, except Heidke skill scores of the empirical prediction model based on
92 the RMM index rather than the OMI are shown for **(a,f)** CAPE, **(b,g)** SRH, **(c,h)** CSRH2, **(d,i)**
93 tornado events, and **(e,j)** hail events for the **(a-e)** Plains and **(f-j)** Southeast.

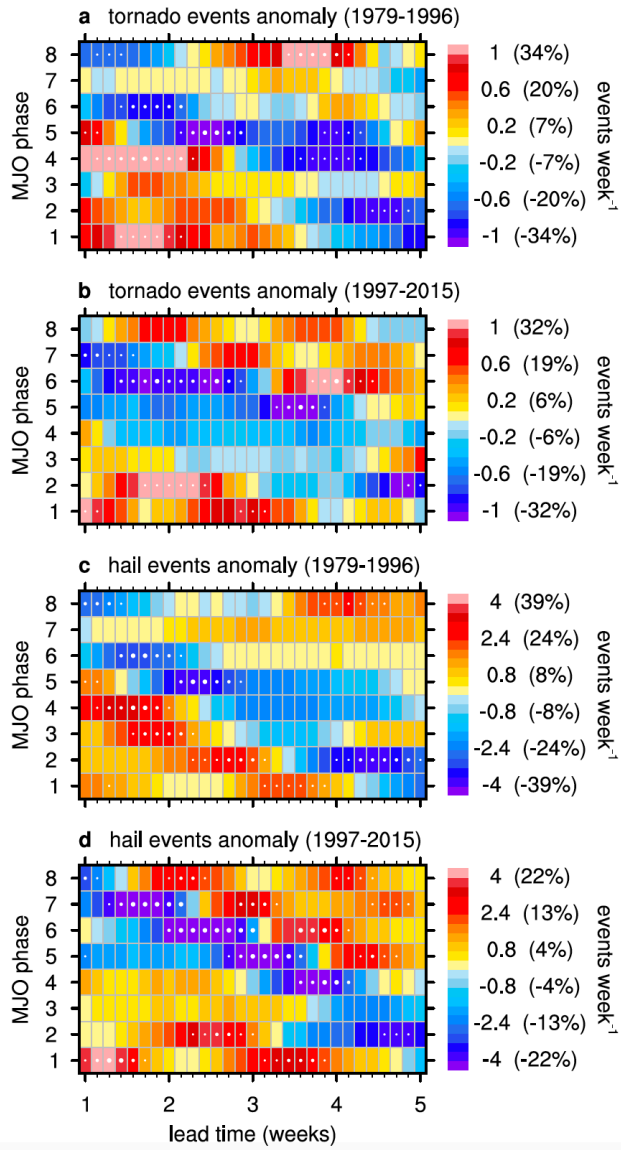


96 **Figure S5.** As in Figure S1, except composites are shown of anomalous **(a,c)** tornado reports and
97 **(b,d)** hail reports rather than tornado events and hail events for the **(a,b)** Plains and **(c,d)**
98 Southeast.

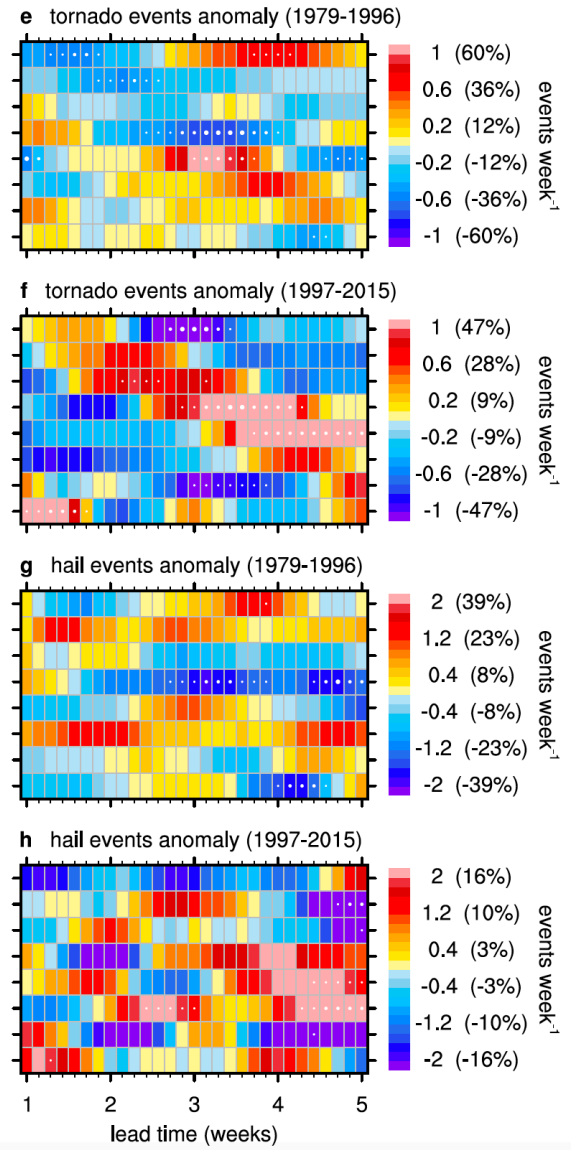


100 **Figure S6.** As in Figure 5, except Heidke skill scores of the empirical prediction model are
101 shown for **(a,c)** tornado reports and **(b,d)** hail reports rather than tornado events and hail events
102 for the **(a,b)** Plains and **(c,d)** Southeast.

Plains



Southeast



104 **Figure S7.** As in Figure S1, except composites for the sub-periods of 1979–1996 and 1997–2015
105 rather than 1979–2015 are shown for anomalous **(a,b,e,f)** tornado events and **(c,d,g,h)** hail events
106 for the **(a-d)** Plains and **(e-h)** Southeast during the sub-periods of **(a,c,e,g)** 1979–1996 and
107 **(b,d,f,h)** 1997–2015.

| a OMI MJO Phase | Sample Size | |
|---------------------------|-------------|----------|
| | n | n_{eq} |
| 1 | 298 | 65 |
| 2 | 315 | 62 |
| 3 | 389 | 69 |
| 4 | 318 | 70 |
| 5 | 291 | 68 |
| 6 | 376 | 82 |
| 7 | 402 | 76 |
| 8 | 332 | 74 |

| b RMM MJO Phase | Sample Size | |
|---------------------------|-------------|----------|
| | n | n_{eq} |
| 1 | 407 | 101 |
| 2 | 351 | 97 |
| 3 | 337 | 90 |
| 4 | 358 | 100 |
| 5 | 324 | 91 |
| 6 | 347 | 83 |
| 7 | 353 | 90 |
| 8 | 397 | 96 |

110 **Table S1.** The number of days n (sample size) that the MJO resides in each phase with an
111 amplitude ≥ 1 during March-June are shown for **(a)** the OMI and **(b)** the RMM index. The MJO
112 typically resides in a particular phase with an amplitude ≥ 1 for “blocks” of consecutive days in a
113 row. The number of these unique blocks n_{eq} (equivalent sample size) are shown for **(a)** the OMI
114 and **(b)** the RMM index. When calculating statistical significance (see Section 2.6), n_{eq} is used to
115 account for the inherent autocorrelation that the MJO exhibits.