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Detection and Attribution of Human Influence on Regional Precipitation

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Understanding how human influence on climate is affecting precipitation around the world is immensely important for defining mitigation policies, and for adaptation planning. Yet despite increasing evidence for the influence of climate change on global patterns of precipitation, and expectations that significant changes in regional precipitation should have already occurred as a result of human influence on climate, compelling evidence of anthropogenic fingerprints on regional precipitation is obscured by observational and modelling uncertainties and is likely to remain so using current methods for years to come. This is in spite of substantial ongoing improvements in models, new reanalyses and a satellite record that spans over thirty years. If we are to quantify how human-induced climate change is affecting the regional water cycle, we need to consider novel ways of identifying the effects of natural and anthropogenic influences on precipitation that take full advantage of our physical expectations.

How rainfall is changing in a particular region is a question of great practical importance to societies. Floods and droughts threaten the lives and livelihoods of many people and enhancing their resilience is of major concern, particularly as anthropogenic climate change is expected to increase the frequency of floods and droughts[1]. These expected changes may, moreover, render risk assessments based purely on the historical record inaccurate. Well-planned adaptation to climate change thus requires information on how hazardous rainfall is changing in response to anthropogenic forcing. Are we observing systematic changes or are we simply experiencing natural variability? This is the business of detection and attribution (Box 1).

New observations and improved models have enabled the detection of anthropogenic change in the water cycle at large spatial scales[2, 3,4], although even here large uncertainties remain. The Intergovernmental Panel on Climate Change[5] (IPCC) in its Fifth Assessment Report (AR5) concludes that it is *likely* that anthropogenic influences have affected the global water cycle since 1960. In Section TS. 6.3 of AR5, two key uncertainties which limit confidence in attribution assessments of the causes of precipitation changes are recognised as 1) observational and modelling uncertainties, and 2) the large effect of internal variability. Hence there is only *medium confidence* that there is an anthropogenic contribution to global-scale changes in precipitation patterns over land since 1950, with higher levels of confidence precluded by uncertainty in models and observations and the large internal variability in precipitation[6].

At continental scales, there has been some limited success in detecting anthropogenic changes in land precipitation. Anthropogenically driven changes in zonal averages of land precipitation were detected by e.g., ref. 7 – although in some cases the results were found to be sensitive to the observational dataset used. Anthropogenic trends in precipitation have also been detected in the northern mid-to-high latitude lands[8, 9] and southwest Australia[10], where in both regions there are large expected trends that are coherent over wide areas (Figure TS.16 of IPCC, 2013). In general, however, detection and attribution of an anthropogenic signal at these scales is hampered by observational uncertainty and model error[2, 6,8,9,11]. Even the continental-scale studies described above are too coarse to inform assessments of the extent to which human-induced climate change has affected changes affecting many people locally. Because internal variability in precipitation tends to increase with reducing spatial scale there may be a tendency to assume that detection of an anthropogenic signal of change is more likely at global or continental scales than at regional scales. In this context, by regional scales we refer to smaller spatial scales than 'continental', typically thinking of areas of the globe characterised by specific geographic and climatological features[5].

This perspective argues that analysis of changes in the processes governing internal variability in precipitation should facilitate the detection and attribution of anthropogenic changes at a range of spatial scales. In some cases an anthropogenic signal may be easier to detect at regional scales, where we have a clearer expectation of forced changes[8, 9,10]. Above all progress in detection and attribution of changes in the water cycle requires the development of novel metrics, which should help facilitate the identification of significant changes in precipitation even in the presence of substantial modelling and observational uncertainty[12]. This should enable faster progress to be made than would be possible by simply waiting for models or observations to improve or by simply waiting for the signal of climate change to strengthen sufficiently to emerge from the noise of internal variability.

We first compare physical expectations of global and regional anthropogenic changes in precipitation. Next, we describe how spatial scale modifies the impact of model error and observational uncertainty on detection of these changes. We then consider how novel methods of analysis can be brought to bear on detection and attribution of regional changes in precipitation. Finally, we reflect on how our current models and observations can best be utilised to provide a robust view of anthropogenic change in regional precipitation.

Expected changes on global and continental scales

Based on the physical relation of Clausius-Clapeyron, surface warming is expected to result in an increase in water vapour concentrations at a rate of 6-7% per Kelvin[13], given that the relative humidity is expected to remain nearly constant[14]. This thermodynamic expectation of an intensification of the water cycle has been confirmed in changes in observed and simulated atmospheric moisture content over land and ocean[15, 16,17,18], albeit in observations from recent years there is some evidence of a reduction of relative humidity over land[19].

Global mean precipitation is not, however, expected to scale with the increase in atmospheric moisture because it is controlled not by specific humidity, but by the energy budget of the troposphere. The two complementary energy budget arguments are 1) the tropospheric latent heating during precipitation formation is balanced by the radiative cooling to outer space[14], and 2) at the surface the latent heat flux (which is proportional to global mean evaporation and hence global mean precipitation) is balanced by the sensible and radiative heat fluxes [14,13,15,20]. The warming of the troposphere increases the radiative cooling rate and hence the precipitation. However, if the warming is driven by an increase in greenhouse gases (GHGs), the increase in the radiative cooling rate is partly offset by the direct radiative effect of the GHGs, which is to decrease the radiative cooling rate. This implies that the precipitation response to GHG forcings is smaller per unit change in forcing, than it is for short wave radiative forcings like volcanic aerosol[14]. Overall anthropogenic forcings result in a lower rate of increase in precipitation globally than suggested by the Clausius-Clapeyron relation[14, 13,15,20,21,22].

A pioneering study[14] quantified the expected range of change in total global precipitation in response to CO_2 driven warming, but found that even at large scales there was considerable variation in the expected spatial pattern of change. A key advance in the physical explanation of the response pattern of precipitation changes due to increasing GHGs was made by a later study[15]. They identified robust features of anthropogenic changes such as enhancement of the patterns of precipitation minus evaporation (P-E), poleward movement of the Hadley circulation and subsequent shifting of the arid subtropical subsidence regions and storm tracks, leading to the 'wet gets wetter' and 'dry gets drier' paradigm. It has recently been found that although this paradigm has some validity over wet higher latitudes and dry subtropical land regions, it does not hold true everywhere. For example, humid to transitional regimes are shifting to drier conditions[23]. Other changes in large-scale rainfall patterns have been explained through a 'warmer-get-wetter' mechanism, by which warm SST patterns over the tropics cause increases in precipitation[24].

Expectation of regional changes

Change in regional rainfall is a consequence both of thermodynamics and anthropogenic influence on dynamics[25]. Human-induced depletion in stratospheric ozone, for example, is found to cause a poleward shift of the southern extratropical jets, which affect regional precipitation patterns in the Southern Hemisphere[26, 27]. The storm track in the Northern Hemisphere, and hence rainfall in Europe, are also affected by changes in stratospheric circulation[28].

More generally, the regional precipitation response to naturally occurring modes of variability, such as ENSO and the NAO, is influenced by the basic state of the atmosphere and ocean[14, 29,30]. It is to be expected therefore that anthropogenic perturbations to the basic state would lead to changes in regional teleconnection patterns.

The regional character of anthropogenic precipitation change, therefore, results from complex interactions between natural variability and anthropogenic forcing. This is especially the case at regional scales. Indeed, variability related to teleconnections is not likely to affect total precipitation over very large domains, because wetter conditions in one place tend to be balanced by dryer conditions elsewhere[31]. In short, in order to disentangle the complex causes of regional precipitation change, we need to consider the following three aspects of the response: 1) external forcing may project onto internal variability, changing the amplitude or frequency of modes of climate variability, or altering the teleconnections that govern precipitation response, 2) the fingerprint of external forcing may reflect both thermodynamic and dynamic changes through forced changes to atmospheric energetics, moisture content, and large-scale circulation, and 3) the precipitation responses to different external drivers such as greenhouse gases, aerosols, ozone, natural events will differ.

Modelling and observational uncertainties

Recent studies that have sought to detect and attribute anthropogenic signals in large-scale zonal precipitation have compared observations to CMIP5 (Coupled Model Intercomparison Project 5) model simulations with and without anthropogenic forcings[2, 3]. Anthropogenic increases in precipitation on global land and ocean are clear in model simulations (Figure 1a-c). However attribution approaches require that like is compared with like by comparing observations of the historical period to models that have been masked with the observational coverage. This means that the clear signals seen in models are obscured by sparse observational coverage[2]. These findings indicate that global as well as zonal trends are distorted by the aliasing of sparse observational coverage onto the multi-model means.

The robustness of the detection of global and large-scale trends (Figures 10.10 & 10.A.2 of ref. 6) needs to be tested by comparing model data with different datasets of long-term observations. Ref. 2, for example, detected seasonal changes in zonal-mean precipitation attributable to human activities in four observational datasets – albeit only for March-April-May and December-January-February. However, the magnitudes of the temporal fingerprint of mid-to-high latitude positive trends and low latitude negative trends vary between observational datasets (Figure 2). In fact, anthropogenic changes are detected for all seasons in only one of the observational datasets[3]. The sensitivity of findings to observational dataset illustrates the barriers imposed by observational uncertainty.

The above discussion has focussed on uncertainties in observations of precipitation. It should not be forgotten, however, that effective model-observation comparison relies on accurate observations, not only of the variable in question, but also of forcing factors, including natural and anthropogenic aerosol. It has been found, for example, that natural desert dust aerosols from North Africa and West Asia are positively correlated to Indian summer monsoon rainfall on short time scales, with the dust-induced heating favouring increased moisture convergence over the Arabian peninsula and hence the westerly flow and precipitation over the Indian subcontinent[32]. Such model based findings point to the increasing need for an improved understanding of the climatic response to aerosols, which will require more systematic modelling experiments exploring the sensitivity of the precipitation response to aerosol forcing uncertainty as well as improvements in the representation of aerosol forcing in models.

Many of the impacts of a changing water cycle are felt at regional and local scales rather than at continental or global scales. Observational uncertainty at any given grid point (of resolution of a few hundreds of kms) may be greatest at these scales (http://sciforum.net/conference/66/paper/2901). Paradoxically, however, observational uncertainty may be less of a barrier to attribution at the regional than at the global level. At the largest spatial scales, many of the detection and attribution issues related to observational uncertainty stem from sparse spatial sampling[2] in observations which means that the trends from models and observations can be badly distorted, losing much of the underlying signals. At local scales, in contrast, inconsistency in spatial sampling is less likely to contribute significantly to observational uncertainty. Instead, observational uncertainty reflects the sparcity of ground observations and consequent measurement/calibration errors. Such uncertainty may not, in itself, preclude robust detection and attribution of anthropogenic change in some regions, providing there exist temporally consistent ground or satellite based rainfall estimates. Indeed, at these scales, detection and attribution may be hampered more by the challenge of comparing models and observations, than by observational uncertainty itself. This is, in part because there are large discrepancies between the locations of simulated and observed features in the climatologies of precipitation which might be expected to cause differences in the anthropogenic response[33]. These discrepancies are compounded by the lack of robustness in model-simulated internal variability[34] causing uncertainty in the fingerprint[3, 35], or under sampling of the observed variability[36] – which as described in earlier sections are a particularly serious issue at the regional scale.

A clearer view

The success of any approach to detection and attribution is contingent on the model's ability to represent the relevant processes over a particular region and season. Structural uncertainties in climate models (due to the differences in models' structure leading to individual model errors), although reduced since the Fourth Assessment Report[37, 38] (AR4), remain as a barrier to quantifying robust change in precipitation on regional scales[39].

The need for improved process-representation has motivated recent work on improved model dynamics and resolution[40], and the incorporation of individual processes and complex models of individual parts of the climate system[41]. High horizontal and vertical resolution and improved parameterisations in climate models have been shown to improve representation in models of processes, such as the vorticity of tropical cyclones, storm dynamics, atmospheric fronts, convection and blocking, clouds and their interactions with aerosols, gravity waves, ocean-biogeochemistry, land and sea-ice, boundary layer and land-surface processes, and strength of the local hydrological cycle[40, 41, 42, 43, 44, 45]. The development of both high-resolution climate models and Earth System Models (ESMs) are thus instrumental in tackling regional climate problems. Ref. 40, for example, performed climate change experiments using a 1.5 km resolution regional climate model and projected future increase in heavy downpours over the UK. They illustrated that explicit convection and local storm dynamics are important in simulating the fine temporal and spatial scales of UK summer rainfall.

Compared to CMIP3 models, many CMIP5 models represent first and second indirect effect of aerosols and improved aerosol-cloud representations. On large spatial scales, these significant improvements in climate model representation of aerosols have now enabled improved simulation of inter-decadal variability in temperature and precipitation[35, 46]. A weakening of the Northern Hemisphere land precipitation between the 1950s and 1980s and a subsequent recovery has been detected and attributed to increasing anthropogenic aerosols during 1950 to 1980s followed by a reemergence of the greenhouse gas signal relative to the anthropogenic aerosol signal in later years[35]. Models with representation of the indirect effect of sulphate aerosols, together with the direct effect of sulphate aerosols perform better in representing the rate of decrease of precipitation in the 1950s and the recovery in the 1980s than the models that exclude the indirect effect[46] although models still have shortcomings in representing the timing of the recovery. There is thus a scientific opportunity to use these newly available simulations to decipher the joint influence of anthropogenic aerosols and greenhouse gas emissions on regional precipitation, and hence to detect anthropogenic trends.

New methodologies

The base climate is expected to vary from one model to another. Averaging simplistically over output from many models may therefore obscure signals of anthropogenic change. For instance, variation between models of the location and seasonal timing of precipitation may hamper robust assessment of changes in the mean[33, 47,48]. Novel methods of accounting for the mismatches between model climatologies offer a means of tackling the problem of consistent model changes being distorted by differences in climatological features (eg. convergence zones) both between models, and between models and observations[33, 49]. In order to correct feature location errors in GCMs, ref. 33 applied a warping method, which has been used in brain imagery registration, to monthly precipitation fields. The warping technique was found to improve the detectability of human influence[49]. Other model-observation comparison methods such as the model-by-model approach[48] and space-scale smoothing[47], which consider individual model runs as opposed to the multi-model ensemble mean, have also been shown to reduce feature-location biases and hence to identify robust changes in the location and magnitude of zonal extremes.

Natural variability, as well as systematic bias in models, can obscure part of the signal of anthropogenic change in precipitation. For example, the anthropogenic effect on the precipitation response to natural modes of variability is superposed on natural variation in the amplitude and frequency of these modes[50, 51,52,53]. Aliasing natural internal variability and changes due to anthropogenic forcing in this manner would be expected to cause variations in the anthropogenic effect on regional precipitation. So if, say, greenhouse gas forcing modifies the precipitation response to ENSO in a given region, the anthropogenic expression of precipitation change is more pronounced during periods when ENSO is active. These periods cannot be expected to coincide in free-running coupled climate models. Averaging precipitation over large model ensembles will therefore not reveal this component of the signal of anthropogenic influence. Rather detection and attribution tecnhniques need to take explicit account of the drivers of precipitation variability (e.g. ENSO, NAO) and to their effects on precipitation (e.g. ENSO teleconnections) rather than just treating such variability as noise in the analysis. This type of process-based approach complements the application of detection and attribution techniques directly to regional precipitation [8,9] and can yield a clearer understanding of the role of natural and anthropogenic factors[71].

On regional scales, therefore, in addition to analysing precipitation directly, it is productive to investigate the processes underlying precipitation change (process-based fingerprints). Examples of such fingerprints are the increased risk of heavy rainfall during mid-latitude atmospheric river events in the UK[54, 55] and New Zealand[56]; the poleward migration of the storm track[47] (Figure 3) and the large scale dynamical implications of an expected intensification of the hydrological cycle[15, 20, 57,58] that, at least over non-water limited regions[23] of the earth including the oceans, many wet regions tend to get wetter and dry regions drier. As pointed out earlier it should be noted that the over simplicity of this expectation from theory and models is currently under discussion[23]. However, a temporal response pattern with wet tropical regions getting wetter and dry regions getting drier was apparent in simulations of the recent past and future projections from CMIP5 models and was consistent with satellite rainfall observations for the tropical region[20]. ENSO variability can cause increase or decrease of regional rainfall over the land depending on the sign of the phase[58] suggesting if the ENSO characteristics change such precipitation response which is governed by remote SST patterns may change too. On fine scales, shifting of the wet and dry regions may make it difficult to identify this expected pattern of change[23, 59,60]. However, using two fingerprints of wet and dry processes, ref. 57 detected an expected intensification of the water cycle partly attributable to human-induced greenhouse gas forcing.

Anthropogenic change in precipitation is driven not only by greenhouse gas emission, but also by aerosol forcing which modulates regional precipitation. Sulphate aerosol and desert dust forcings influence changes in the wet and dry conditions of Sahelian water cycle caused primarily by changes in West African Monsoon rains through changes in SST feedbacks and subsequent shifts in tropical convergence zones[61, 62]. Simulated Sahel rainfall is found to weaken due to rapid changes in anthropogenic sulphur dioxide emissions from Asia and Europe through a fast (less than 3 weeks) aerosol-radiation and aerosol-cloud response and a slow (more than 3 weeks) response (i.e. decrease in West African Monsoon by adjustment of Walker circulation) caused by atmosphere and land-surface feedbacks[63]. While there was a decrease of Sahel rainfall during the 1970s and 1980s since then there has been some recovery of Sahel rainfall which could have been influenced by increasing levels of greenhouse gases in the atmosphere as well as changes in anthropogenic aerosol precursor emissions[64].

Event attribution

The previous discussion has highlighted the importance of identifying and isolating processes underlying anthropogenic change in precipitation. This can be accomplished, as described in the studies cited above, by explicitly isolating candidate processes and investigating how they are affected by anthropogenic climate change. A further refinement is to investigate the anthropogenic contribution to the processes underpinning individual extreme events – a technique known as event attribution.

Event attribution studies seek to determine how anthropogenic forcings have altered the magnitude or probability of a particular type of extreme weather or climate-related event as experienced in the observed record[65, 66, 67]. In recent years efforts have been made to carry out such studies shortly after the events in question, for example in the publication of an annual series of reports which explain extreme events of the previous year from a climate perspective[68]. However while there is increasing evidence that robust attribution statements can be made about an anthropogenic contribution to the likelihood of many extreme warm events, the role of human influences on extreme precipitation events is decidedly mixed[69] consistent with previous findings about the difficulties of robustly attributing precipitation events. Nevertheless such diagnostic approaches to attribution have made some headway in breaking down the problem into thermodynamic and dynamical components[70] and in devising modelling strategies to quantify the different contributions from anthropogenic and natural forcings and aspects of internal variability[64]. It is therefore becoming possible to attribute changes in probability of some types of regional extreme precipitation event through developing an understanding of the thermodynamic and dynamic contributors[71, 72]. Ref. 73 argues that in attributing extreme climate events it is more useful to regard the extreme circulation regime or weather event as being largely unaffected by climate change and to concentrate solely on the thermodynamic component of an anthropogenic impact on the event in question. However it is important to consider dynamic factors as well as thermodynamic factors and to consider the extent to which dynamical aspects may have changed since it is both that contribute to the risk of a particular event[74, 71,72,75]. Also attention should be given as to whether there are non-linear interactions between the two, as discussed above.

The way ahead

Based on our discussion of scientific opportunities and challenges, we emphasise that quantification of the effects of human influence on precipitation across the globe crucially depends on developing and applying process understanding. Given current observational uncertainties[4] and limitations in models[38] simply waiting for improvements in observations and models to deliver clearer detection and attribution results seems an insufficient response to the challenge of better understanding how climate change is affecting precipitation around the globe. For example some of the important recommendations proposed by ref. 4 such as the observational data rescue, improvements in the observational coverage and models could take years to implement. Clearly observations and models are continuously improving and detection and attribution analyses should take advantage of such advances. But adaptation decisions could be even better informed if it were possible to incorporate process understanding more in detection and attribution studies. Those adaptation decisions that are based on robust climate projections are much stronger where the projections are based on firm foundation of physical understanding and underpinned by robust attribution studies. Hence attribution studies are central to informed adaptation planning and decision making. Even where large uncertainties remain, additional useful information could be obtained and applied in a risk-based framework[60] based on an understanding of the likely mechanisms at work.

In particular, we need to better understand the expected effect of anthropogenic climate change on modes of variability and their teleconnections with regional precipitation[29]. Disentangling these effects will allow an improved understanding of the extent to which regional changes are anthropogenically caused versus being caused by natural variations, either internally generated within the climate system or externally forced, such as by solar variability or explosive volcanic eruptions. It is not always reasonable to consider internal variability simply as 'noise' to be filtered out.

Recent process-based detection and attribution approaches[47], which consider the signal or the forced response being thermodynamic and/or dynamic in origin, have shown some success. There is indication that the anthropogenic signal could also be expressed in part through changes in amplitude, frequency and modes of natural internal variability. An alternative approach would be to look directly at the anthropogenic signal as a net effect of rainfall changes due to a) thermodynamic contribution, b) dynamic contribution (which includes changes in circulation, modes of variability and changes in teleconnections due to changes in modes of variability). Analyses quantifying changes in natural internal variability[76] would be a valuable addition to quantifying forced changes over regions where internal variability on interannual timescales is changing. However, it is very difficult to robustly detect changes in observed variability for a highly noisy climate variable as precipitation.

New metrics that best express robust changes in the water cycle would aid in identifying anthropogenic changes. For example this could involve calculating areas of land with precipitation changes at particular thresholds[12] or could involve combining terrestrial observations of precipitation with oceanographic observations of salinity[6].

In summary, we have shown that, even in the face of imperfect models and observations, progress can be made in detecting and attributing changes in regional precipitation. Improved process understanding, innovations in detection and attribution methodologies, and novel methods of confronting models with observations can now be brought to bear on this highly challenging problem. Development of high quality observational datasets and high-resolution models will be undoubtedly helpful and are likely to have substantial pay off over the longer term. But in the meantime, innovative methods for analysing the observations and models we have available now could yield important additional information to inform societies and policy makers about the nature of changing precipitation at fine spatial-scales.

Box 1. What is detection and attribution?

Detection of a change is the process of demonstrating that climate has changed in some defined statistical sense, without providing a reason for that change[77]. *Attribution* of causes of the change is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with an assignment of statistical confidence[6]. *Fingerprints* are metrics or space-time patterns of the response of climate variables to anthropogenic forcings, such as greenhouse gas emissions, atmospheric pollutants, or natural forcings such as solar radiation changes and aerosols from explosive volcanic eruptions. Most of the recent detection and attribution studies use climate models[78] to estimate the expected fingerprints of change and the uncertainty of their estimate in observations of the real world. For an overview of techniques, see Appendix 9.2 of AR4[62] and Section 10.2.1 of AR5[6].

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Author Contributions

B.B.S. developed the content and led the writing; P.A.S and E.B. designed the outline of the article, contributed to discussions, text, and commented on the drafts.

Competing Financial Interests statement

The authors declare no competing financial interests.

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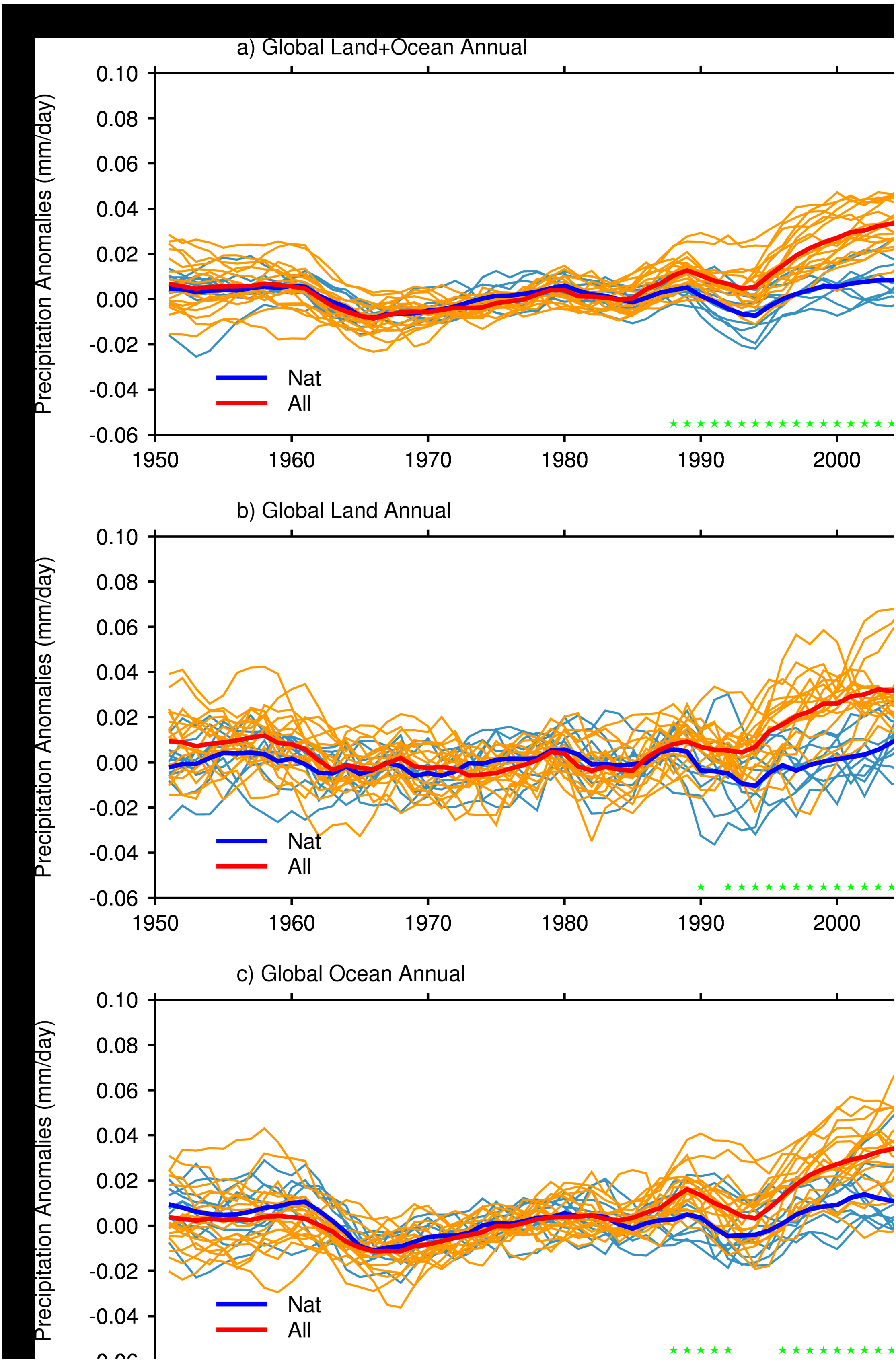
Figure Legends

Figure 1| Observational uncertainties due to sparse coverage obscure expected fingerprints of change: Time-series of global mean precipitation anomalies (mm/day) w.r.t the baseline period of 1961-90, simulated by CMIP5 models forced with, both anthropogenic and natural forcings (ALL in orangish red lines) and natural forcings only (NAT in blue lines). a) Land and Ocean, b) Land, and c) Ocean, with all grid points. Multi-model means are shown in thick solid lines. Green stars show statistically significant changes at 5 % level. The clear signals seen in simulations (above) are obscured by sparse observational coverage when the global land precipitation is masked by observational coverage (Ref. 2).

Figure 2| Magnitudes of zonal mean land precipitation trends are dependent on observational datasets: Comparison of observed trends (solid lines) using 4 observational datasets (Refs. 11, 79, 80, 81) for 1951-2005 (top). Range of CMIP5 simulations are in grey shading and multi-model ensemble mean (MM) in black dashed line. Blue (orange) shadings show latitudes where all observed datasets show positive (negative) trends. Comparison of simulated trends (bottom) using CMIP5 historical (ALL) simulations (individual simulations in grey dashed lines, multi-model mean in black dashed line), and the natural forcing only (NAT) simulations (MM in blue dashed lines) with the future (2006-2050) trend using RCP4.5 simulations (5-95 % range is in green shading, and MM in green dashed lines). Blue (orange) shading indicates latitudinal regions where more than two thirds of the historical simulations show positive (negative) trends (Ref. 4).

Figure 3| An example of simulated process-based fingerprint of anthropogenic precipitation change: Zonal mean boreal winter precipitation observations for 1990 (left). Local extrema are marked in dark blue (midlatitude storm tracks), red (subtropical dry zones), and green (equatorial tropical peak). Cyan, purple, and yellow circles indicate half-max points. Multivariate fingerprint $F_m(D,T)$ of forced precipitation change as thermodynamic (T) and dynamic (D) process indicators (right). Thermodynamic EOF loading is plotted on the vertical axis and the direction and magnitude of dynamic EOF loading are displayed as arrows showing the wet-gets-wetter and dry-gets-drier pattern in precipitation intensity and the poleward extension of precipitation over storm track and subtropical arid latitudes in both hemispheres (Ref. 47).

Figures



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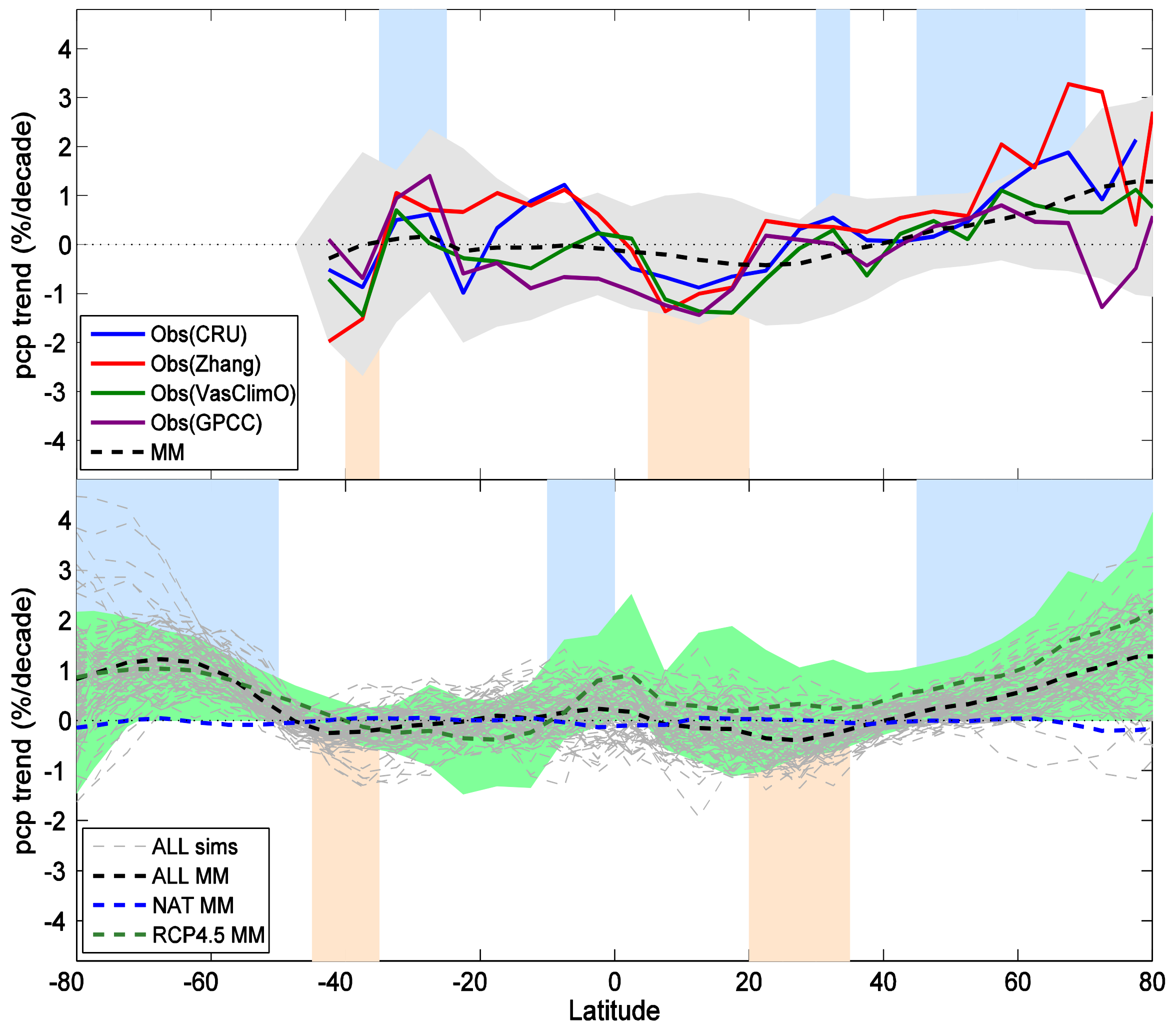

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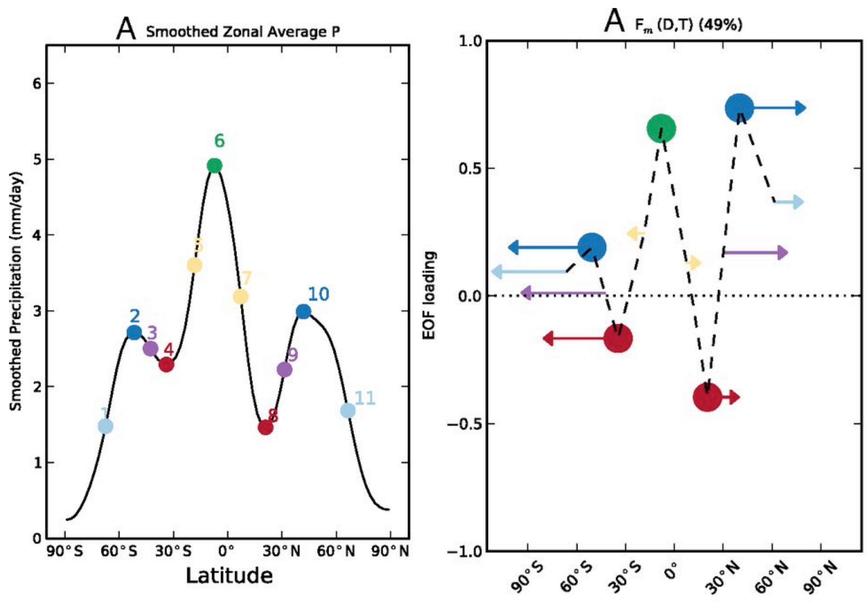

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