The Role of Zonally Averaged Climate Change in Contributing to Intermodel Spread in CMIP5 Predicted Local Precipitation Changes

CHAIM I. GARFINKEL, ORI ADAM, EFRAT MORIN, YEHOUDAH ENZEL, AND EILAT ELBAUM

Fredy and Nadine Herrmann Institute of Earth Sciences, Hebrew University, Jerusalem, Israel

MAYA BARTOV

Fredy and Nadine Herrmann Institute of Earth Sciences, Hebrew University, Jerusalem, and Department of Natural Sciences, The Open University of Israel, Raanana, Israel

DORITA ROSTKIER-EDELSTEIN

Department of Applied Mathematics, Environmental Sciences Division, Israel Institute for Biological Research, Ness-Ziona, Israel

URI DAYAN

Department of Geography, Hebrew University, Jerusalem, Israel

(Manuscript received 28 March 2019, in final form 21 October 2019)

ABSTRACT

While CMIP5 models robustly project drying of the subtropics and more precipitation in the tropics and subpolar latitudes by the end of the century, the magnitude of these changes in precipitation varies widely across models: for example, some models simulate no drying in the eastern Mediterranean while others simulate more than a 50% reduction in precipitation relative to the model-simulated present-day value. Furthermore, the factors leading to changes in local subtropical precipitation remain unclear. The importance of zonal-mean changes in atmospheric structure for local precipitation changes is explored in 42 CMIP5 models. It is found that up to half of the local intermodel spread over the Mediterranean, northern Mexico, East Asia, southern Africa, southern Australia, and southern South America is related to the intermodel spread in large-scale processes such as the magnitude of globally averaged surface temperature increases, Hadley cell widening, polar amplification, stabilization of the tropical upper troposphere, or changes in the polar stratosphere. Globally averaged surface temperature increases account for intermodel spread in land subtropical drying in the Southern Hemisphere but are not important for land drying adjacent to the Mediterranean. The factors associated with drying over the eastern Mediterranean and western Mediterranean differ, with stabilization of the tropical upper troposphere being a crucial factor for the former only. Differences in precipitation between the western and eastern Mediterranean are also evident on interannual time scales. In contrast, the global factors examined here are unimportant over most of the United States, and more generally over the interior of continents. Much of the rest of the spread can be explained by variations in local relative humidity, a proxy also for zonally asymmetric circulation and thermodynamic changes.

Supplemental information related to this paper is available at the Journals Online website: <https://doi.org/10.1175/JCLI-D-19-0232.s1>.

Corresponding author: Chaim I. Garfinkel, chaim.garfinkel@mail.huji.ac.il

DOI: 10.1175/JCLI-D-19-0232.1

© 2020 American Meteorological Society. For information regarding reuse of this content and general copyright information, consult the [AMS Copyright Policy](#) (www.ametsoc.org/PUBSReuseLicenses).

1. Introduction

It has been known for nearly four decades that climate models project an aridification of the poleward edge of the subtropics in response to increased greenhouse gas concentrations (Manabe and Wetherald 1980; Mitchell 1983; Cubasch et al. 2001; Allen and Ingram 2002).

FIG. 1. (a) Change in annual mean precipitation in RCP8.5 from 2009–29 to 2079–99 (mm day^{-1}). (b) Percentage change for the ensemble average of 42 CMIP5 models. Stippling indicates regions where more than 90% of models agree on the sign of the change. (c),(d) As in (a) and (b), but for the average of the 15 models with the strongest drying at 32°N, 35°E. (e),(f) As in (a) and (b), but for the average of the 15 models with the weakest drying at 32°N, 35°E.

The results from these early studies were supported by model projections performed for phases 3 and 5 of the Coupled Model Intercomparison Project (CMIP3 and CMIP5) and assessed by the Intergovernmental Panel on Climate Change (IPCC) Fourth and Fifth Assessment Reports (AR4 and AR5) (IPCC 2007; Giorgi and Lionello 2008; Kelley et al. 2012; IPCC 2013; Seager et al. 2014). To provide context for the rest of this study, these results are repeated in Figs. 1a and 1b, which show the changes in precipitation from the current 20-yr period (January 2009–December 2028) to the end of the century (January 2079–December 2098) in the multimodel mean of 42 CMIP5

models for the high-emissions RCP8.5 scenario. While precipitation is projected to increase over most extratropical and deep tropical regions, it is projected to decrease over the poleward edges of the subtropical dry zone [consistent with Seager et al. (2010), Scheff and Frierson (2012a,b), He and Soden (2017), and IPCC (2013)]. This subtropical drying is especially pronounced over ocean regions and over the Mediterranean, with aridification in the Mediterranean region locally exceeding 30% of the early twenty-first-century precipitation (Fig. 1b).

Large-scale atmospheric circulation and temperature gradients will change in a warmer climate (Shepherd

TABLE 1. List of models used. An asterisk (*) indicates models with surface relative humidity, and a plus sign (+) indicates models without meridional winds for the Hadley cell computation.

1	ACCESS1.0*	2	ACCESS1.3*	3	BNU-ESM
4	CCSM4*	5	CESM1-BGC*	6	CESM1-CAM5*
7	CESM1-CAM5.1-FV2 ⁺	8	CMCC-CESM	9	CMCC-CM
10	CMCC-CMS	11	CNRM-CM5*	12	CSIRO-Mk3.6.0*
13	CanESM2*	14	EC-EARTH	15	FGOALS-g2
16	FGOALS-s2 ⁺	17	FIO-ESM	18	GFDL CM3*
19	GFDL-ESM2G*	20	GFDL-ESM2M*	21	GISS-E2-H*
22	GISS-E2-H-CC*	23	GISS-E2-R*	24	GISS-E2-R-CC*
25	HadGEM2-AO*	26	HadGEM2-CC*	27	HadGEM2-ES*
28	IPSL-CM5A-LR*	29	IPSL-CM5A-MR*	30	IPSL-CM5B-LR*
31	MIROC-ESM*	32	MIROC-ESM-CHEM*	33	MIROC5*
34	MPI-ESM-LR	35	MPI-ESM-MR	36	MRI-CGCM3*
37	MRI-ESM1*	38	NorESM1-M*	39	NorESM1-ME*
40	BCC-CSM1.1*	41	BCC-CSM1.1-m	42	INM-CM4*

2014; Vallis et al. 2015), but the importance of these large-scale changes for regional precipitation changes in the eastern Mediterranean region specifically and in the subtropics more generally is not yet clear. Earth will not warm uniformly in response to climate change, and two of the most robust regions of enhanced warming are the tropical upper troposphere and the Arctic near-surface (Shepherd 2014; Vallis et al. 2015), while projected warming trends in other regions are comparatively modest. Another robust change is that the subtropical edge of the Hadley cell is projected to shift poleward (Hu et al. 2013; Staten et al. 2018; Hu et al. 2018). All of these changes can be plausibly linked to (or are manifest in) regional-scale changes in precipitation; however, there is substantial uncertainty as to the extent to which these processes are relevant for regional changes in precipitation over land. For example, Schmidt and Grise (2017) showed that interannual variability in land precipitation is only associated with the zonal-mean Hadley cell edge latitude in certain specific subtropical regions, and most of Earth's subtropical land precipitation is independent of Hadley cell width variations. Furthermore, He and Soden (2017) argue that the land drying and ocean drying are caused by fundamentally different mechanisms, with drying over oceans largely a direct consequence of the rise in CO₂ itself via “fast” ocean-to-land zonal circulation responses, which enhances convection over land and weakens convection over oceans. Only the land-based drying (which is confined to certain regions only) is significantly associated with planetary warming. The relative weakness of the connection between drying over subtropical continents and Hadley cell expansion motivates the two questions this manuscript seeks to answer: To what extent is drying over subtropical land related to large-scale zonal-mean changes in atmospheric structure? And in what regions are large-scale zonal-mean processes most important?

While the ensemble mean of the CMIP5 models in the RCP8.5 scenario indicates a ~20% decrease in precipitation over the eastern Mediterranean over this century, there is a wide spread among the models (Zappa et al. 2015). Some models project a 60% decrease in precipitation at 32°N, 35°E (the southern Levant), while others predict changes of less than 3%; a similar diversity is also evident over southeastern Europe, with model projections ranging from a 40% reduction to no change. Figures 1c and 1d show the change in precipitation averaged over the 15 models with the most severe projected drying in the eastern Mediterranean, and Figs. 1e and 1f show the averaged change for the 15 models with the least pronounced projected drying in the eastern Mediterranean. While increases in subpolar precipitation are similar in both groups of models, changes over the eastern Mediterranean exceed 50% of present-day climatology in Figs. 1c and 1d and are minimal in Figs. 1e and 1f. A 50% reduction in precipitation in this already water-stressed region would have drastic consequences and would require substantial adaptation and investment, but such an investment of resources may be unnecessary if the reduction in precipitation turns out to be minimal. Better understanding of the causes of intermodel diversity in the drying of the eastern Mediterranean is therefore critical for improving policy-relevant projections.

Here, we analyze the extent to which this diversity in projected subtropical drying is associated with diversity in the large-scale zonal-mean changes simulated by each model. We also consider the specific large-scale factors that are of particular importance for each region of the subtropics, with a particular focus on the Mediterranean. We do so by first considering whether the spread in changes in precipitation among the models is related to the spread in changes in these processes, and then forming a regression model, taking these zonal-mean

TABLE 2. Correlation of each predictor in the MLR with the others, and also with precipitation at 32°N, 35°E, based on annual-mean data. The HC edge, stratospheric vortex, and polar amplification indices are computed for the Northern Hemisphere. Boldface font indicates when a null hypothesis of no correlation can be rejected at the 95% level.

	Stratification, 30°S–30°N	Tsurf globe	HC edge	U10hPa, 60°–75°	Polar amplification	Precip, 32°N, 35°E
Stratification, 30°S–30°N	1.00	0.33	−0.13	−0.11	−0.36	−0.58
Tsurf globe	0.33	1.00	0.39	0.32	−0.01	−0.20
HC edge	−0.13	0.39	1.00	0.29	0.15	−0.31
U10hPa, 60°–75°	−0.11	0.32	0.29	1.00	−0.08	0.14
Polar amplification	−0.36	−0.01	0.15	−0.08	1.00	0.32
Precip, 32°N, 35°E	−0.58	−0.20	−0.31	0.14	0.32	1.00

processes as predictors, that aims to reconstruct the precipitation changes simulated by each CMIP5 model. Overall, we will show that in specific land areas of the subtropics (e.g., the Mediterranean), up to half of the intermodel variance in projections of precipitation is associated with zonally symmetric forcings, and much of the remainder is due to changes in local moisture, a proxy both for local thermodynamic changes and also for zonally asymmetric circulation changes. In other regions, such as most of the United States and more generally well inland of coastal areas, zonally symmetric factors are comparatively unimportant and local factors dominate.

2. Data and methods

The comprehensive model simulations used here are taken from those submitted to CMIP5 that compose the IPCC AR5 archive (Taylor et al. 2012). CMIP5 is the latest fully available set of model simulations (the database of output from CMIP6 is just starting to be filled), comprising over 40 different models (42 examined here) for future climate. We focus on the high-emissions scenario RCP8.5. Chosen models are listed in Table 1. All data were interpolated to a common $1^\circ \times 1^\circ$ grid, using linear interpolation. Only one realization is used for each model. Observed precipitation is sourced from the E-OBS database, version 18 (Haylock et al. 2008). We use the daily precipitation sum (RR) ensemble-mean product from 1950 through 2017.

The various models suffer from biases in precipitation, and for some regions (such as the eastern Mediterranean) these biases can exceed a factor of 5 of the observed annual mean values (not shown). Models with a dry bias are incapable of simulating a larger decrease in precipitation because they start off with too little precipitation. We therefore focus on changes in the percentage of precipitation as this allows us to more meaningfully compare different models regardless of their initial estimation for the regional precipitation amounts. Specifically, we first compute the change in precipitation

between January 2009–December 2028 (i.e., 2019 is in the middle of this period) and January 2079–December 2098 for each model, and then divide by the precipitation from January 2009 through December 2028. We refer to this quantity as $\Delta\%$ precipitation in the rest of this manuscript: $\Delta\%$ precipitation = $[(\text{precip}_{2079\text{to}2098} - \text{precip}_{2009\text{to}2028})/\text{precip}_{2009\text{to}2028}] \times 100$.

We assess the extent to which model spread in $\Delta\%$ precipitation is associated with model spread in changes over the same period of the following zonal-mean climate indices:

- 1) Δ Vertical stratification: Calculated as the ratio of the changes in potential temperature θ between 250 and 850 hPa, averaged from 30°N to 30°S [$\Delta S = (\theta_{250\text{hPa};2079\text{to}2098} - \theta_{250\text{hPa};2009\text{to}2028})/(\theta_{850\text{hPa};2079\text{to}2098} - \theta_{850\text{hPa};2009\text{to}2028})$]. Like Zappa and Shepherd (2017) we consider 250-hPa changes, although instead of normalizing by globally averaged changes as in Zappa and Shepherd (2017) we divide by local lower-tropospheric changes. This leads to an index of atmospheric vertical stratification that has low correlation with globally averaged surface temperature. Atmospheric vertical stratification directly modifies rising motion (e.g., Holton and Hakim 2013), and we prefer to focus on processes that have physical connections to precipitation. As is evident in Fig. 12.12 of IPCC (2013), projected changes in stratification extend into the subtropics.
- 2) Δ Globally averaged surface temperature: Calculated as the difference in area-weighted global surface temperatures.
- 3) Δ Subtropical edge of the Hadley cell: Defined by the zero crossing of the streamfunction at 500 hPa (Garfinkel et al. 2015; Waugh et al. 2015) calculated as in Adam et al. (2018).
- 4) Δ Stratospheric polar vortex: The zonal wind speed at 10 hPa from 60° to 75° following Simpson et al. (2018) is used to track changes in the stratosphere. We include stratospheric variability here, as it has been shown to account for intermodel variance in projected precipitation over Europe (Manzini et al.

TABLE 3. Correlation of each predictor in the MLR with the others, and also with precipitation at 34°S, 115°E, based on annual-mean data. The HC edge, stratospheric vortex, and polar amplification are computed for the Southern Hemisphere. Boldface font indicates when a null hypothesis of no correlation can be rejected at the 95% level. As discussed in the text, polar amplification is not used as a regressor in the MLR.

	Stratification, 30°S–30°N	Tsurf globe	HC edge	U10hPa, 60°–75°	Polar amplification	Precip, 34°S, 115°E
Stratification, 30°S–30°N	1.00	0.33	0.29	0.25	−0.28	−0.18
Tsurf globe	0.33	1.00	0.30	0.09	0.06	−0.51
HC edge	0.29	0.30	1.00	0.44	−0.42	−0.37
U10hPa, 60°–75°	0.25	0.09	0.44	1.00	−0.56	−0.23
Polar amplification	−0.28	0.06	−0.42	−0.56	1.00	0.39
Precip, 34°S, 115°E	−0.18	−0.51	−0.37	−0.23	0.39	1.00

2014; Zappa and Shepherd 2017; Manzini et al. 2018; Simpson et al. 2018) and has affected Southern Hemisphere precipitation through ozone depletion (Kang et al. 2011; Polvani et al. 2011; Gonzalez et al. 2014).

- 5) Δ Polar amplification of surface temperature increases: Calculated as the ratio of surface temperature changes from 60°N/S to 87.5°N/S as compared to changes from 30°N to 30°S [$\Delta T_{\text{grad}} = (T_{60^{\circ}\text{to}87.5^{\circ}}^{2079\text{to}2098} - T_{60^{\circ}\text{to}87.5^{\circ}}^{2009\text{to}2028}) / (T_{30^{\circ}\text{to}30^{\circ}}^{2079\text{to}2098} - T_{30^{\circ}\text{to}30^{\circ}}^{2009\text{to}2028})$]. A similar regressor was considered by Manzini et al. (2014) and Zappa and Shepherd (2017), though we divide by tropical warming rather than by globally averaged warming. Polar amplification was shown by Zappa and Shepherd (2017) to be important for precipitation changes in Northern Hemisphere subpolar latitudes, and in certain parts of the Mediterranean basin (such as Turkey) as well. We do not use this index for the Southern Hemisphere $\Delta\%$ precipitation for reasons discussed later.

Note that we explicitly include Δ globally averaged surface temperature, unlike Zappa and Shepherd (2017), as we are interested in the total contribution of large-scale processes (both thermodynamic and circulation driven) for local precipitation changes. Spatial averages have been area weighted, and when considering Northern Hemisphere $\Delta\%$ precipitation, we compute the polar amplification, Hadley cell, and stratospheric vortex indices for the Northern Hemisphere. Similarly, when considering Southern Hemisphere $\Delta\%$ precipitation we compute these indices for the Southern Hemisphere. We intentionally include a Hadley cell predictor [unlike Zappa and Shepherd (2017)] as the relevance of changes in the Hadley cell for subtropical precipitation has been the topic of recent debate (Schmidt and Grise 2017); the online supplemental material demonstrates that nearly all of the key results of this paper are unchanged if we remove this regressor. We also consider the additional skill that can be gained by considering changes in local surface relative humidity. Note that for two models

(indicated in Table 1) not all data that are necessary to compute these five indices were available for download, and therefore only 40 models are used when considering how these processes may influence precipitation. Of these 40 models, surface relative humidity is only available for 30 models, and therefore only 30 models are included when considering how these five processes and local surface relative humidity affect precipitation. We use as many models as possible to reduce overfitting of data.

An underlying assumption of our approach is that if the spread among the models of a change in a given zonal-mean process is well correlated with the spread of $\Delta\%$ precipitation in a given region, then that specific process contributes to precipitation changes in that region. The validity of this assumption should be tested using more idealized experiments for future work. Nonetheless, the statistical relationships identified herein are qualitatively consistent with separate experimental and observational evidence of how these components of the climate system affect precipitation as discussed above, which gives credence to interpreting the statistical results as physically meaningful [as in Manzini et al. (2014) and Zappa and Shepherd (2017)].

All changes are calculated for the annual mean and also for the extended boreal winter of November–April, and the results in the main text focus on the annual mean with comparable figures for November–April (NDJFMA) in the online supplemental material. When considering annual-averaged (NDJFMA) $\Delta\%$ precipitation, we consider annual-averaged (NDJFMA) changes in these five indices.

While shifts in these five processes are not independent of each other (indeed a leading mechanism to explain the Hadley cell shift is the enhanced vertical stratification of the tropics; e.g., Tandon et al. 2013), there is considerable scatter in the magnitude of changes among the models as we now quantify. Table 2 lists the correlation of the Δ of each index with the Δ of the others in the Northern Hemisphere, and also with the $\Delta\%$ precipitation at 32°N, 35°E (southern

FIG. 2. Correlation across the multimodel ensemble between $\Delta\%$ precipitation and (a) tropical vertical stratification, (b) globally averaged surface temperature, (c) the subtropical edge in the Hadley cell, (d) zonal wind at 10 hPa from 60° to 75° , and (e) polar amplification. Stippling in this figure and subsequent similar figures indicates grid boxes that are significant based on a false discovery rate of 15% following Wilks (2016). The contour interval is 0.1. For (c) and (d), we focus on Southern Hemisphere changes in the indices when focused on Southern Hemisphere precipitation and on Northern Hemisphere changes when focused on Northern Hemisphere precipitation.

Levant). The maximum correlation between predictors is 0.39 in the Northern Hemisphere. One way of quantifying if cross-correlation of predictors is a problem when computing a multiple linear regression (MLR) is the variance inflation factor (VIF), and here the largest

VIF is less than 1.6, which is well below the cutoff of 5 typically used for evaluating the usefulness of predictors included in a MLR (Sheather 2009, p. 203). The highest correlation is between Δ globally averaged surface temperature and Δ Hadley cell, and the online supplemental material shows that results are generally similar if we remove the Hadley cell predictor.

Corresponding correlations for the Southern Hemisphere and for precipitation at 34°S , 115°E (southwest Australia) are shown in Table 3. The maximum correlation between predictors is higher in the Southern Hemisphere than in the Northern Hemisphere, and is particularly large for the polar amplification index. As the physical meaning of this polar amplification index is less straightforward in the Southern Hemisphere (where polar amplification is weak) than in the Northern Hemisphere, we do not use the polar amplification regressor for Southern Hemisphere precipitation. The largest VIF after removing the polar amplification regressor is 1.4. The next largest correlation between regressors is between the Hadley cell and stratospheric vortex indices. The supplemental material explores sensitivity to removing the Hadley cell predictor and shows that the results are generally similar.

Statistical significance for the pairwise correlation coefficient (hereafter correlations) and for regression coefficients is computed using a two-tailed Student's t test at the 95% confidence level. For figures showing maps of anomalies, stippling indicates grid boxes that are significant based on a false discovery rate of 15% calculated as in Wilks (2016).

3. Results

We now consider whether the large-scale, zonally symmetric processes introduced in section 2 are associated with the spread in regional precipitation changes. Figure 2 shows the correlation of the intermodel spread in $\Delta\%$ precipitation with the intermodel spread in Δ tropical vertical stratification (Fig. 2a), Δ global-mean surface temperature (Fig. 2b), Δ subtropical edge of the Hadley cell (Fig. 2c), Δ stratospheric polar vortex (Fig. 2d), and Δ polar amplification (Fig. 2e). Increased tropical-mean vertical stratification is associated with enhanced precipitation over subpolar latitudes in the Southern Hemisphere and reduced precipitation over the subtropical North Atlantic Ocean and southern and eastern Mediterranean, and also over the South Pacific Ocean and Indian Ocean (Fig. 2a). Enhanced global warming is associated with precipitation changes that generally match the ensemble-mean response shown in Figs. 1a and 1b. A larger poleward expansion in the Hadley cell edge is associated with reduced precipitation over southern Europe, southern Africa, New

FIG. 3. Comparison of actual precipitation changes and precipitation changes predicted by the MLR with the MLR computed using leave-one-out for (a) 32°N, 35°E (southern Levant); (b) 40°N, 20°E (Albania); (c) 34°S, 115°E (southwestern Australia); and (d) 34°S, 18°E (southwest Africa). The correlation is indicated in light blue, and the correlation when the MLR is trained and tested on all the models is indicated in light orange. Numbers correspond to the model numbering in Table 1.

Zealand, and southern South America (Fig. 2c), consistent with Schmidt and Grise (2017). A larger poleward expansion is also associated with reduced precipitation over the southeastern United States, although this effect is not evident over the historical period (Schmidt and Grise 2017). A strengthening of zonal winds in the subpolar stratosphere is associated with more precipitation over Great Britain and less precipitation over the western Mediterranean (Fig. 2d), consistent with Karpechko and Manzini (2012) and Simpson et al. (2018). In the Southern Hemisphere, a stronger vortex is associated with reduced precipitation over parts of southern Africa and southern South America, consistent with Kang et al. (2011), Polvani et al. (2011), and Gonzalez et al. (2014). A decreased Northern Hemisphere meridional temperature gradient (i.e., polar amplification) is associated with increased precipitation in subpolar latitudes of North America and eastern Russia, and also over the Sahel–Sahara and East

Asia (Fig. 2e); the increase in Sahel precipitation is consistent with Monerie et al. (2019) and references therein, while the increase in subpolar precipitation is consistent with Bintanja and Selten (2014).

In many regions several of these processes are well correlated with the spread in projected $\Delta\%$ precipitation; for example, the spread in southeastern Europe and southern South America projected $\Delta\%$ precipitation is statistically significantly correlated with all processes. Hence, there is ambiguity as to which specific process is most crucial for projected $\Delta\%$ precipitation. As discussed in section 2, these various processes are in turn correlated with each other. To clarify the relative importance of these processes in a statistical sense, we now build a statistical model using multiple linear regression [MLR; as in Zappa and Shepherd (2017)] to objectively calculate the process(es) most closely associated with the intermodel spread in precipitation.

FIG. 4. Correlation of MLR predicted $\Delta\%$ precipitation with $\Delta\%$ precipitation simulated by the models (a) with the regression model cross validated using the leave-one-out approach in which the model being tested is not included in the training set; (b) with the regression model calculated on the first 20 models and tested on the last 20 models; and (c) with the regression model trained and tested on all models. The threshold for statistical significance at the 95% level using a two-tailed Student's t test is a correlation of 0.31.

MLR is used to calculate the β coefficients in Eq. (1) below such that the predicted $\Delta\%$ precipitation most closely matches the actual $\Delta\%$ precipitation, using the intermodel variability in the five structural changes introduced in section 2 as predictors:

$$\begin{aligned} \Delta\% \text{precip}_{\text{predicted}}(m) = & \beta_0 + \beta_S S(m) + \beta_{Ts} Ts(m) \\ & + \beta_{HC} HC(m) + \beta_V V(m) \\ & + \beta_P P(m). \end{aligned} \quad (1)$$

For model m , $S(m)$ refers to Δ tropical vertical stratification, $Ts(m)$ refers to Δ globally averaged surface temperature, $HC(m)$ refers to Δ Hadley cell subtropical extent, $V(m)$ refers to Δ stratospheric polar vortex, and

FIG. 5. As in Figs. 4a and 4c, but also using local changes in surface relative humidity as an additional predictor.

$P(m)$ refers to Δ polar amplification. As discussed in section 2, the polar amplification term is only included for the Northern Hemisphere. We remove the mean and divide by the intermodel standard deviation for each of the five regressors before performing the regression so that the regression coefficients β have common units (percentage change in precipitation per standard deviation of the intermodel spread) and can be intercompared. The intercept (i.e., multimodel mean $\Delta\%$ precip) is β_0 , and the regression coefficients are $\beta_S, \beta_{Ts}, \beta_P, \beta_{HC}$, and β_V ; β is a function of latitude and longitude. The MLR model is validated using the leave-one-out iterative approach, in which the model whose response is being predicted is not used to train the regression (section 7.4.4 of Wilks 2011). Zappa and Shepherd (2017) adopted a similar methodology, but here we adopt a global perspective on how these processes affect precipitation changes.

How closely does $\Delta\% \text{precip}_{\text{predicted}}(m)$ match the $\Delta\%$ precipitation actually simulated by the CMIP5 models? Figure 3 compares the MLR-predicted and simulated $\Delta\%$ precipitation on the x axis and y axis, respectively, for four locations, using the leave-one-out approach. Figure 3a focuses on changes at $32^\circ\text{N}, 35^\circ\text{E}$ (the southern Levant), and Fig. 3b focuses on changes at $40^\circ\text{N}, 20^\circ\text{E}$ (Albania). In both regions the predicted $\Delta\%$ precipitation is significantly correlated with the actual $\Delta\%$ precipitation, and approximately one-third of the variance is accounted for by large-scale processes. The variance explained increases to approximately 50% when the regression model is trained on all models, although there is still skill in these regions even when the regression

FIG. 6. As in Fig. 4a, but for the difference between an MLR with all zonal-mean processes plus local changes in surface relative humidity and an MLR with only surface relative humidity.

model is trained on independent data (i.e., using leave-one-out). Zonal-mean processes also explain $\sim 20\%$ of the variance in local precipitation in the Southern Hemisphere on the poleward edge of the subtropics in southwestern Australia and southwestern Africa (Figs. 3c,d), though the quality of the fits are somewhat less than for the Northern Hemisphere.

Figure 4 extends the results of Fig. 3 to most of the globe, and specifically Fig. 4a shows the correlation of the MLR-predicted $\Delta\%$ precipitation with the GCM-simulated $\Delta\%$ precipitation using the leave-one-out approach to validate the regression model. Over most of the Mediterranean, southern South America, coastal South Africa, and coastal southern Australia, the zonal-mean circulation features account for more than a third, and in some regions up to half, of the variance. Farther inland however, the importance of zonal-mean processes diminishes. The lack of any explanatory ability of the regression model over California is considered in the discussion. Results are similar if we train the MLR on the first 20 models in Table 1 and test on the second group of 20 models (Fig. 4b). When the MLR model is trained on all models and the predicted $\Delta\%$ precipitation is compared to the actual $\Delta\%$ precipitation, the MLR succeeds in capturing at least half of the variance over much of the globe, and over most regions the correlations exceed 0.5 [Fig. 4c; similar to Zappa and Shepherd (2017)]. The remaining unexplained variance is due to intermodel differences that cannot be explained by large-scale changes in the five parameters examined, such as regional scale gradients in moisture transport, other large-scale processes, stationary wave changes, model peculiarities, or internal variability.

If we add local changes in surface relative humidity as a predictor to the MLR in addition to the zonal-mean processes, correlations exceed 0.9 over many regions, including the interior continental United States, Australia, sub-Saharan Africa, and western Eurasia (Fig. 5a) even when cross-validating using leave-one-out.

FIG. 7. Regression coefficients from the MLR for the annual average, with the MLR trained with all models for (a) tropical vertical stratification, (b) globally averaged surface temperature, (c) the subtropical edge in the Hadley cell, (d) zonal wind at 10 hPa and 60° – 75° , and (e) polar amplification. For (c) and (d), we focus on Southern Hemisphere changes in the indices when focused on Southern Hemisphere precipitation and on Northern Hemisphere changes in the indices when focused on Northern Hemisphere precipitation. The polar amplification regressor is only included for the Northern Hemisphere and hence represents Arctic amplification.

For regions far from oceans, the limiting factor in precipitation is moisture availability and a relative increase in relative humidity is directly associated with increased precipitation, although changes in $\Delta\%$ precipitation associated with surface relative humidity in Fig. 5 may reflect zonally asymmetric circulation changes in addition to thermodynamic changes. The zonal-mean processes discussed in section 2 are unable to account for these changes in local or regional processes.

FIG. 8. Contribution of each of the zonal-mean processes to precipitation changes at 32°N, 35°E relative to the multimodel mean for (a) the four models that simulate little drying from Fig. 3a and (b) the five models that simulate the most pronounced drying from Fig. 3a. The multimodel-mean drying is 24% of model-simulated present-day values.

An alternative method to assess the importance of the five zonal-mean processes is to form a regression model with local surface relative humidity as the sole predictor, and compare the variance it explains to the variance when surface relative humidity and the five zonal-mean processes are included. Figure 6 shows the square root of the difference of these two variances. The regions in which zonal-mean processes add skill are broadly similar to those shown in Fig. 4a, though the variance explained is smaller in Fig. 6 over North America, southern Africa, and southern Europe, similar over the eastern Mediterranean and North Africa, and larger in Fig. 6 over northern Europe and Australia.

Which large-scale factor is most important for each region? The regression coefficients [β in Eq. (1)] are shown in Fig. 7, and for this figure we compute the MLR using all models in order to improve the robustness of the estimated regression coefficients, though results are similar if we focus on a subset of the models (not shown). In the eastern Mediterranean and coastal North Africa Δ vertical stratification variability is most important,¹ while this factor is less important over the western Mediterranean. The Δ global surface temperature is the most important factor over Australia specifically and land areas in the Southern Hemisphere subtropics more generally, but over land adjacent to the Mediterranean other regressors are more important. The Δ Hc variability is important mainly over southern

Europe and Turkey, East Asia, and the southeastern United States. Stratospheric vortex changes in the annual average are not significantly correlated with local precipitation changes almost everywhere, although in boreal winter stratospheric vortex changes are important for Eurasian precipitation (Fig. S6 in the online supplemental material). Furthermore, as will be discussed later, Southern Hemisphere precipitation changes are sensitive to vortex changes if the Hadley cell regressor is removed. The Δ Arctic amplification is important mainly over North Africa and East Asia. The Δ Arctic amplification and Δ global surface temperature are also important over subpolar latitudes in the Northern Hemisphere. In some regions, all or nearly all processes are important (e.g., southern South America, Texas, and Mexico).

These β coefficients provide a framework with which to interpret the spread in $\Delta\%$ local precipitation across models, and specifically elucidate why some models simulate weak future drying and others much stronger future drying. Figure 8a shows the contribution of each of the five zonal-mean processes to precipitation changes in the southern Levant (at 32°N, 35°E) relative to the multimodel mean for the four models that simulate little drying (models 11, 14, 18, and 40 in Fig. 3). For all of these models, a relatively weak increase in tropical stratification is the most important factor in accounting for an increase in precipitation relative to the multimodel mean, while changes in the other four processes are inconsistent among the models. Figure 8b is similar to Fig. 8a, but it focuses on the five models that simulate the most pronounced drying (models 3, 17, 31, 32, and 35 in Fig. 3). For all of these models, a relatively strong increase in tropical stratification is the most important factor in

¹ Note that the false-discovery-rate calculation restricts the region of significance to the coastal regions only. If the false-discovery-rate calculation is not applied, then a broader region would be indicated as significant.

FIG. 9. Spatial decorrelation of precipitation in NDJFMA using E-OBS data on interannual time scales. (a) One-point correlation map with a central point at 32°N, 35°E. (b) Correlation with the North Atlantic Oscillation index sourced from NOAA ESRL.

accounting for a strong decrease in precipitation, while the second most important factor differs among the models. While factors other than stratification contribute to the model spread, Δ stratification is the most important discriminant between models with strong projected drying over the southern Levant and models with little projected drying over the southern Levant. This result is consistent with Zappa and Shepherd (2017), who find that stratification and polar vortex changes are crucial for winter changes in precipitation in the Mediterranean basin (see their Fig. 8).

4. Summary and discussion

While CMIP5 models robustly project drying of the subtropics by the end of the century, the mechanisms causing regional drying are uncertain especially over land. Furthermore, the magnitude of this drying varies widely, and taking the southern Levant as an example, some models show essentially no drying and others show drying of more than 50%. Here, we exploit the inter-model variance in projected precipitation changes in 42 CMIP5 models to better understand the role of large-scale processes for projected local precipitation changes.

Up to half of the spread in the projected decrease in precipitation over the Mediterranean basin across the models can be related to large-scale processes such as Hadley cell widening, the magnitude of global warming, stabilization of the tropical upper troposphere, polar amplification, or changes in the polar stratosphere. Stabilization of the upper troposphere is an important factor related to drying only over the eastern Mediterranean

and not the western Mediterranean. A possible explanation for this effect is the relatively lower latitudes in the eastern Mediterranean as compared to the western Mediterranean, and as is evident in Fig. 12.12 of IPCC (2013), changes in tropical vertical stratification extend to 30°N. While it may seem surprising that different zonal-mean processes are associated with western Mediterranean drying as compared to eastern Mediterranean drying, we emphasize that precipitation in the far eastern Mediterranean is largely independent of precipitation in the western Mediterranean on both interannual and centennial time scales. On centennial time scales, models that project strong drying over the southern Levant are no more likely to project strong drying over the Iberian Peninsula than a model that projects a more muted response over the southern Levant: the correlation of $\Delta\%$ precipitation at 32°N, 35°E and 40°N, 7°W across the 42 models considered here is 0.02. On interannual time scales, the correlation between precipitation in these two basins, and even between the southern Levant and Greece, is negative. This negative correlation is demonstrated in Fig. 9a, which shows a one-point correlation map of NDJFMA-mean precipitation of 32°N, 35°E with all other grid points for which E-OBS data are available over the period 1950–2017. In fact, the one-point correlation map of NDJFMA-mean precipitation of 32°N, 35°E with all other grid points qualitatively resembles the correlation of the North Atlantic Oscillation with precipitation (Fig. 9b): a positive phase of the North Atlantic Oscillation leads to enhanced precipitation poleward of 55°N and reduced precipitation over most of the Mediterranean, but over the far eastern Mediterranean precipitation increases.

Note that precipitation over the western United States does not seem to be associated with the predictors included in our MLR (Fig. 4). Motivated by the results of Zappa et al. (2015) and Zappa and Shepherd (2017), we have experimented with replacing the Hadley cell extent regressor with a regressor of subtropical winds at 850 hPa, by averaging the zonal wind from 25° to 35°. Such an MLR can account for a third of the variance in California precipitation when validated using leave-one-out, and half of the variance when tested in-sample (not shown).² Note that the Δ of subtropical winds is generally tightly coupled to changes in Δ Hadley cell extent: the correlation between these two is -0.56 in the Northern Hemisphere and -0.71 in the Southern Hemisphere for the annual average, whereby a stronger poleward expansion of the Hadley cell extent is associated with weaker subtropical winds. It is therefore problematic to include both regressors in the regression model, and we elect to include a Hadley cell regressor rather than a wind regressor in the MLR results shown above. However, zonal-mean processes do contribute to the spread in projected California precipitation changes, in addition to the spread in stationary wave changes (Simpson et al. 2016).

In the Southern Hemisphere, changes in subtropical precipitation near the coasts of Australia and South Africa are associated with zonal-mean processes, and over South America the explained variance extends inland too. The dominant predictor of these changes in local precipitation is globally averaged surface temperature. Note that a relative increase in stratospheric winds appears to be correlated with increased subpolar precipitation and reduced midlatitude precipitation (Fig. 2d). This change is likely associated with the recovery of the austral spring ozone hole, whereby models with a stronger ozone recovery (i.e., a weakening of stratospheric winds) simulate more midlatitude precipitation. In the Southern Hemisphere, there is a relatively large (as compared to the Northern Hemisphere) correlation among the regressors, and hence there is ambiguity as to whether the correlation analysis of Fig. 2d should be interpreted as a forced signal from the ozone recovery, and indeed no such signal is evident in vortex regressor in the multiple linear regression (Fig. 7d). However, if we remove the Hadley cell regressor, then the relative importance of changes in the polar stratosphere increases (Fig. S8c) and is associated with significant changes both over South America and Africa.

As the pathway whereby ozone recovery affects precipitation involves changes in, for example, the Hadley cell, there is no disagreement between our results and those of Gerber and Son (2014), who found similar regression coefficients for tropical upper-tropospheric warming and stratospheric polar cap warming when considering projected changes in jet location in austral summer. Note also that the stratospheric vortex regressor is more important in the Northern Hemisphere winter than in the annual average (Fig. S6) for Northern Hemisphere precipitation changes.

Inland, much of the spread in $\Delta\%$ precipitation is due to variations in surface relative humidity, which we interpret here as changes in moisture availability. Changes in moisture availability could be due to a variety of processes, such as changes in moisture advection either by transients or by stationary waves, or changes in local evaporation (e.g., Seager et al. 2014). For future work we plan to explore the factors that govern these regional variations in relative humidity.

More pronounced polar amplification appears to be associated with enhanced precipitation over most of East Asia (Figs. 2e and 7e). This effect is even more pronounced when we form the MLR using raw, rather than percentage, changes in precipitation (not shown). A somewhat similar effect was found by Guo et al. (2014) in response to reduced sea ice, but the pattern in Guo et al. (2014) resembled more a dipole with enhanced precipitation over northern East Asia and reduced precipitation farther south. Future work is needed to better understand the apparent connection between Arctic amplification and East Asian precipitation.

Of the zonal-mean processes examined, changes in tropical vertical stratification are most strongly correlated with the spread in projected precipitation over parts of the subtropics, including water-stressed regions such as the Levant and coastal North Africa (Figs. 7 and 8). The implication of this result is that the biggest source (on large scales) of uncertainty in future projections of precipitation in these regions is to what extent the tropical upper troposphere will warm relative to the tropical lower troposphere. In the historical period, this warming is, if anything, exaggerated in CMIP models (Po-Chedley and Fu 2012; Seidel et al. 2012; Santer et al. 2017), although the extent to which this mismatch exists is controversial (Mitchell et al. 2013), and the mismatch is reduced when models are forced with historical sea surface temperatures (Flannaghan et al. 2014). However, some of the mismatch may be due to systematic deficiencies in some of the post-2000 external forcings used in the model simulations (Santer et al. 2017), and if a similar deficiency exists for the future forcing,

² Such an MLR has a corresponding reduction in explained intermodel variance of western Mediterranean $\Delta\%$ precipitation, however.

then it is possible that some of the more extreme drying scenarios can be ruled out as improbable. However, even a 20% or 30% decrease in precipitation in semiarid subtropical regions would have a large impact on water availability, and adaptation efforts must begin.

Acknowledgments. This work is supported by the Israel Ministry of Science (Grant 61792). Correspondence and requests for data should be addressed to C.I.G. (email: chaim.garfinkel@mail.huji.ac.il). We thank the three anonymous reviewers for their constructive comments. We acknowledge the E-OBS dataset from the EU-FP6 project ENSEMBLES (<http://ensembles-eu.metoffice.com>) and the data providers in the ECA&D project (<https://www.ecad.eu>). The NAO index is sourced from <https://www.esrl.noaa.gov/psd/data/timeseries/daily/NAO/>.

REFERENCES

- Adam, O., and Coauthors, 2018: The TropD software package (v1): Standardized methods for calculating tropical-width diagnostics. *Geosci. Model Dev.*, **11**, 4339–4357, <https://doi.org/10.5194/gmd-11-4339-2018>.
- Allen, M. R., and W. J. Ingram, 2002: Constraints on future changes in climate and the hydrologic cycle. *Nature*, **419**, 228–232, <https://doi.org/10.1038/nature01092>.
- Bintanja, R., and F. Selten, 2014: Future increases in Arctic precipitation linked to local evaporation and sea-ice retreat. *Nature*, **509**, 479–482, <https://doi.org/10.1038/nature13259>.
- Cubasch, U., and Coauthors, 2001: Projections of future climate change. *Climate Change 2001: The Scientific Basis*, J. T. Houghton et al., Eds., Cambridge University Press, 526–582.
- Flannaghan, T., S. Fueglistaler, I. Held, S. Po-Chedley, B. Wyman, and M. Zhao, 2014: Tropical temperature trends in atmospheric general circulation model simulations and the impact of uncertainties in observed SSTs. *J. Geophys. Res. Atmos.*, **119**, 13 327–13 337, <https://doi.org/10.1002/2014JD022365>.
- Garfinkel, C. I., D. W. Waugh, and L. M. Polvani, 2015: Recent Hadley cell expansion: The role of internal atmospheric variability in reconciling modeled and observed trends. *Geophys. Res. Lett.*, **42**, 10 824–10 831, <https://doi.org/10.1002/2015GL066942>.
- Gerber, E. P., and S.-W. Son, 2014: Quantifying the summertime response of the austral jet stream and Hadley cell to stratospheric ozone and greenhouse gases. *J. Climate*, **27**, 5538–5559, <https://doi.org/10.1175/JCLI-D-13-00539.1>.
- Giorgi, F., and P. Lionello, 2008: Climate change projections for the Mediterranean region. *Global Planet. Change*, **63**, 90–104, <https://doi.org/10.1016/j.gloplacha.2007.09.005>.
- Gonzalez, P. L., L. M. Polvani, R. Seager, and G. J. Correa, 2014: Stratospheric ozone depletion: A key driver of recent precipitation trends in south eastern South America. *Climate Dyn.*, **42**, 1775–1792, <https://doi.org/10.1007/s00382-013-1777-x>.
- Guo, D., Y. Gao, I. Bethke, D. Gong, O. M. Johannessen, and H. Wang, 2014: Mechanism on how the spring Arctic sea ice impacts the East Asian summer monsoon. *Theor. Appl. Climatol.*, **115**, 107–119, <https://doi.org/10.1007/s00704-013-0872-6>.
- Haylock, M., N. Hofstra, A. Klein Tank, E. Klok, P. Jones, and M. New, 2008: A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. *J. Geophys. Res.*, **113**, D20119, <https://doi.org/10.1029/2008JD010201>.
- He, J., and B. J. Soden, 2017: A re-examination of the projected subtropical precipitation decline. *Nat. Climate Change*, **7**, 53–57, <https://doi.org/10.1038/nclimate3157>.
- Holton, J., and G. Hakim, 2013: *An Introduction to Dynamic Meteorology*. Academic Press, 532 pp.
- Hu, Y., L. Tao, and J. Liu, 2013: Poleward expansion of the Hadley circulation in CMIP5 simulations. *Adv. Atmos. Sci.*, **30**, 790–795, <https://doi.org/10.1007/s00376-012-2187-4>.
- , H. Huang, and C. Zhou, 2018: Widening and weakening of the Hadley circulation under global warming. *Sci. Bull.*, **63**, 640–644, <https://doi.org/10.1016/j.scib.2018.04.020>.
- IPCC, 2007: *Climate Change 2007: The Physical Science Basis*. S. Solomon et al., Eds., Cambridge University Press, 996 pp.
- , 2013: *Climate Change 2013: The Physical Science Basis*. T. F. Stocker et al., Eds., Cambridge University Press, 1535 pp.
- Kang, S. M., L. M. Polvani, J. C. Fyfe, and M. Sigmond, 2011: Impact of polar ozone depletion on subtropical precipitation. *Science*, **332**, 951–954, <https://doi.org/10.1126/science.1202131>.
- Karpechko, A. Y., and E. Manzini, 2012: Stratospheric influence on tropospheric climate change in the Northern Hemisphere. *J. Geophys. Res.*, **117**, D05133, <https://doi.org/10.1029/2011JD017036>.
- Kelley, C., M. Ting, R. Seager, and Y. Kushnir, 2012: Mediterranean precipitation climatology, seasonal cycle, and trend as simulated by CMIP5. *Geophys. Res. Lett.*, **39**, L21703, <https://doi.org/10.1029/2012GL053416>.
- Manabe, S., and R. T. Wetherald, 1980: On the distribution of climate change resulting from an increase in CO₂ content of the atmosphere. *J. Atmos. Sci.*, **37**, 99–118, [https://doi.org/10.1175/1520-0469\(1980\)037<0099:OTDOCC>2.0.CO;2](https://doi.org/10.1175/1520-0469(1980)037<0099:OTDOCC>2.0.CO;2).
- Manzini, E., and Coauthors, 2014: Northern winter climate change: Assessment of uncertainty in CMIP5 projections related to stratosphere–troposphere coupling. *J. Geophys. Res. Atmos.*, **119**, 7979–7998, <https://doi.org/10.1002/2013JD021403>.
- , A. Y. Karpechko, and L. Kornbluh, 2018: Nonlinear response of the stratosphere and the North Atlantic–European climate to global warming. *Geophys. Res. Lett.*, **45**, 4255–4263, <https://doi.org/10.1029/2018GL077826>.
- Mitchell, D., P. Thorne, P. Stott, and L. Gray, 2013: Revisiting the controversial issue of tropical tropospheric temperature trends. *Geophys. Res. Lett.*, **40**, 2801–2806, <https://doi.org/10.1002/grl.50465>.
- Mitchell, J. F., 1983: The seasonal response of a general circulation model to changes in CO₂ and sea temperatures. *Quart. J. Roy. Meteor. Soc.*, **109**, 113–152, <https://doi.org/10.1002/qj.49710945906>.
- Monerie, P.-A., T. Oudar, and E. Sanchez-Gomez, 2019: Respective impacts of Arctic sea ice decline and increasing greenhouse gases concentration on Sahel precipitation. *Climate Dyn.*, **52**, 5947–5964, <https://doi.org/10.1007/s00382-018-4488-5>.
- Po-Chedley, S., and Q. Fu, 2012: Discrepancies in tropical upper tropospheric warming between atmospheric circulation models and satellites. *Environ. Res. Lett.*, **7**, 044018, <https://doi.org/10.1088/1748-9326/7/4/044018>.
- Polvani, L. M., M. Previdi, and C. Deser, 2011: Large cancellation, due to ozone recovery, of future Southern Hemisphere

- atmospheric circulation trends. *Geophys. Res. Lett.*, **38**, L04707, <https://doi.org/10.1029/2011GL046712>.
- Santer, B. D., and Coauthors, 2017: Causes of differences in model and satellite tropospheric warming rates. *Nat. Geosci.*, **10**, 478–485, <https://doi.org/10.1038/ngeo2973>.
- Scheff, J., and D. Frierson, 2012a: Twenty-first-century multi-model subtropical precipitation declines are mostly mid-latitude shifts. *J. Climate*, **25**, 4330–4347, <https://doi.org/10.1175/JCLI-D-11-00393.1>.
- , and —, 2012b: Robust future precipitation declines in CMIP5 largely reflect the poleward expansion of model subtropical dry zones. *Geophys. Res. Lett.*, **39**, L18704, <https://doi.org/10.1029/2012GL052910>.
- Schmidt, D. F., and K. M. Grise, 2017: The response of local precipitation and sea level pressure to Hadley cell expansion. *Geophys. Res. Lett.*, **44**, 10 573–10 582, <https://doi.org/10.1002/2017GL075380>.
- Seager, R., N. Naik, and G. A. Vecchi, 2010: Thermodynamic and dynamic mechanisms for large-scale changes in the hydrological cycle in response to global warming. *J. Climate*, **23**, 4651–4668, <https://doi.org/10.1175/2010JCLI3655.1>.
- , H. Liu, N. Henderson, I. Simpson, C. Kelley, T. Shaw, Y. Kushnir, and M. Ting, 2014: Causes of increasing aridification of the Mediterranean region in response to rising greenhouse gases. *J. Climate*, **27**, 4655–4676, <https://doi.org/10.1175/JCLI-D-13-00446.1>.
- Seidel, D. J., M. Free, and J. S. Wang, 2012: Reexamining the warming in the tropical upper troposphere: Models versus radiosonde observations. *Geophys. Res. Lett.*, **39**, L22701, <https://doi.org/10.1029/2012GL053850>.
- Sheather, S., 2009: *A Modern Approach to Regression with R*. Springer, 393 pp.
- Shepherd, T. G., 2014: Atmospheric circulation as a source of uncertainty in climate change projections. *Nat. Geosci.*, **7**, 703–708, <https://doi.org/10.1038/ngeo2253>.
- Simpson, I. R., R. Seager, M. Ting, and T. A. Shaw, 2016: Causes of change in Northern Hemisphere winter meridional winds and regional hydroclimate. *Nat. Climate Change*, **6**, 65–70, <https://doi.org/10.1038/nclimate2783>.
- , P. Hitchcock, R. Seager, Y. Wu, and P. Callaghan, 2018: The downward influence of uncertainty in the Northern Hemisphere stratospheric polar vortex response to climate change. *J. Climate*, **31**, 6371–6391, <https://doi.org/10.1175/JCLI-D-18-0041.1>.
- Staten, P. W., J. Lu, K. M. Grise, S. M. Davis, and T. Birner, 2018: Re-examining tropical expansion. *Nat. Climate Change*, **8**, 768–775, <https://doi.org/10.1038/s41558-018-0246-2>.
- Tandon, N. F., E. P. Gerber, A. H. Sobel, and L. M. Polvani, 2013: Understanding Hadley cell expansion versus contraction: Insights from simplified models and implications for recent observations. *J. Climate*, **26**, 4304–4321, <https://doi.org/10.1175/JCLI-D-12-00598.1>.
- Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.*, **93**, 485–498, <https://doi.org/10.1175/BAMS-D-11-00094.1>.
- Vallis, G. K., P. Zurita-Gotor, C. Cairns, and J. Kidston, 2015: Response of the large-scale structure of the atmosphere to global warming. *Quart. J. Roy. Meteor. Soc.*, **141**, 1479–1501, <https://doi.org/10.1002/qj.2456>.
- Waugh, D. W., C. Garfinkel, and L. M. Polvani, 2015: Drivers of the recent tropical expansion in the Southern Hemisphere: Changing SSTs or ozone depletion? *J. Climate*, **28**, 6581–6586, <https://doi.org/10.1175/JCLI-D-15-0138.1>.
- Wilks, D. S., 2011: *Statistical Methods in the Atmospheric Sciences*. 3rd ed. Academic Press, 676 pp.
- , 2016: “The stippling shows statistically significant grid points”: How research results are routinely overstated and over-interpreted, and what to do about it. *Bull. Amer. Meteor. Soc.*, **97**, 2263–2273, <https://doi.org/10.1175/BAMS-D-15-00267.1>.
- Zappa, G., and T. G. Shepherd, 2017: Storylines of atmospheric circulation change for European regional climate impact assessment. *J. Climate*, **30**, 6561–6577, <https://doi.org/10.1175/JCLI-D-16-0807.1>.
- , B. J. Hoskins, and T. G. Shepherd, 2015: The dependence of wintertime Mediterranean precipitation on the atmospheric circulation response to climate change. *Environ. Res. Lett.*, **10**, 104012, <https://doi.org/10.1088/1748-9326/10/10/104012>.