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¹ Decreased monsoon precipitation in the Northern ² Hemisphere due to anthropogenic aerosols

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3 **Abstract.** The Northern Hemisphere monsoons are an integral compo-
4 nent of Earth's hydrological cycle and affect the lives of billions of people.
5 Observed precipitation in the monsoon regions underwent substantial changes
6 during the second half of the 20th century, with drying from the 1950s to
7 mid-1980s and increasing precipitation in recent decades. Modeling studies
8 suggest anthropogenic aerosols has been a key factor driving changes in trop-
9 ical and monsoon precipitation. Here we apply detection and attribution meth-
10 ods to determine whether observed changes are driven by human influences
11 using fingerprints of individual forcings (i.e. greenhouse gas, anthropogenic
12 aerosol and natural) derived from climate models. The results show that the
13 observed changes can only be explained when including the influence of an-
14 thropogenic aerosols, even after accounting for internal climate variability.
15 Anthropogenic aerosol, not greenhouse gas or natural forcing, has been the
16 dominant influence on Northern Hemisphere monsoon precipitation over the
17 second half of the 20th century.

1. Introduction

18 Human induced changes to the hydrological cycle are amongst the most serious impacts
19 of climate change, with potential consequences for water resources, health, agriculture
20 and ecosystems worldwide. Warming of the atmosphere due to increasing greenhouse
21 gas concentrations causes atmospheric water vapor to increase in line with the Clausius
22 Clapeyron relationship at $\sim 7\%K^{-1}$ [*Held and Soden, 2006; Willett et al., 2010*]. Conse-
23 quently, global precipitation also increases, though at a lower rate ($\sim 2\%K^{-1}$) due to energy
24 balance constraints [*Allen and Ingram, 2002; Trenberth et al., 2003*]. Increasing moisture
25 transport is expected to enhance the existing pattern of precipitation minus evaporation,
26 with increasing tropical and decreasing subtropical precipitation [*Held and Soden, 2006;*
27 *Seager and Naik, 2012*]. The increase in precipitation due to warming is partly offset
28 by anthropogenic aerosols. Aerosols scatter and absorb incoming solar radiation, caus-
29 ing cooling at the surface and heating of the atmosphere [*Ming and Ramaswamy, 2009*].
30 Aerosols also influence precipitation by interacting with clouds [*Rotstayn and Lohmann,*
31 *2002*], and models that include this process tend to better reproduce observed tempera-
32 ture and precipitation records of the 20th century [*Wilcox et al., 2013*]. The asymmetrical
33 cooling from aerosols between the Northern and Southern Hemispheres also affects tropi-
34 cal precipitation by causing a southward shift of the ITCZ [*Rotstayn and Lohmann, 2002;*
35 *Ackerley et al., 2011; Hwang et al., 2013*].

36 The counter-acting effects of greenhouse gases and aerosols on precipitation, and the
37 similar spatial response patterns, can make distinguishing their influence challenging [*Xie*
38 *et al., 2013*]. Detection and attribution studies have shown that greenhouse gas forcing

39 has influenced changes in global precipitation [*Polson et al.*, 2013a, b; *Wu et al.*, 2013].
40 These studies attribute observed changes to individual forcings using statistical analysis
41 techniques that account for the internal variability of the climate. However, the influence
42 of aerosols has yet to be separated from the combined anthropogenic forcing [*Zhang et al.*,
43 2007; *Polson et al.*, 2013b] or the combined influence of all non-greenhouse gas forcings,
44 though this is assumed to be dominated by aerosols [*Wu et al.*, 2013]. Anthropogenic aerosol
45 emissions rapidly increased from the 1950s (Figure 1) and are thought to have contributed
46 to a reduction in precipitation in monsoon regions in Africa [*Held et al.*, 2005] and Asia
47 [*Lau and Kim*, 2006; *Meehl et al.*, 2008; *Guo et al.*, 2013]. Climate models that include
48 anthropogenic aerosol forcing better reproduce the observed decrease in South Asian mon-
49 soon precipitation [*Bollasina et al.*, 2011]. Here we investigate the influence of individual
50 forcings on summer monsoon land precipitation for the whole Northern Hemisphere dur-
51 ing 1951-2005, for which there are reliable long-term observational records. By analysing
52 the Northern Hemisphere monsoon system as a whole, rather than its regional manifes-
53 tations, we can more easily identify how external forcings have affected this important
54 component of the global overturning circulation. Detection and attribution [*Allen and*
55 *Stott*, 2003] provides a unique and rigorous technique to ascertain whether the observed
56 changes can be explained by internal climate variability alone, or whether external forcing
57 has played a role in driving the changes. Previous studies of monsoon precipitation are
58 limited to individual models or do not make use of such rigorous statistical methods. In
59 this study, large climate model ensembles are used to derive "fingerprints" of forcing for
60 individual and combined external forcings. Detection and attribution methods are applied
61 to determine which forcing, if any, can explain the observed changes.

2. Data: Observations and Models

62 Four observational datasets were used to calculate the mean summer (May-September)
63 precipitation anomalies in Northern Hemisphere summer monsoon (NHSM) region:
64 CRUTS3.21 (CRU) [Harris *et al.*, 2014], Global Precipitation Climatology Centre (GPCC)
65 [Schneider *et al.*, 2014], VasclimO [Beck *et al.*, 2005] and an updated version of the dataset
66 from Zhang *et al.* [Zhang *et al.*, 2007]. Each dataset is aggregated to the same 5°x5° grid,
67 which is the lowest resolution among them. A grid box is only included in the analysis if
68 over 70% of the grid box is land and if it has coverage in over 95% of years.

69 Multi-model ensembles of climate model simulations from the Climate Model Inter-
70 comparison Project 5 (CMIP5) archive were used to derive response patterns to various
71 forcings including all external forcings (ALL), which combines anthropogenic (greenhouse
72 gases, aerosols, land use and ozone) and natural forcing (volcanic and solar), greenhouse
73 gas forcing (GHG), anthropogenic aerosol forcing (AA), natural forcing (NAT) and all
74 anthropogenic forcings (ANT) (Supplementary Table S1).

3. Northern Hemisphere Summer Monsoon Region

75 Following Hsu *et al.* [2011], the NHSM region encloses grid boxes for which the mean
76 annual range (difference between the May-September and November-March averages) in
77 precipitation for all years exceeds 2 mm day⁻¹ and the mean May-September precipita-
78 tion exceeds 55% of the annual total. Grid boxes are excluded if they are north of the
79 subtropics (40° N) or isolated. The region is fixed for all years, therefore any spatial shift
80 of monsoon is not captured. However changes in precipitation due to possible variations
81 in the monsoon area should be small compared to the total precipitation in the whole
82 region. Figure 2 shows the NHSM region does not change by much over the observation

83 period, with only a few grid boxes that meet the criteria in at least 1 year excluded from
84 the final NHSM mask. An alternative method would allow the region to change year by
85 year, but this could result in the region changing size, making it difficult to distinguish
86 changes in precipitation rate from changes due to the NHSM region shrinking or growing
87 over time. The NHSM region is defined for each observational dataset and the model data
88 are masked to match the spatial and temporal coverage of each.

4. Detection and Attribution

89 The 1951-2005 timeseries for the mean May-September precipitation anomalies (with
90 respect to the mean for 1951-2005, 2000 for the VasclimO dataset) are calculated for the
91 NHSM region. The analysis ends in 2005 as many historical model simulations do not run
92 beyond that year. A 5-year running mean is applied to smooth the data prior to analysis,
93 and the smoothed timeseries are used in a total least squares regression [*Allen and Stott,*
94 2003]. The model derived fingerprints of forcing, \mathbf{F} , are scaled to the observations, \mathbf{y} , to
95 estimate the contribution of p forcings to the NHSM precipitation using

$$\mathbf{y} = (\mathbf{F} + \varepsilon_{finger})\beta + \varepsilon_{noise} \quad (1)$$

96 where \mathbf{F} is a $l \times p$ matrix for p forcing fingerprints of length l representing time and \mathbf{y} is
97 a rank- l vector representing the observed monsoon precipitation change. β is a vector of
98 scaling factors with p entries giving the magnitude of each fingerprint in the observations,
99 ε_{noise} is the residual associated with internal climate variability and ε_{finger} is variability
100 that remains in the fingerprint after multi-model averaging.

101 To ensure the observations can not be explained by internal climate variability alone,
102 multiple samples of climate noise, estimated from the model internal variability, are added
103 to the noise-reduced (see below) $\tilde{\mathbf{F}}$ and $\tilde{\mathbf{y}}$ and β is recalculated. If $\beta > 0$ at 5% significance
104 level, then the fingerprint response pattern is detected in the observations [*Hegerl and*
105 *Zwiers, 2011*]. If $0 < \beta < 1$, the models overestimate the observations and if $\beta > 1$ then the
106 models underestimate observations. Because climate models tend to underestimate the
107 observed variability in precipitation (supplementary Figure S14), the model variance is
108 doubled when calculating the noise samples.

109 Best estimates of the noise reduced observations and model fingerprints are calculated
110 using

$$\tilde{\mathbf{Z}} = \mathbf{Z} - \mathbf{Z}\tilde{\mathbf{v}}\tilde{\mathbf{v}}^T \quad (2)$$

111 where $\mathbf{Z} \equiv [\mathbf{F}, \mathbf{y}]$ and $\tilde{\mathbf{v}}$ contains the eigenvector coefficients used to calculate β when
112 solving Eq. 1. The robustness of the result is assessed by comparing the regression
113 residual, ε_{noise} , to samples of model variability using the F-test described in *Allen and*
114 *Stott [2003]*.

115 In this analysis the noise samples are taken from the greenhouse gas only ensemble by
116 subtracting the multi-model mean from each individual model simulation, and multiplying
117 by $\sqrt{\frac{n}{n-1}}$, where n is the number of simulations in the ensemble, to avoid bias in the
118 variance. The estimate of internal variability should not be sensitive to the choice of a
119 specific ensemble, and though the ALL forced ensemble would provide the most samples of
120 noise, it was prohibitively large so was not used (note that use of the ALL ensemble for the
121 1-signal and 2-signal analysis yielded very similar results). The ALL ensemble was used

122 to calculate samples of noise for the residual consistency check. All the results presented
123 here are based on non-optimised fingerprints. While optimising the fingerprints using
124 the internal variability covariance matrix can enhance detectability, it also complicates
125 interpretation by requiring truncation to a lower-dimensional space. See *Allen and Stott*
126 [2003] for more details.

127 The ALL fingerprint is regressed onto the observation in a 1-signal analysis to determine
128 whether external forcing is detectable in the observations. To separately investigate the
129 aerosol impact on radiation (direct effect) and the effect on clouds (indirect effect), the
130 ALL forced models are also divided into two groups, those that include both effects
131 and those that include the direct effect only (see Table S1 and Figure S3). The ALL
132 fingerprint is a combination of a number of different individual forcings that for the whole
133 NHSM region add approximately linearly in models (Supplementary Information). A 2-
134 signal analysis was applied to distinguish the role of these individual forcings in driving
135 the observed changes by simultaneously regressing ANT&NAT, AA&GHG, AA&NAT
136 and GHG&NAT fingerprints onto the observations. We also apply a further test by
137 simultaneously regressing the AA, GHG and NAT fingerprints onto observations in a 3-
138 signal analysis. For the 2-signal and 3-signal analysis, all available models were used to
139 produce the fingerprints of forcing, meaning that a different number of simulations and
140 different models were used for different forcings. To ensure this did not influence the
141 results, the detection and attribution analysis was repeated with the same models used
142 to produce the fingerprints in each pair of forcings for the 2-signal analysis and the GHG,
143 NAT and AA fingerprints for the 3-signal analysis. The detection results were the same for
144 all cases regardless of the ensemble used to produce the fingerprints (see supplementary

145 Figure S12). The residual consistency check passes for all results presented here except
146 for 1 case where the ALL fingerprint is regressed onto the Zhang observational data
147 (highlighted in the Figure 3 caption).

5. Results

148 The observed 1951-2005 monsoon precipitation anomalies show a distinctive drying pat-
149 tern from 1951 to the mid-1980s, followed by increasing precipitation until 2000 (Figure
150 1(a)). During 2000-2005, there is a striking inconsistency amongst the available obser-
151 vational datasets, likely due to the drop in the number of stations during this period
152 [*Schneider et al.*, 2014]. Nevertheless, all observational datasets show a decrease in pre-
153 cipitation from 1951 to 2005; fitting linear trends gives an overall decrease of 4%–10% of
154 the mean precipitation, depending on dataset.

155 Including anthropogenic aerosols substantially improves models' ability to reproduce
156 the observations. The precipitation changes (Figure 1(a)) of the ALL, ANT and AA
157 multi-model means have the same general behaviour as observations, with decreasing
158 precipitation from 1951 to mid-1980s, followed by a recovery during the 1990s. In contrast
159 to observations, the GHG multi-model mean shows precipitation consistently increasing
160 during this period. The NAT multi-model mean has no overall trend but has short term
161 drying following volcanic eruptions.

162 The signature of anthropogenic forcing is distinctly recognisable over other forcings
163 and is mostly associated with aerosols. While the ALL and ANT multi-model mean
164 unsmoothed timeseries correlate with AA (0.25 and 0.33 respectively, p -value <0.1), GHG
165 is negatively correlated with both ALL and ANT (-0.27 in both cases). ALL and ANT
166 also resemble the observations (correlation >0.36 and p -values <0.05 in all cases). AA

167 is positively correlated with observations while GHG and observations are negatively
168 correlated. Spatial linear trend patterns also show more similarity between observed, ALL,
169 ANT and AA, which show drying in many areas, than GHG which results in increasing
170 precipitation over most of the NHSM region (Supplementary Figure S2).

171 That aerosols may be a key factor implicated in the 20th century monsoon precipitation
172 changes is also suggested by increasing global aerosol emissions from the 1950s to mid-
173 1980s, followed by a period of decreasing emissions (Figure 1(b)), which mirrors the
174 changes in precipitation, though local emissions continue to increase during this period.
175 This hints that aerosols from remote sources also contribute to the NHSM changes, as
176 several studies have suggested to be the case for the Asian monsoon (see e.g. *Cowan and*
177 *Cai* [2011]). However, it is not possible to quantify the relative influence of remote and
178 local emissions from the analysis in this paper.

179 Results for the detection and attribution analysis confirm that external forcing has
180 played a substantial role in driving the observed changes. When the ALL fingerprint is
181 scaled to the observations, we find that it is detectable (Figure 3(a)), and larger than
182 simulated in models (scaling factors range from 2.6 to 3.7). Repeating the regression for
183 direct effect and indirect effect groups suggests that at least in the CMIP5 models, inclu-
184 sion of the indirect effect does not significantly improve detection and attribution results
185 (Figure 3(a)). However different spatial trend patterns suggest the indirect effect does
186 play an important role over parts of Asia. Models that include the indirect effect tend
187 to simulate more drying than models that only include the direct effect (Supplementary
188 Figure S2). We add a note of caution that currently models still have limited representa-

189 tion of the indirect effect, which additionally can lead to counteracting changes [*Stevens*
190 *and Feingold, 2009*].

191 Simultaneous regression of the ANT and NAT fingerprints onto the observations shows
192 that while the ANT fingerprint is detectable, NAT can not be distinguished from internal
193 climate variability (Figure 3(b)). Results for AA&GHG, AA&NAT and GHG&NAT show
194 that anthropogenic aerosol forcing is largely responsible for changes in NHSM precipita-
195 tion, with its fingerprint detectable in observations (when estimated against GHG, NAT;
196 Figs 3c, S1), while that of other forcings generally is not. GHG estimated against NAT
197 yields a detectable NAT signal in some cases.

198 Simultaneously regressing the AA, GHG and NAT fingerprints onto observations in
199 a 3-signal analysis (Figure 3(d)) confirms that anthropogenic aerosol forcing, which is
200 detectable in observations, is driving changes in NHSM precipitation, while the influence
201 of greenhouse gas and natural forcing can not be distinguished from internal climate
202 variability.

203 Given the significance of the detected signal for the whole NHSM region, we tested if
204 all regions contributed to this finding or if it is attributable to one specific region. The
205 analysis was repeated excluding first South America (Supplementary Figure S11a), then
206 Africa (Supplementary Figure S11(b)) and finally Asia (Supplementary Figure S11(c)).
207 The results show that the detection of anthropogenic aerosol forcing is largely insensitive
208 to the exclusion of any one region. The detection and attribution results were also not
209 affected by including the mid-latitude sector of the NHSM region (supplementary Figure
210 S11(d)).

6. Discussion and Conclusions

211 Northern Hemisphere monsoon precipitation underwent substantial changes during the
212 second half of the 20th century. Climate models suggest that increasing greenhouse gas
213 concentrations alone would have caused an increase in precipitation during this period.
214 However, this is more than offset by the influence of anthropogenic aerosols, resulting in
215 a decrease in precipitation over the last 50 years. Internal climate variability is also likely
216 to have played in role in driving the observed changes. As temperatures in the Atlantic
217 ocean have been shown to influence Northern Hemisphere monsoon precipitation [*Chiang*
218 *and Friedman, 2012*], studies of multidecadal temperature variability in the tropical north
219 Atlantic suggest internal climate variability to be important [*Zhang et al., 2013*]. Satellite
220 observations of precipitation over both land and ocean show an intensification of monsoon
221 precipitation over the last 30 years [*Hsu et al., 2011*] which has also been linked to climate
222 variability such as ENSO [*Wang et al., 2013*]. However, the analysis in this paper shows the
223 influence of anthropogenic aerosol forcing on NHSM precipitation is detectable above this
224 internal climate variability. It provides compelling evidence that anthropogenic aerosols
225 are the dominant external factor influencing the observed changes in NHSM precipitation
226 over the second half of the 20th century, and that these changes can not be explained by
227 greenhouse gas forcing, natural forcing, or by internal climate variability alone.

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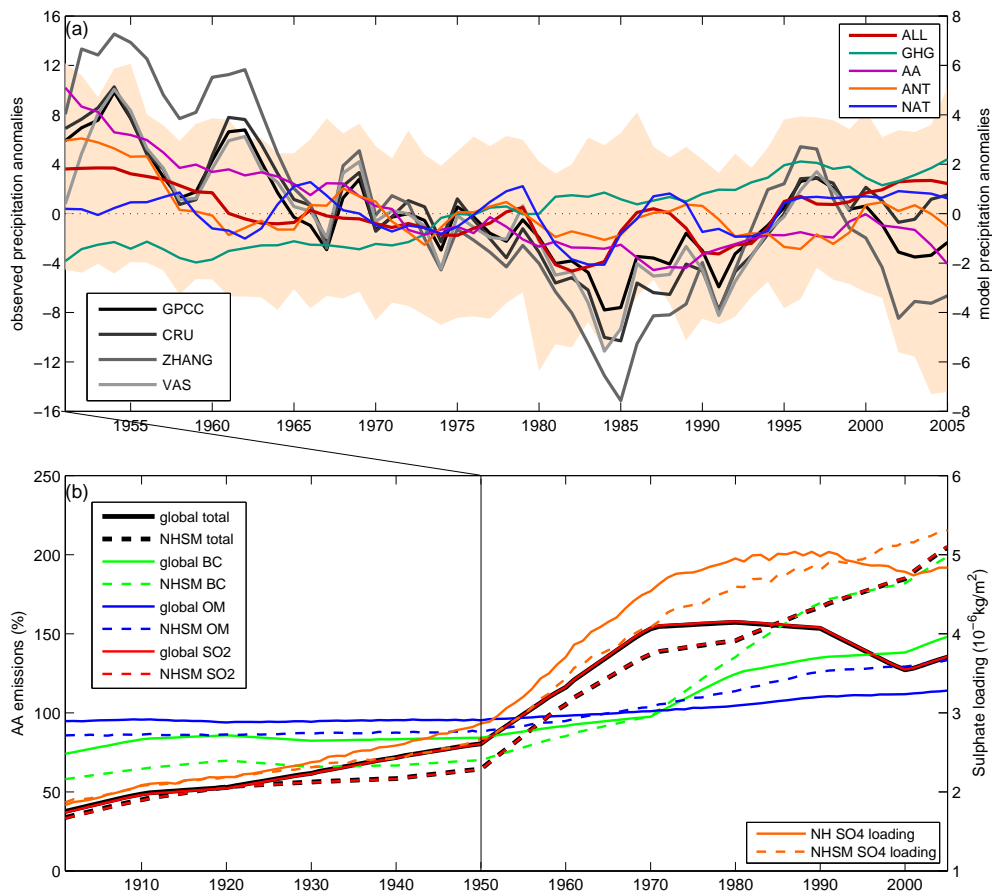


Figure 1. (a), May-Sep NHSM precipitation anomalies (mm/month) for 1951-2005 for observational datasets, CRU, GPCC, Zhang and VasClimO (VasClimO is 1951-2000). Multi-model mean anomalies (different scale to observations) are for all external forcings (ALL), greenhouse gas (GHG), anthropogenic aerosol (AA), natural (NAT) and anthropogenic (ANT) forcing. Anomalies are with respect to 1951-2005 and smoothed with a 5-year running mean. Orange shading shows the ALL ensemble 5%-95% range, (same scale as observations). Models are masked to the GPCC dataset. (b) Global and NHSM annual anthropogenic aerosol emissions, (% of 1901-2005 mean emissions). NHSM emissions are for 0° - 40° N. Total is BC+OM+SO₂, BC is black carbon, OM is organic matter and SO₂ is sulphur dioxide. The annual sulphate loading for the NH and NHSM region are also shown. Aerosol emissions are the CMIP5 emissions based on *Lamarque et al.* [2010] and sulphate loading is the mean of 11 climate models.

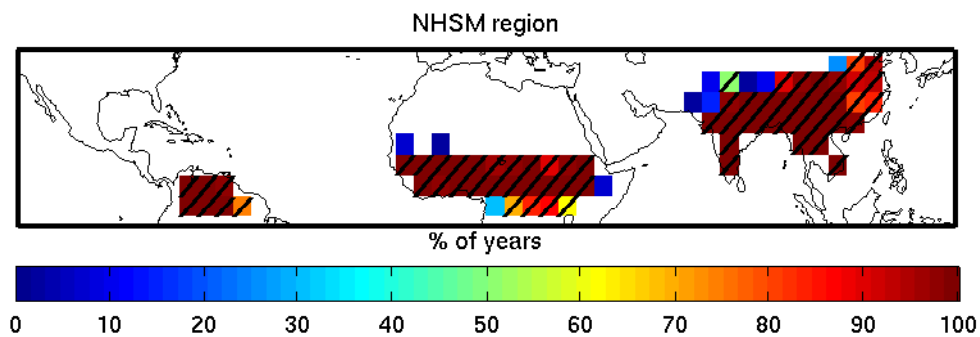


Figure 2. Northern Hemisphere summer monsoon region for GPCP. Percentage of years a grid box meets the NHSM precipitation criteria for GPCP dataset. Hatched areas show grid boxes defined in NHSM region based on mean annual range and May to September precipitation for all years in 1951-2005.

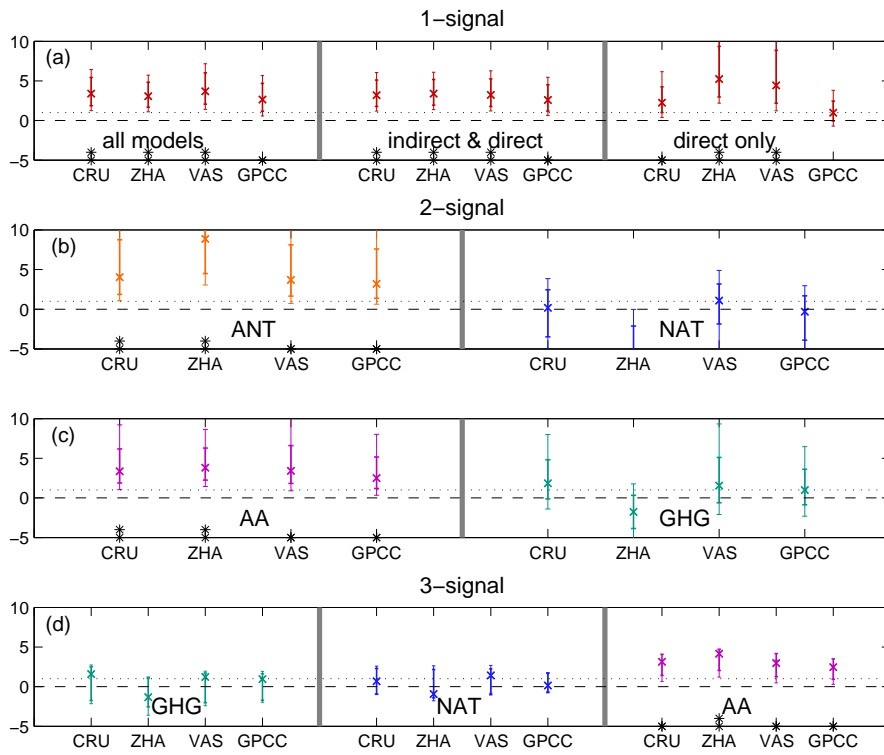


Figure 3. Detection and attribution of observed changes in Northern Hemisphere summer monsoon precipitation. (a), 1-signal regression for all external forcings (ALL), all external forcings for models with indirect and direct effects and all external forcings for models with direct effect only. (b), 2-signal regression for anthropogenic (ANT) and natural (NAT) forcing. (c), 2-signal regression for anthropogenic aerosol (AA) and greenhouse gas (GHG) forcing. (d), 3-signal regression for greenhouse gas (GHG), natural (NAT) and anthropogenic aerosol (AA) forcing. Results are shown for four observational datasets, CRU (CRU), Zhang (ZHA), VasClimO (VAS) and GPCC (GPCC). Crosses show the best-guess scaling factor for the multi-model mean, thick lines are the 90% confidence interval based on the raw variance and thin lines are the 90% confidence intervals when model variance has been doubled. The residual consistency test is passed, except for 1-signal ALL analysis for ZHA. Stars (*) show where forcing is detected and two stars (**) show where forcing is detected but inconsistent with a scaling factor of 1.