Orographic Controls on Asian Hydroclimate, and an Examination of Heat Wave Temporal Compounding

Jane Wilson Baldwin

A Dissertation
Presented to the Faculty
of Princeton University
in Candidacy for the Degree
of Doctor of Philosophy

Recommended for Acceptance
by the Program in
Atmospheric and Oceanic Sciences
Adviser: Professor Gabriel A. Vecchi

June 2018
Abstract

Global warming is projected to induce changes in phenomena ranging from hurricanes to heat waves to droughts. Preparing for these changes requires both fundamental understanding of the climate system, and applied understanding of the risks posed by such events. This dissertation engages with both these areas of inquiry by analyzing diverse observations and global climate model (GCM) simulations.

Two studies in this dissertation explore a basic climate dynamics question: what role does orography (i.e. mountains and other topographic features) play in shaping patterns of precipitation over Asia? Both studies are conducted by comparing a control GCM simulation incorporating modern day orography to a perturbation simulation where specific orography is flattened.

The first study examines the influence of the Tian Shan, a mountain range branching north from the Tibetan Plateau, on extratropical deserts in Asia. The western and eastern deserts in this region exhibit strikingly different seasonal cycles of precipitation. The Tian Shan’s role in this zonal gradient of precipitation is examined, and an important role for the Tian Shan in enhancing the East Asian Monsoon is highlighted.

The second study examines the influence of the Tibetan Plateau and related orography on Asian monsoons and tropical cyclones. Asian orography is found to increase precipitation over the Western North Pacific (WNP) throughout the summer monsoon, but decrease precipitation over the Arabian Sea. The mountains also alter tropical cyclones, enhancing and suppressing their formation in the WNP and Arabian Sea, respectively. The roles of model resolution and atmosphere-ocean coupling in these responses are differentiated using a hierarchy of GCM simulations.

The third study of this dissertation focuses on an applied, policy-motivated question: what is the hazard of heat waves occurring close together in time (i.e. temporally compounding), and how will that change with global warming? Definitions of heat
wave compounding are developed and applied to GCM simulations with increased at-
mospheric carbon dioxide. It is argued that the hazard of compound heat waves will
disproportionately increase with global warming. Prior events will then play an in-
creasingly large role in heat wave vulnerability. Policy implications of this conclusion
are discussed.
Acknowledgements

Towards the beginning of my graduate studies, I adopted the habit of listing three things I was grateful for every night before I went to sleep, and endeavored to be as specific as possible. Fortunately, the last six years have provided a diverse array of people and things to be grateful for. The acknowledgments for this dissertation comprise a hall of fame from those daily lists.

First, I am grateful to all the academic groups that provided support and inspiration. This dissertation work was generously funded by a National Science Foundation Graduate Research Fellowship, a Princeton Environmental Institute-Science Technology Environmental Policy (PEI-STEP) Fellowship, a Princeton University Centennial Fellowship, and the Cooperative Institute for Climate Science. The diverse academic communities at Princeton, including the Program in Atmospheric and Oceanic Sciences, NOAA Geophysical Fluid Dynamics Laboratory, Princeton Environmental Institute, Woodrow Wilson School Program in Science, Technology and Environmental Policy, and Geosciences Department provided warm academic homes and inspiration for my disciplinary and interdisciplinary interests.

I am grateful to all the resources and people that kept me going. Seth Underwood, Sergey Malyshev, Hiroyuki Murakami, Zhi Liang, William Cooke, Andrew Wittenberg, and Xiaosong Yang at the Geophysical Fluid Dynamics Laboratory provided critical technical support. Geoscience students Jay Dessy and James Tralie were both a pleasure to work with and help advise. Anna Valerio and the rest of the AOS and GEO administration were always on top of their game and so helpful. Alex Levine from the Whole Earth Center, the Rockefeller dining hall staff, and Small World Coffee kept me well fed, caffeinated, and encouraged. Gemma Farrell’s classes at Gratitude Yoga provided an excellent respite from research.

I am grateful to my friends for the companionship and support they have provided over the past 6 years. I am certainly a better scientist from working alongside my brill-
liant PhD cohort-mates Nick Lutsko, Rob Nazarian, and Anna Trugman. My other AOS classmates, particularly including but certainly not limited to Sarah Schlunegger, Geeta Persad, Andrew Ballinger, and Anna Fitzmaurice, have been sources of great advice and camaraderie. Cleo Chou, Janam Jhaveri, and the other members of Princeton Energy and Climate Scholars have been inspirational colleagues, and wonderful friends. Greta Shum, D.J. Bozym, Annie Edmundson, Elsa Voytas, Camille Rullán, Robert Deluca, Alex Piotrowski, Lucy Lee and many others made Rocky College a very fun and stimulating community. Other members of my village that deserve special thanks include: Alex Andrews, Karen Mckinnon, Stef Rojas, Amanda Peery, Gillian Shaffer, Marcelo Mattar, and Tim Treuer. Last but certainly not least, Eric Wengrowski has been an absolute joy to find in the last year of my Ph.D.

I am grateful to all my mentors, teachers, and research advisers. My committee members Tom Delworth and Chris Milly were ever generous with their time and intellect, providing critical direction throughout the research process. Isaac Held was an excellent academic adviser the first year of graduate school, and continued to lend his incisive research critiques, kindness, and wry sense of humor as a member of my committee. Peter Huybers, Simona Bordoni, Sarah Kapnick, Rob Socolow, Stephan Fueglistaler, Sonya Legg, Elena Shevliakova, Marian Westley, Tom Knutson, Xinning Zhang, and Mike Lemonick alternately provided both mentoring and scientific guidance, depending on what the occasion required. Dan Carlin (via his podcasts) made Arid Asia come alive by teaching me everything there is to know about Genghis Khan and the Mongol Empire.

My PEI-STEP project adviser Michael Oppenheimer went above and beyond, not only supplying great scientific and policy wisdom for that particular project, but also consistently encouraging my broader ambitions as a researcher.

“Doctoral adviser” only begins to describe the many roles that Gabe Vecchi has played throughout my PhD. He’s been my teacher, coach, advocate, sounding board,
IT service, compatriot, collaborator, role model, and friend. Working with him has been a great privilege, and a great deal of fun. I hope I can someday spread his insight and enthusiasm to other young researchers.

Finally, I am eternally grateful for my parents, Rone and Carol, and my sister Grace. Their unwavering belief in me and their love have been my rock for the past 6 years.
To Archie, Uli, Mellie, Sampson, Delilah, Elise, Eduardo, Alice, Eddy, Blair, Serena, Bandit, Spree, Dewdrop, Magellan, Konishiki, Nicky, Buddy, Mao, others too small to name, and, of course, their caregivers Carol and Rone.
# Contents

Abstract ................................................................. iii
Acknowledgements ......................................................... v
List of Tables .............................................................. xii
List of Figures .............................................................. xiv

1 Introduction ............................................................. 1

2 Influence of the Tian Shan on Arid Extratropical Asia .......... 5
   2.1 Abstract ............................................................. 5
   2.2 Introduction ....................................................... 6
   2.3 Methods ............................................................ 14
      2.3.1 Observational Estimates .................................. 14
      2.3.2 Global Coupled Model .................................... 15
      2.3.3 Experiment Design ......................................... 16
   2.4 AEA Climatology and Model Evaluation ......................... 18
   2.5 Modeled Climatic Effects of the Tian Shan .................... 22
      2.5.1 Precipitation in AEA ...................................... 22
      2.5.2 Temperature in AEA ....................................... 35
   2.6 Summary & Discussion ........................................... 39
   2.7 Acknowledgements ................................................ 43
<table>
<thead>
<tr>
<th>Chapter</th>
<th>Section</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 The Ocean-Mediated Influence of Asian Orography on Tropical Precipitation and Cyclones</td>
<td>3.1 Abstract</td>
</tr>
<tr>
<td></td>
<td>3.2 Introduction</td>
</tr>
<tr>
<td></td>
<td>3.3 Methods</td>
</tr>
<tr>
<td></td>
<td>3.3.1 Models</td>
</tr>
<tr>
<td></td>
<td>3.3.2 Observational datasets</td>
</tr>
<tr>
<td></td>
<td>3.3.3 Experiments</td>
</tr>
<tr>
<td></td>
<td>3.3.4 Analysis strategy</td>
</tr>
<tr>
<td></td>
<td>3.4 Results</td>
</tr>
<tr>
<td></td>
<td>3.4.1 Model Validation</td>
</tr>
<tr>
<td></td>
<td>3.4.2 Precipitation</td>
</tr>
<tr>
<td></td>
<td>3.4.3 Tropical cyclones</td>
</tr>
<tr>
<td></td>
<td>3.5 Summary &amp; Discussion</td>
</tr>
<tr>
<td></td>
<td>3.6 Acknowledgements</td>
</tr>
<tr>
<td>4 Temporally Compound Heat Wave Events and Global Warming: An Emerging Risk</td>
<td>4.1 Abstract</td>
</tr>
<tr>
<td></td>
<td>4.2 Introduction</td>
</tr>
<tr>
<td></td>
<td>4.3 Methods</td>
</tr>
<tr>
<td></td>
<td>4.3.1 Compound heat wave definition</td>
</tr>
<tr>
<td></td>
<td>4.3.2 Temperature data</td>
</tr>
<tr>
<td></td>
<td>4.4 Results</td>
</tr>
<tr>
<td></td>
<td>4.4.1 GCM validation</td>
</tr>
<tr>
<td></td>
<td>4.4.2 GCM sensitivity</td>
</tr>
<tr>
<td></td>
<td>4.4.3 Understanding the increase in compound proportion</td>
</tr>
<tr>
<td></td>
<td>4.4.4 Projections from observationally-derived data</td>
</tr>
</tbody>
</table>
4.5 Discussion ................................................................. 107

4.6 Acknowledgements ..................................................... 112

5 Summary ........................................................................ 113

5.1 Chapter 2: Influence of the Tian Shan on Arid Extratropical Asia . 113

5.2 Chapter 3: The Ocean-Mediated Influence of Asian Orography on Tropical Precipitation and Cyclones ........................................ 115

5.3 Chapter 4: Temporally Compound Heat Wave Events and Global Warming: An Emerging Risk ............................................ 117

Bibliography .................................................................... 121
List of Tables

2.1 FLOR simulations analyzed in this study. . . . . . . . . . . . . . . . . 17
2.2 Regions examined in this study. Listed spatial limits are the precise
region bounds used when calculating the area average seasonalities for
Figures 2.4 and 2.5. . . . . . . . . . . . . . . . . . . . . . . . . . . . . 20
3.1 CMIP5 GCMs used for validation of the FLOR and LOAR simulations,
and the modeling centers that created each GCM. We use monthly
precipitation data from each GCM’s pre-industrial control run. . . . . 53
3.2 GCM simulations employed in this study. Note that an additional set
of simulations for the fully coupled model experiments was performed,
identical in all respects to this except with dynamic rather than static
vegetation. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 55
4.1 Mortality estimates associated with the four most deadly heat waves in
Europe and the USA respectively since 1980 as determined by a review
of the existing literature. Note that the size of the region affected and
the methods for estimating mortality differ. . . . . . . . . . . . . . . 86
4.2 Options for the temporally flexible heat wave definition used in this study. We test definitions using all combinations of the parameter options shown here. Note that we refer to days that exceed the threshold as hot days, and a set of consecutive hot days plus hot days separated by short breaks as a heat wave.
List of Figures

2.1 Arid places globally, with AEA shaded. Desert area is determined with three different annual mean precipitation thresholds (<0.50, 0.75, or 1.00 mm/day) applied to the University of Delaware precipitation dataset. Note that the deserts in Extratropical Asia are the only major extratropical deserts, excluding the far polar regions. .................. 7

2.2 Elevation in AEA for Control and NoTianshan. (a) and (c) are high-resolution observed topography (USGS 1-minute digital elevation model). (b) and (d) are FLOR’s 50 km resolution surface height boundary conditions. Comparison of (a) and (b) demonstrates the accuracy of FLOR’s topography. Comparison of (a) and (b) versus (c) and (d) demonstrates where the Tian Shan were flattened in model simulations. .......................... 8
2.3 Observed versus simulated area of AEA, and sub-regions examined in this study. ETOPO5 topography (shaded) is overlaid with outlines of deserts (annual mean precipitation <0.75 mm/day) according to (a) precipitation observed from satellites and ground-based measurements, (b) precipitation from reanalysis, and (c) precipitation from the FLOR Control run. Boxes in (c) designate particular regions examined in this analysis (i.e., West Deserts, East Deserts, the Western-East, and the Eastern-East). Regional seasonal cycles are calculated by averaging over only desert points within the region’s box, excluding major inland lakes and seas, except for the Tian Shan region where only non-desert points are averaged over.

2.4 Desert seasonal cycles in FLOR versus observationally-derived datasets. Monthly precipitation (P) and evaporation (E) are shown in mm/day. Seasonal cycles are calculated by averaging over places in each dataset that receive <0.75 mm/day of precipitation in the annual mean, excluding major inland lakes and seas by averaging over places with elevation greater than 70 m. The left column shows area-average seasonal cycles for the West Deserts, and the right column shows the same for the East Deserts. The first row shows seasonal cycles derived from observations and reanalysis, with gridded observed precipitation (black), reanalysis precipitation (blue), and reanalysis evaporation (red). The second row shows precipitation (blue) and evaporation (red) from the FLOR Control run. Each line for the model seasonal cycles is derived from 31 years of model data to match the observational/reanalysis time series length, starting every 5 years from 150 simulation years yielding 30 seasonal cycles total.
2.5 Influence of the Tian Shan on seasonal cycles of different desert regions. Regional area average seasonal cycles of precipitation (first column) and evaporation (second column) are plotted with one standard deviation above and below shaded. Each row corresponds to a different region: the Tian Shan (a,b), the West Deserts (c,d), the East Deserts (e,f), the Western-East (g,h) and the Eastern-East (i,j). Control results are colored, and NoTianshan results are in black/grey. Averaging is done over grid cells that are desert (mean precipitation <0.75 mm/day) in the Control run within the regions defined in Table 2.2 and shown in Figure 2.3c, except for the Tian Shan region where averaging is done over grid cells that are not desert (mean precipitation >0.75 mm/day). Additionally, major inland lakes and seas (such as the Caspian and Aral Seas) are excluded by averaging only over places with elevation greater than 70 m.

2.6 Influence of the Tian Shan on seasonal mean precipitation of AEA. Precipitation is shaded for different seasonal means (rows) and FLOR runs (Control, left, and NoTianshan, right). The black contours designate the annual (not seasonal) mean desert (precipitation <0.75 mm/day) as defined for each FLOR run. The dark red contours designate places with elevation greater than 1700 m in each FLOR run’s boundary conditions. The blue contours designate lakes and coastlines.

2.7 Seasonal percent change in precipitation by the Tian Shan (Control-NoTianshan). The black contour designates deserts (mean precip. <0.75 mm/day) in the FLOR Control run. Shading is masked for significance. Percent changes are calculated by normalizing changes by the average of the Control and NoTianshan seasonal means (i.e., a change from or to zero precipitation would be a 200% change).
2.8 Decomposition of moisture flux convergence due to the Tian Shan in East Asia. (a) shows summer (JJA) Control-NoTianshan change in moisture flux convergence \((P_{\text{Cont}}-E_{\text{Cont}})-(P_{\text{NoT}}-E_{\text{NoT}})\). The blue contour designates land, and the black contour designates desert. (b) shows components of summer moisture flux convergence averaged over the red box in (a). Note that monthly changes account for most of the moisture convergence due to the Tian Shan, and this moisture convergence is primarily caused by dynamical (wind) not thermal (humidity) changes. ................................................................. 29

2.9 Change in 850mb JJA climatological moisture fluxes from adding in the Tian Shan \((\Delta \mathbf{u} q)\). The black contour designates the Control desert and the blue contour designates land. Units for moisture fluxes are \(\frac{m}{s} \frac{g}{kg}\). 31

2.10 The Tian Shan's influence on geopotential height and wind in summer (JJA). Shown are anomalies (Control-NoTianshan) in geopotential height (m) zonally averaged over 65°E-100°E (a), and anomalies in 850 mb geopotential height overlaid with wind anomaly vectors \((\Delta \mathbf{u}; m/s)\) (b). All anomalies are contoured in black, but only significant anomalies are shaded, and places with only topography at the relevant pressure-level are masked in grey. Note the baroclinic structure in (a), and the correspondence south of the Tibetan Plateau between wind vectors and the zero-anomaly contour of geopotential height in (b) with moisture flux vectors shown in Figure 2.9. ................................................. 32

2.11 Mean 850 mb geopotential height and wind vectors in summer (JJA) for NoTianshan (a) and Control (b). Geopotential height is in meters, and wind in m/s. Note the blocking of westerly flow by the Tian Shan, and corresponding difference in geopotential height in the lee of the Tian Shan (the Western-East). ................................................. 33
2.12 The Tian Shan’s stationary wave in summer (JJA). Shown are Control-NoTianshan differences in 200 mb geopotential height (m) with the zonal mean removed. All anomalies are contoured in grey, but only significant anomalies are shaded. The black contour designates desert and the blue contour designates land. Note that circulation corresponding to the low-high pattern over East Asia explains the flux of moisture from the Pacific Ocean and East China Sea into this region (seen in Figure 2.9).

2.13 Remote warming by the Tian Shan and possible mechanisms. Shown are Control-NoTianshan changes in (a) surface temperature (°C), (b) snowfall (cm) and shortwave radiation reflected from the surface (purple contour $\Delta < -10 \frac{W}{m^2}$), and (c) Bowen ratio. All shaded quantities are masked for significance. The Tian Shan are masked out in light grey to highlight effects remote from the Tian Shan. The black contour designates the Control desert, and the blue contours designate lakes/seas. Note that the greatest changes in each quantity are co-located with mountains east of the Tian Shan (Altai in the north and Kunlun in the south).
2.14 Control-NoTianshan changes in the surface energy balance for 3 different regions: (a) the Altai Mountains, defined as areas directly north of the Tian Shan that warm by more than 2°C, (b) the Kunlun Mountains, defined as areas directly south of the Tian Shan that warm by more than 2°C, and (c) places in India that warm by more than 0.4°C. “Cloud” is the change in surface radiative forcing (both shortwave and longwave) due to changes in clouds. Positive forcing implies greater energy into the surface while negative implies greater energy leaving the surface. All changes are in \( \frac{W}{m^2} \). Note that clear-sky shortwave radiation dominates energy balance change in the mountains directly north and south of the Tian Shan, while latent heat flux dominates energy balance change in India.

3.1 Topographic boundary conditions for the GCM simulations. Surface height is shown for the Control (a,b,c) and FlatAsia (d,e) experiments. Observed 5’ resolution modern day topography (a; 51) is presented for comparison to FLOR (b) and LOAR (c) boundary conditions.

3.2 Influence of Asian orography on precipitation in an atmosphere-only model. Change in precipitation (AMIP Control-FlatAsia) is shaded and AMIP FlatAsia mean precipitation is contoured globally for the annual mean (a), and over the WNP and northern Indian Ocean for AMJ (b), and JAS (c). Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test.

3.3 Seasonal cycle of WNP precipitation in FLOR compared to observations and other models. Precipitation averaged over 0 to 40°N and 110 to 180 °W is plotted for TRMM, GPCP, and CMAP observed data (black), CMIP5 models (grey), and LOAR and FLOR fully coupled (blue) and nudged simulations (red).
3.4 Annual mean precipitation changes induced by the Asian mountains.

Annual mean change in precipitation (Control-FlatAsia) is shaded and FlatAsia mean precipitation is contoured for FLOR (a) and LOAR (b). Anomalies are only shown where statistically significant at the 95% level based on a two-sided $t$-test.

3.5 TC density changes induced by Asian orography. FLOR Control-FlatAsia TC changes are shaded, and Control TC density is contoured for the fully coupled runs (a) and nudged SST runs (b). For this analysis only, all available years (1000 total) of the fully coupled Control simulation are used, with years 1-30 still thrown out to allow for model spin-up. Anomalies are only shown where statistically significant at the 90% level based on a two-sided $t$-test. Note that the FLOR nudged simulations have only 30 years, which contributes to making those results less statistically significant.

3.6 Seasonal precipitation changes induced by the Asian mountains and role of atmosphere-ocean coupling. Change in precipitation (Control-FlatAsia) is shaded and FlatAsia mean precipitation is contoured for LOAR AMJ (a) and JAS mean (b). The percent of precipitation change due to SST changes induced by the Asian mountains is shaded for AMJ (a) and JAS (b) by comparing the fully coupled and nudged SST LOAR simulations (see Section 3.3). Anomalies are only shown where statistically significant at the 95% level based on a two-sided $t$-test.
3.7 WNP precipitation climatology changes due to Asian orography for different GCMs. Results for AM2.1 (a,b), FLOR (c,d), and LOAR (e,f) are compared. In the left panels (a,c,e), precipitation climatology is averaged over the WNP (0-40°N, 110-180 °W) and plotted for Control (black) and FlatAsia (blue) runs, with one standard deviation above and below shaded. In the right panels (b,d,f), absolute (thick dash) and percent (thin dash) differences between Control and FlatAsia climatologies are plotted, showing results for the standard settings for each model in black (atmosphere-only for AM2.1, fully coupled for FLOR and LOAR), in red for simulations nudged to model SST climatology, and in blue for simulations nudged to observed SST climatology, where those simulations are available.

3.8 SST changes induced by the Asian mountains. Shaded are annual mean Control-FlatAsia differences in SST from LOAR, with FlatAsia SST contoured. Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test. The blue and red dashed shapes demarcate the WNP regions of cooling and warming averaged over for Figure 3.10.

3.9 Ocean versus atmospheric drivers of SST change. Shaded is Control-FlatAsia change in energy transfer from the atmosphere to the surface (HFLUX; a) and change in ocean heat transport (OCEAN; b). Data is from LOAR, and these metrics are calculated as part of the SST nudging in the GCM. Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test.
3.10 WNP surface energy balance changes. Nudged Control-FlatAsia change in different components of the surface energy balance is calculated from LOAR. Averages are calculated over the northern blue box (a) and southern blue box (b) shown in Figure 3.8. The nudged simulation data is used because it shows the initial atmospheric forcing on the ocean surface from Asian orography that drives the SST changes. The fully coupled simulation data is equilibrated with the surface already and so is less informative.

3.11 Cloud changes induced by the Asian mountains. Nudged LOAR-Control-FlatAsia change in total cloud amount (a) and change at low (b), mid (c), and high (d) levels in the atmosphere. The location of modified topography is contoured green and the regions of WNP SST cooling and warming are boxed blue and red respectively. Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test. Nudged simulation data is used to highlight that these changes are directly driven by atmospheric circulation changes without SST response to the orography. However, results from the fully coupled runs are largely similar.

3.12 Stationary wave pattern induced by the Asian mountains. Annual mean Control-FlatAsia differences in geopotential height with the zonal mean removed at 200 mb (a) and 850 mb (b). Green contours designate the region of topographic modification and grey shading shows where Control topography is higher than the relevant pressure level. Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test.
3.13 Seasonal changes in winds and wind speed induced by Asian mountains. Shaded nudged Control-FlatAsia differences in surface wind magnitude; nudged FlatAsia and nudged Control-FlatAsia 850 mb wind vectors are plotted in grey and black, respectively. Seasonal averages for AMJ, JAS, OND, and JFM are shown in panels a, b, c, and d, respectively. Green contours designate the region of topographic modification. Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test. Nudged simulation data is used to highlight that these changes are directly driven by atmospheric circulation changes without SST response to the orography. However, results from the fully coupled runs are largely similar.

3.14 Seasonal 50-m depth ocean upwelling changes induced by the Asian mountains. LOAR change in upwelling is shown for JFM (a), AMJ (b), JAS (c), and OND (d) seasonal means. Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test.

3.15 TC GP changes due to Asian orography. Results are shown for Control-FlatAsia with FLOR fully coupled (a) and nudged runs (b). % changes are calculated as (Control-FlatAsia)/Control.

3.16 TC GP component changes due to Asian orography. Shown are changes in components for 600 mb relative humidity (a,b), potential intensity (c,d), vertical wind shear (d,e), and 850 mb absolute vorticity (f,g), from the fully coupled (a,c,e,g), and nudged (b,d,f,h) FLOR simulations. Each plot represents % change of the relevant component in Equation 3.4.3 including the factors (e.g., the wind shear term is differences in \( (1 + 0.1V_{\text{shear}})^{-2} \) so positive implies a positive contribution to GP).
3.17 Annual mean wind changes induced by the Asian mountains overlaying mean specific humidity. Control-FlatAsia change data is from the nudged FLOR runs, and specific humidity is from the nudged FLOR FlatAsia run. Anomalies are only shown where statistically significant at the 95% level based on a two-sided \( t \)-test. Nudged simulation data is used to highlight that these changes are directly driven by atmospheric circulation changes without SST response to the orography. However, results from the fully coupled runs are largely similar.

4.1 Past heat waves that resulted in high mortality. MERRA2 daily minimum temperature (black) and the corresponding seasonally varying thresholds (red) are averaged over regions and plotted against summer days. The location name, latitude-longitude range, and year of each heat wave are listed at the bottom of each panel. These heat waves were chosen to illustrate temperature time series for the four most deadly heat waves in Europe and the USA respectively since 1980 (see Table 4.1 for mortality estimates). These events were initially selected by aggregating information from various sources \[156,142,194,113\].

4.2 Schematic temperature time series to build intuition regarding the heat wave definitions. Cartoon temperature (black) and a seasonally varying threshold (red) are plotted against time. At the top of the figure, threshold-exceeding hot days are marked with red H’s while below threshold cooler days are marked with black minus signs. According to prior heat wave definitions \( i.e., [169] \) this would constitute two three-day-long heat waves. In this paper we count this event as having a total duration of seven days, composed of an initial three-day long heat wave with four additional hot days compounded onto it.
4.3 Regional average comparison of reanalysis and GCM results. Summer compound proportion is determined using daily minimum temperature and three different temporal structure definitions, using MERRA2 re-analysis (red) and FLOR ensemble members (grey). These values are then averaged over land points in Western Europe (a,b,c; -10 to 40°E, 40 to 60°N), the USA (d,e,f; -125 to 65°E, 20 to 50°N), and Asia (g,h,i; 70 to 140°E, 0 to 60°N) and plotted against time in years. The mean of FLOR’s ensemble members is also plotted (black).

4.4 Reanalysis versus GCM results across locations. Comparison between MERRA2 and the FLOR ensemble over 1980-2015 for means (a,c,e) and trends (b,d,f) of all heat wave days (a,b), compound days (c,d), and compound proportion (e,f). For the heat wave definition daily minimum temperature, a 90th percentile threshold, and the temporal structure 311 are used. All values over bodies of water are masked white, and over land places where the MERRA2 value falls within the range of the FLOR ensemble are masked white. Places where the MERRA2 value falls outside the range of the ensemble are shaded with the percent deviation compared to the ensemble mean for the mean bias (a,c,e) and percent deviation compared to the ensemble range for the trend bias (b,d,f). Positive values and red colors show a high bias of the model, while negative values and blue colors show a low bias of the model.
4.5 FLOR Control versus MERRA2 summer temperature standard deviation and autocorrelation. Standard deviation (a) and lag 1-day autocorrelation (b) are calculated from daily minimum temperature, and only summer months for each hemisphere. The log of the Control versus MERRA2 ratio is taken such that places where FLOR Control variance is greater are positive, and where MERRA2 variance is greater are negative. Bodies of water are masked out.

4.6 FLOR output heat wave hazard and compound proportion. Control (a,b) and 2xCO$_2$ (c,d) total summer heat wave days (a,c) and proportion of those heat wave days that are compounded in percent terms (b,d), calculated from all 100 years of the model daily minimum temperature data. Temporal structure definition is 311 and threshold is the seasonally varying 90$^{th}$ percentile calculated from years 1981-2010. Global means are noted on each panel.

4.7 MERRA2 reanalysis heat wave hazard and compound proportion. Total heat wave days on average over the summer months (May-September) (a) and compound proportion of those days in percent terms (b) for MERRA2 1980-2015 daily minimum temperature data. Temporal structure definition is 311 and the threshold is the seasonally varying 90$^{th}$ percentile calculated from years 1981-2010. Spatial means over all locations with data are listed on each panel; note that this is not the full globe as in maps of FLOR data due to MERRA data availability.
4.8 Compound proportion across definitions. Control versus 2xCO$_2$ summer, global mean compound proportion is plotted in percent terms. The black line is a one-to-one line to highlight that the compound proportion is higher in the 2xCO$_2$ simulation across definitions. Colors, symbols, and numbers note daily minimum versus maximum temperature, threshold percentile, and allowed temporal structure, respectively (as shown in the key to the right).

4.9 Change in compound proportion and bias from synthetically shifting the mean. Differences are shown in compound proportion [%] between the 2xCO$_2$ and Control simulations (a; difference between Figure 4.6b and d) and the Control simulation and Control+ΔGMT (b). Same heat wave definition as in Figure 4.7 and 4.6 is used. The blue dashed rectangles designate regions that spatial correlations are calculated over in Figure 4.10.

4.10 Spatial correlation of 2xCO$_2$-Control and (Control+ΔGMT)-Control over the globe and various smaller regions. The regions that the spatial correlation is calculated over are shown in Figure 4.9. The grey bars designate the spatial correlation calculated for the definition used in Figure 4.9 (daily minimum temperature, 90$^{th}$ percentile threshold, 311), and the markers represent spatial correlations calculated for the full range of definition variants. Blue and red designate daily minimum and maximum temperature, and stars and circles designate 90$^{th}$ and 95$^{th}$ percentile thresholds, respectively; temporal structures are not noted but include the full parameter space of Table 4.2.
4.11 Influence of autocorrelation and variance on change in compound proportion. Change in compound proportion with warming is shaded and plotted against lag 1-day autocorrelation and standard deviation normalized by mean warming. For the GCM, i.e., FLOR, data (a,b,c), lag 1-day autocorrelation and standard deviation are calculated from the Control simulation at each location. For the AR1 synthetic data, standard deviation and mean warming are assigned to be consistent with the GCM data, while autocorrelation is varied across the full possible range (0-1). Three temporal definitions are used: 311 (a,d), 333 (b,e), and 621 (c,f). For the 621 definition, some of the AR1 synthetic time series at lower autocorrelations are not able to generate long enough periods of hot days to meet the definition event duration requirements particularly for the “Control” climate; where this occurs, the shaded compound proportion is colored grey.

4.12 Mechanism for change in proportion of compound days. Cartoon temperature time series and threshold prior in original (e.g., pre-industrial) climate (a), and after increase in CO2 (b). To reasonable approximation, the change in the proportion of compound days can be understood as the result of the mean shift of a time series resulting in more threshold exceedances, and hence those threshold exceedances occurring closer together.
4.13 Change in compound proportion for MERRA2 with different amounts of warming. Temperature at all locations is increased by the estimated daily minimum temperature warming over land corresponding to global average near-surface warming of 1.5°C (a), 2°C (b), or that from the FLOR 2xCO₂ compared to its Control (∼2.7°C; c), and then compared to the original MERRA2 data with no warming. Spatial means over locations with data are listed in each panel. The heat wave definition is the same as in prior figures.

4.14 Heat wave metrics for example cities under different levels of warming. MERRA2 and FLOR Control daily minimum temperature data from Manaus, Brazil and Chicago, USA are analyzed under a range of warming values (0-6°C). Plotted are all heat wave days (blue solid line), compound days (blue dashed line), percent of summer that is a heat wave day (red dotted), and compound proportion of all heat wave days (red dashed). The standard deviation of summer daily minimum temperature is labeled for each location and dataset. Manaus is chosen to represent a typical tropical location with low temperature variance, and Chicago is chosen to represent a typical extratropical location with high temperature variance.
Chapter 1

Introduction

In fall of 2012, shortly after I began my doctoral studies, Superstorm Sandy beset New York City. Originally sustained by hurricane strength winds, the meteorological event was downgraded to a superstorm as it approached the New York coast. Nonetheless, the city was devastated by extreme precipitation, howling winds, and storm surge. Subway systems and buildings flooded; plate glass windows shattered and trees crashed, scattering glass and large branches across sidewalks and roads. The day after the storm, power remained out for most of lower Manhattan. I was staying in the Financial District at the time, in a skyscraper, which was eventually condemned due to storm-related damage. Many other downtown city-dwellers and I migrated uptown in search of a working power outlet and hot shower.

This event, as with any natural disaster, raised many questions. What climatic conditions led it to occur? Was anything special about that hurricane season or was this in a sense a “typical” extreme? Will more events like this occur in the future with global warming? Why was it so devastating? And what could New York City and the surrounding areas do to be better prepared for such storms? The answers to these questions are highly consequential: altogether, Superstorm Sandy is estimated to have killed 159 people, destroyed 650,000 homes, and cost $65 billion in damages [186].

1
The topic of this dissertation is not Superstorm Sandy, but I open with this example to motivate the variety of questions this dissertation engages with. With increasing atmospheric levels of carbon dioxide and the associated climate change, climatic extremes that are, by definition, historically infrequent may become all too frequent. Heat waves, droughts, extreme precipitation, and tropical cyclones are some of the many climatic disasters projected to potentially increase in frequency or severity. To properly assess the risk associated with these and other climate changes requires answering both basic science and more applied questions.

On the basic science side, understanding the physical mechanisms that control the average state of the climate system, and its seasonal variation, seem prerequisite to understanding any trends. For example, suppose a future projection with a climate model simulates a change in tropical cyclone frequency. To have confidence that the projection is reasonable, it is critical to know the core mechanisms responsible for the usual occurrence of tropical cyclones, and whether that model can capture such mechanisms. At the same time, engaging with more applied questions is necessary to relate changes in physical quantities like wind speed and vorticity, which characterize tropical cyclones, to human-relevant impacts, including but not limited to mortality, property damage, and agricultural and energy system failures. How should climatic events be defined for impact-relevance? And what aspects of the human system including policy decisions can increase or decrease vulnerability to such events? Answering both these applied questions related to the human system and basic climatic science questions is necessary to address the challenges posed by climate change. I have been drawn to both these avenues of inquiry over the course of my doctoral studies, and examples from both are represented in this dissertation.

Following this introduction, Chapters 2 to 4 present the research projects that comprise this dissertation, while Chapter 5 summarizes these chapters.
Chapters 2 and 3 engage with fundamental climate science questions, namely what controls the spatial and seasonal distributions of precipitation and tropical cyclones? More specifically, these chapters explore the role of mountains in shaping patterns of precipitation and tropical cyclones in and around Asia.

Chapter 2 focuses on a mountain range north of the Tibetan Plateau, the Tian Shan, and its influence on the vast deserts across extratropical Asia. While these extremely dry landscapes are relatively inhospitable to life, expansion across their neighboring grasslands in recent years (desertification) has devastated the local agriculture and motivated resettlement of the local nomadic herders \[^{[233, 240]}\]. Unfortunately, this region remains relatively unexplored in the climate literature, making it difficult to disentangle whether climate or land-use change is responsible for the desertification. Chapter 2 describes Global Climate Model (GCM) simulations with and without the Tian Shan. The results of these simulations contribute to our basic understanding of the mechanisms that shape the climatology of this harsh landscape. They also point to an important role for the Tian Shan in enhancing the East Asian Monsoon.

Chapter 3 examines the role of Asian orography more broadly, exploring its influence on summer tropical precipitation and cyclones. There are strong societal motivations to understand the climatic drivers of both these phenomena: seasonal precipitation associated with the Asian monsoon plays a critical role in the agriculture and economy of the region \[^{[65]}\], while tropical cyclones around Asia can have devastating impacts should they make land-fall \[^{[139]}\]. Studies with the earliest GCMs indicated that the Tibetan Plateau and related mountains play an important role in driving the Asian monsoon \[^{[79]}\]. Follow-on work has nuanced this conclusion, suggesting that orography greatly enhances precipitation during the Asian monsoon onset but not its peak \[^{[165]}\], and debating whether the orographic influence is primarily mechanical or thermal \[^{[153]}\]. Chapter 3 updates these prior studies by running sim-
ulations with and without Asian orography and atmosphere-ocean coupling, and at different atmospheric resolutions. Results from these experiments highlight the importance of the mountains remote influence on sea-surface temperatures (SSTs) in enhancing the precipitation changes. Additionally, the high resolution GCM employed permits the formation of tropical cyclones, demonstrating a previously unexplored strong influence of Asian orography on the genesis of tropical cyclones.

While Chapters 2 and 3 contribute fundamental understanding of regional climate dynamics, Chapter 4 addresses questions more immediately relevant to disaster preparedness and policy. In particular, this chapter examines how multiple heat waves combine, or “compound”, and how this hazard might change with global warming. Heat waves, which are prolonged periods of extremely high temperatures, cause significant mortality and morbidity, power system outages, and adverse impacts on food production [114, 177, 2]. Additionally, heat wave hazard, defined in almost any way, is expected to increase with global warming [85, 171, 208]. Much prior work has examined the risk of individual extreme climatic events, but literature assessing the risk of compound events (i.e. multiple extreme events occurring closely in time or space) is quite sparse [57, 160]. This chapter describes human systems that allow an initial heat wave to increase vulnerability to following heat extremes, and argues that many dangerous historical heat waves might be better characterized as compound in time. Using a combination of observed, GCM, and statistical model data, this chapter then demonstrates that the hazard of such compound heat wave events will disproportionately increase with global warming. The chapter concludes by discussing possible policy implications of this result for heat wave risk mitigation.

Given the diversity of topics explored in this dissertation, discussion and conclusions of results from Chapters 2 to 4 are presented at the end of each individual chapter. Chapter 5, the final chapter of this dissertation, presents a summary of the results from Chapters 2 to 4.
Chapter 2

Influence of the Tian Shan on Arid Extratropical Asia

2.1 Abstract

Arid Extratropical Asia (AEA) is bisected at the wetter Tian Shan mountains (a northern offshoot of the Tibetan Plateau) into East and West Deserts, each with unique climatological characteristics. The East Deserts (\(\sim 75-115^\circ E, \sim 35-55^\circ N\)) have a summer precipitation maximum, and the West Deserts (\(\sim 45-75^\circ E, \sim 35-55^\circ N\)) have a winter-spring precipitation maximum. A new high-resolution (50 km atmosphere/land) global coupled climate model is run with the Tian Shan Mountains removed to determine whether these mountains are responsible for the climatological East-West differentiation of AEA. Multi-centennial simulations for the Control and NoTianshan runs highlight statistically significant effects of the Tian Shan. Overall, the Tian Shan are found to enhance the precipitation seasonality gradient across AEA, mostly through altering the East Deserts. The Tian Shan dramatically change the precipitation seasonality of the Taklimakan Desert directly to its east (the driest part of AEA), by blocking West winter precipitation, enhancing subsidence over
this region, and increasing East summer precipitation. The Tian Shan increase East summer precipitation through two mechanisms: 1) orographic precipitation which is greatest on the eastern edge of the Tianshan in summer, and 2) remote enhancement of the East Asian Summer Monsoon through alteration of the larger-scale seasonal mean atmospheric circulation. The decrease in East winter precipitation also generates remote warming of the Altai and Kunlun Mountains, northeast and southeast of the Tian Shan respectively, due to reduction of snow cover and corresponding albedo decrease. A previously published version of this chapter is available in Journal of Climate [13].

2.2 Introduction

There are a number of large-scale arid regions in the world, and most of them are in the subtropics. The arid regions in interior Asia are vast and unique. Spanning roughly from 45 – 115°E and 35 – 55°N, these arid lands are located farther into the extratropics than any other major desert, excluding the far polar latitudes (Figure 2.1). The Tibetan Plateau and related orography which exists on the periphery of these deserts plays a number of key roles in shaping this climate, creating local rain shadow and remote monsoon effects [153, 26, 188]. The highest mountain range within AEA is the Tian Shan, which extends northwest of the Tibetan Plateau and reaches 7439 m at the highest peak (Figure 2.2a). In the present climate, AEA is meridionally bisected into West and East Deserts by a relatively wet area centered near 75°E that is co-located with the Tian Shan mountain range (Figure 2.3a,b). These macro-deserts are composed of a number of smaller named deserts, including the Kyzylkum and Karakum in the West, and the Taklimakan and Gobi in the East, among others. Their land surface ranges from grass-covered steppe, to sand dunes, to gravel [247, 261, 130].
In this chronically-water stressed region of the world, slight variations in precipitation and land-use can cause large fluctuations in desert extent \cite{252}, potentially magnified through vegetation feedbacks \cite{31}. These desert variations in turn significantly impact agriculture and natural vegetation \cite{161,12,48}. Given that the East Deserts are a primary source of dust in the atmosphere, these variations can have impacts far afield from AEA as well \cite{179,257,234}. As a result, understanding sources and variability of moisture in AEA is a critical challenge.

Water isotope measurements \cite{6,11,116,8} and modeling approaches \cite{224,218,14} have been used to track water into this continental region. These studies suggest a number of moisture sources for this region. Moisture follows the westerlies from the
Figure 2.2: Elevation in AEA for Control and NoTianshan. (a) and (c) are high-resolution observed topography (USGS 1-minute digital elevation model). (b) and (d) are FLOR’s 50 km resolution surface height boundary conditions. Comparison of (a) and (b) demonstrates the accuracy of FLOR’s topography. Comparison of (a) and (b) versus (c) and (d) demonstrates where the Tian Shan were flattened in model simulations.

Caspian, Aral, Mediterranean and Black Seas, and Atlantic Ocean all the way to AEA, particularly the West Deserts. Monsoonal circulations from the Pacific and Indian oceans also provide a source of precipitation, especially for the East Deserts. Moisture carried by the westerlies tends to travel farther than monsoonal moisture, with the East Deserts receiving more moisture recycled through the land surface than the West Deserts. Interannual precipitation variability in these regions reflects variability in these moisture sources; in particular, the North Atlantic Oscillation and monsoon variability have been shown to modulate precipitation in the East Deserts [250, 3, 198, 128]. Related to these different predominant moisture sources, there is a gradient in seasonality of precipitation across AEA, with precipitation peaking in winter-spring in the West Deserts, and summer in the East Deserts (Figure 2.4). Mountain glacier melt, especially from the Tian Shan, provides a key water resource that allows some resilience against these seasonal and interannual precipitation variations [229, 5].
Figure 2.3: Observed versus simulated area of AEA, and sub-regions examined in this study. ETOPO5 topography (shaded) is overlaid with outlines of deserts (annual mean precipitation < 0.75 mm/day) according to (a) precipitation observed from satellites and ground-based measurements, (b) precipitation from reanalysis, and (c) precipitation from the FLOR Control run. Boxes in (c) designate particular regions examined in this analysis (i.e., West Deserts, East Deserts, the Western-East, and the Eastern-East). Regional seasonal cycles are calculated by averaging over only desert points within the region’s box, excluding major inland lakes and seas, except for the Tian Shan region where only non-desert points are averaged over.
Figure 2.4: Desert seasonal cycles in FLOR versus observationally-derived datasets. Monthly precipitation (P) and evaporation (E) are shown in mm/day. Seasonal cycles are calculated by averaging over places in each dataset that receive <0.75 mm/day of precipitation in the annual mean, excluding major inland lakes and seas by averaging over places with elevation greater than 70 m. The left column shows area-average seasonal cycles for the West Deserts, and the right column shows the same for the East Deserts. The first row shows seasonal cycles derived from observations and reanalysis, with gridded observed precipitation (black), reanalysis precipitation (blue), and reanalysis evaporation (red). The second row shows precipitation (blue) and evaporation (red) from the FLOR Control run. Each line for the model seasonal cycles is derived from 31 years of model data to match the observational/reanalysis time series length, starting every 5 years from 150 simulation years yielding 30 seasonal cycles total.
Beyond interannual time scales, distant past and more recent environmental changes in AEA have been dramatic. Paleoclimatic evidence indicates that this region first became arid around 20-40 million years ago (Myr), corresponding with a combination of Tibetan Plateau uplift, global cooling, and retreat of the inland extending Paratethys Sea [184, 76, 49, 25]. At a smaller scale, the Tian Shan’s uplift was likely simultaneous with, and caused, development of the Taklimakan Desert [258]. Over the Quaternary (last 2 Myr), the deserts have been quite dynamic, with pluvials and droughts since the start of the Holocene (11,700 years ago) implicated in the rise and fall of numerous civilizations [246, 247, 167, 168]. Over this same period, an out-of-phase relationship has been documented between precipitation in monsoonal Asia and the East Deserts of AEA, that is tied to variations in earth’s orbit and insolation [83, 33]. Variations of westerly jet seasonality likely provide the tie between these insolation changes and monsoon changes [155, 36]. Interestingly, the West and East Deserts have also exhibited out of phase precipitation variability over the past millenium, highlighting the climatological differentiation of the regions [32].

Over the past century, both climate and land-use changes have exerted profound impacts across AEA [74]. Rising temperatures due to the increasing concentration of greenhouse gases have been observed across AEA [10, 130]. This warming is paired with more precipitation but less snow and glacial mass [7, 10, 78], which in turn results in greater warming at elevation through albedo decreases [68]. Snowmelt is beginning earlier in the season, a shift which presents significant water resources challenges [206, 213, 223, 46]. Related to these hydrological changes, arable land in the West Deserts is predicted to not necessarily decrease but certainly shift with climate change [19].

Simultaneous with these global warming challenges, local factors have caused significant desertification in the East and West Deserts. The term desertification embodies a number of different changes including soil erosion, drying, and salinization,
decreases in vegetation, and shifts in vegetation types [50]. At the edge of the East Deserts, the Inner Mongolian and Mongolian steppes have become much more barren and water-stressed since the 1980’s, due primarily to changes in land-use, particularly overgrazing, but also precipitation decrease and wind changes [232, 98, 138, 84, 127]. In the West Deserts, the Aral Sea has decreased 74% in area and 90% in volume since the 1960’s due to aggressive expansion of irrigation, eliminating an important water resource for the West Deserts [192, 151]. These environmental changes, which are unlikely to lessen as the climate continues to warm, represent significant political and policy challenges for China and Mongolia in the East, and the former Soviet Union countries in the West [166, 69, 131].

Clear understanding of the basic climatic controls on AEA through modeling exercises is prerequisite to parse these recent environmental trends. Most previous modeling work relevant to AEA falls into two general categories: regional and global modeling studies. Regional modeling studies have examined sub-regions of AEA at a relatively high resolution using regional climate models (RCMs) or hydrological models [e.g., 211, 210, 245, 195, 52, 4, 9, 196, 78, 205, 206, 136]. These studies typically examine either part of the West Deserts, the East Deserts, or local orography (i.e., the Tian Shan) but not all three simultaneously. Other studies have used global climate models (GCMs) to examine Asia, in particular AEA, more broadly [e.g., 26, 244, 35]. A large subset of these studies have studied the impact of the Tibetan Plateau on Asian climate using global climate models (GCMs) typically at around ∼2° resolution [e.g., 141, 242, 231, 164, 123] with particular focus on the impact of these mountains on the South and East Asian Summer Monsoons [e.g., 259, 135, 165, 20]. These studies flatten the Tian Shan as part of the Tibetan Plateau, but due to low resolution they resolve only a fraction of the Tian Shan’s height and do not separate out the Tian Shan’s impact.
As noted previously, in Central Asia’s West Deserts (Kyzylkum and Karakum) precipitation generally peaks in the winter, while in China and Mongolia’s East Deserts (Taklimakan and Gobi) precipitation generally peaks in the summer (Figure 2.4a,b). Given the location of the Tian Shan between the West and East Deserts, the question arises: Are the Tian Shan responsible for both the spatial and seasonality division of AEA? Until recently, only one prior modeling study [195] had focused on the climatic impact of the Tian Shan specifically, simulating 10 years with the Tian Shan removed in a 150 km resolution regional climate model. This study found that the Tian Shan do not significantly change the annual mean aridity of AEA, but did not explore seasonal precipitation changes. Paleoclimate proxies indicating the asynchronous uplift of different parts of the Tibetan Plateau have recently spurred a handful of additional studies examining the contrasting impacts on Asian climate of different parts of the Tibetan Plateau. These studies include experiments with regional climate models over Asia with resolutions 50 km and 1° [220, 134], and a ~2° resolution global atmospheric model forced with climatological SSTs [254]. Notably, all three studies find an enhancement of the East Asian Summer Monsoon by the Northern Tibetan Plateau, which includes the Tian Shan; Liu et al. (2015) [134] also highlights the drying of the Tarim Basin, which is where the Taklimakan Desert exists in the present climate, by this orography.

The present study revisits this question of Tian Shan climatic influence with a more accurate model and new focus on precipitation seasonality differences across AEA. We employ GFDL’s newly developed higher-resolution (50 km atmosphere/land) GCM CM2.5-FLOR (henceforth referred to as FLOR) to simulate global climate with and without the Tian Shan, and explore the Tian Shan’s influence on AEA. Similar to regional models, FLOR simulates Tian Shan topography and desert borders with fidelity. However, using a coupled atmosphere-ocean global model also allows exploration of remote atmospheric influences of orography [i.e., stationary
waves\textsuperscript{89} and interaction with oceans, both which have been shown to be important for monsoons. In summary, the goal of this paper is to employ high-resolution GCM simulations to assess the role of the Tian Shan in creating the differing characteristics of the East and West Deserts of AEA.

The rest of this paper is structured as follows. Section 2.3 describes the methods used in this study, including descriptions of observational estimates, the GCM employed (FLOR), and modeling experiment design. Section 2.4 compares FLOR output with observations to establish the ability of the model to simulate AEA. Section 2.5 describes the climatic effect of the Tian Shan on AEA as found in the modeling experiments. Section 2.6 concludes with a summary of the paper and discussion of the results.

2.3 Methods

2.3.1 Observational Estimates

A significant challenge in studying AEA is the relative lack of observations in this sparsely populated region. The approach taken in this study is to focus on features that are consistent among gridded global datasets, although we believe that regionally focused data products could provide crucial information. The datasets we utilize (described in more detail below) vary in the time period they cover, so we analyzed only the months common to all of the data products (January 1979-December 2009).

We analyze precipitation from five observation-based precipitation datasets (CMAP, GPCP, University of Delaware, CRU TS3.10, and APHRODITE). CMAP\textsuperscript{243} is a merger of five different satellite products, while GPCP\textsuperscript{11} is a merger of both satellite and ground-based observations. Both are available at a 2.5°×2.5° resolution. The University of Delaware and CRU TS3.10 datasets are based on large networks of ground-based observations, and are available at the relatively high-resolution of
0.5°×0.5°. APHRODITE also merges ground-based observations, but at a higher station density and only over Asia and parts of the Middle East. It is available at 0.25°×0.25° and 0.5°×0.5° resolution; we use the higher resolution data in our analysis.

We also analyze precipitation and evaporation from three reanalyses (MERRA, ERA-Interim, NCEP2). MERRA (resolution 1/2°×2/3°) and ERA-Interim (resolution 0.75°×0.75°) both belong to the latest generation of atmospheric reanalyses, while NCEP2 (resolution ~2°×2°) is coarser resolution and an earlier product.

### 2.3.2 Global Coupled Model

In this study we employ a newly developed atmosphere-ocean coupled GFDL GCM called FLOR (Forecast-oriented Low Resolution version of GFDL-CM2.5). FLOR features a relatively high spatial resolution atmosphere and land (~50 km) and a lower spatial resolution ocean (1°). Compared to previous generation GFDL coupled models such as CM2.1, which has a 1° oceanic resolution and ~200 km atmospheric resolution, FLOR is better able to capture high and sharp topographic features. FLOR accounts for the primary features of the Tian Shan, as can be seen by comparing the actual topographic data in Figure 2.2a with topography data smoothed to FLOR’s grid in Figure 2.2b. In addition to its advantages over lower resolution models like CM2.1, FLOR has advantages compared to other recent high-resolution GCMs such as CM2.5 (50 km atmosphere/land, 0.25° ocean) in simulating the terrestrial climate of AEA. With its low-resolution ocean, multi-centennial runs of FLOR are possible without excessive computational expense, allowing detection of statistically significant regional climate effects and multiple perturbation studies. FLOR is described in detail in Vecchi et al. (2014), with discussions of its skill predicting patterns of precipitation and temperature in Jia et al. (2014) and extratropical
storms in Yang et al. (2015) [218]. FLOR’s predecessor model CM2.5 is described in Delworth et al. (2012) [45], and notably was found to have significantly greater skill than CM2.1 in simulating the South Asian Monsoon and spatial variability of Koppen climate types.

2.3.3 Experiment Design

To understand the influence of the Tian Shan on AEA’s climate, we alter the topography in FLOR. Topography plays three main roles in current GFDL GCMs including FLOR: it controls surface height, gravity wave drag, and boundary layer roughness. High resolution boundary conditions derived from a USGS 1-minute topography dataset control each of these topographic influences. Surface height is calculated by averaging this topography dataset over FLOR’s 50 km gridcells. The regridding has the side-effect of smoothing the topography, reducing the height of the highest peaks (Figure 2.2a,b). Gravity wave drag and boundary layer roughness are parameterized in the model as proportional to variance of the high-resolution topography dataset, averaged to the lower-resolution model grid [176]. Additional boundary conditions in the land model which control vegetation type and runoff flow are also influenced by topography, but in this study we focus on the direct physical impacts of topography and leave the vegetation and hydrologic feedbacks for future work.

We utilize three different FLOR model simulations in our analysis, a control simulation (Control), and two perturbation simulations (NoTianshan and NoTianshan-Drag). These simulations are described here and summarized in Table 2.1. Control simulates 200 years with 1990 radiative forcings, static vegetation, and standard modern-day topography in all three topographic boundary conditions (surface height, gravity wave drag, and boundary layer roughness). Only years 51-200 are used to allow for model spin-up. NoTianshan and NoTianshan-Drag are identical to the Control run in all aspects except Tian Shan topography. In NoTianshan, the Tian Shan are
flattened in all three topographic boundary conditions (surface height, gravity wave
drag, boundary layer roughness). In NoTianshanDrag, the Tian Shan are flattened
only in boundary conditions controlling gravity wave drag and boundary layer rough-
ness; surface height is identical to that of Control. For the perturbation experiments,
the flattening is accomplished by defining an irregularly shaped region surrounding
the Tian Shan, and setting all places within that region with elevation greater than
800 m to 800 m (Figure 2.2). The topography was set to 800 m to reflect the elevation
of the surrounding landscape.

Table 2.1: FLOR simulations analyzed in this study.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Control</th>
<th>NoTianshan</th>
<th>NoTianshanDrag</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length</td>
<td>200 years (years 51-200 analyzed)</td>
<td>&quot; &quot;</td>
<td>&quot; &quot;</td>
</tr>
<tr>
<td>Radiative Forcing</td>
<td>Year 1990</td>
<td>&quot; &quot;</td>
<td>&quot; &quot;</td>
</tr>
<tr>
<td>Vegetation</td>
<td>static</td>
<td>&quot; &quot;</td>
<td>&quot; &quot;</td>
</tr>
<tr>
<td>Surface Height</td>
<td>standard</td>
<td>Tian Shan flat</td>
<td>standard</td>
</tr>
<tr>
<td>Gravity Wave Drag</td>
<td>standard</td>
<td>Tian Shan flat</td>
<td>Tian Shan flat</td>
</tr>
<tr>
<td>Boundary Layer Roughness</td>
<td>standard</td>
<td>Tian Shan flat</td>
<td>Tian Shan flat</td>
</tr>
</tbody>
</table>

Assuming effects of perturbing different boundary conditions can be added lin-
early to recover their combined effect, the difference of the Control and NoTian-
shan simulation outputs (Control-NoTianshan) is the simulated climatic influence
of the Tian Shan’s surface height, gravity wave drag, and boundary layer roughness,
while the difference of the Control and NoTianshanDrag simulation outputs (Control-
NoTianshanDrag) is the simulated climatic influence of only the Tian Shan’s gravity
wave drag and boundary layer roughness (not surface height). The three runs together
allow analysis of how the Tian Shan affect climate, and whether these changes are
primarily generated by the the height versus drag aspects of the mountains’ influence.

The long run length of 200 years (years 51-200 analyzed) was chosen to increase
the signal-to-noise ratio of the results and test the robustness of remote effects of
the Tian Shan especially over East Asia. Maps of Control-NoTianshan differences represent the difference between 150-year averages of each simulation. In Control-NoTianshan maps, locations are masked white where changes are not determined statistically significant at a 99% level by a two-sided t-test.

2.4 AEA Climatology and Model Evaluation

The first step in exploring the climatology of AEA is choosing a definition of arid regions. One option is to use a Koppen climate classification, which combines both precipitation and temperature climatologies to estimate different climate states, and has been verified for many different climate types around the globe. We explored defining arid region extent with the area of desert and semi-arid land types from a Koppen climate classification scheme, using the methodology of Gnanadesikan and Stouffer (2006) [71] to process the climate data. We also explored simpler precipitation threshold-based definitions (i.e., locations that receive <0.75 mm/day of precipitation). We found that the Koppen-defined AEA had similar large-scale characteristics to that of precipitation threshold-based definitions for values of <0.5, <0.75, and <1 mm/day of annual mean precipitation. Both types of definitions capture the major deserts of AEA, including the Karakum and Kyzylkum among the West Deserts, and the Gobi and and Taklimakan among the East Deserts. Both definitions also find an East-West break in aridity at the Tian Shan. Given these similarities, we employ the simpler definition: we define deserts as places that receive <0.75 mm/day of precipitation on an annual average basis. We choose <0.75 mm/day of precipitation as a desert definition rather than <0.5 or <1.0 mm/day as <0.75 mm/day just creates a clear spatial differentiation between the East and West Deserts (Figure 2.1).

Using this definition, we examined the area of AEA in observations, reanalysis, and FLOR Control (Figure 2.3). There is some variation among the observed and
reanalysis datasets’ desert extents, not all of which is clearly attributable to differences in resolution. For example, the reanalyses generally indicate smaller/wetter deserts than the rain gauge/satellite-based precipitation datasets, and ERA-Interim indicates a smaller/wetter West Desert than the other reanalyses. However, all eight datasets agree that there is a collection of East Deserts (including the Gobi and Taklimakan) that extends roughly from 75 to 120°E and a collection of West Deserts (including the Kyzylkum and Karakum) that extends from just beyond the Caspian Sea at about 45°E to 75°E. All the datasets also co-locate the wetter East-West division with the Tian Shan. FLOR Control simulates the extent of AEA generally within the range of the observed and reanalysis estimates, including distinct East and West Deserts divided at the Tian Shan. Compared to the high-resolution observed datasets, FLOR’s simulated East Deserts extent is biased small, but it is similar to that of the reanalysis. Due to its relatively high land/atmosphere resolution, FLOR also simulates boundary details only captured by the higher resolution observed datasets (CRU, UDelaware, APHRODITE) and reanalyses (MERRA, ERA-Interim).

We also examined AEA’s climatology of moisture fluxes (precipitation and evaporation) in the observations, reanalysis, and model. Climatologies were computed by finding monthly average values of these quantities, averaged spatially over arid land locations (precipitation < 0.75 mm/day) in specified latitude-longitude regions (for region details see Table 2.2 and Figure 2.3c). Major lakes including the Aral and Caspian Seas and Lake Balkash were excluded from the area averaging by selecting only places with elevation greater than 70 m. Additionally, averaging regions for the East and West Deserts are truncated on the southern end around 36°N to focus on the extratropical deserts, and also to remove locations on parts of the Tibetan plateau where observations are quite sparse. For all observations and reanalyses, there is a clear pattern of precipitation peaking in the West Deserts around March to April, and in the East Deserts around July (Figure 2.4a,b). In the East Deserts evaporation
peaks in the summer at the same time as precipitation, as is typical in a very dry region where evaporation is moisture limited and any moisture that reaches the ground is quickly evaporated. In contrast, in the West Deserts evaporation peaks in April or May, one or two months lagged from the peak in precipitation, and remains quite substantial throughout the summer even when precipitation is at its minimum. While we are currently pursuing a related study which seeks to characterize the sources of the West Deserts’ dry season evaporation, key questions the present study seeks to address are whether the Tian Shan’s division of the deserts is requisite for the aridity and clear difference in seasonality of the East and West Deserts.

Table 2.2: Regions examined in this study. Listed spatial limits are the precise region bounds used when calculating the area average seasonality for Figures 2.4 and 2.5.

<table>
<thead>
<tr>
<th>Region</th>
<th>Longitude</th>
<th>Latitude</th>
<th>Major Constituent Deserts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tian Shan</td>
<td>65.0-88.0° E</td>
<td>38.0-46.0° N</td>
<td>n.a.</td>
</tr>
<tr>
<td>West</td>
<td>44.5-75.5° E</td>
<td>36.5-55.0° N</td>
<td>Kyzylkum, Karakum</td>
</tr>
<tr>
<td>East</td>
<td>75.5-117.0° E</td>
<td>36.0-55.0° N</td>
<td>Gobi, Taklimakan</td>
</tr>
<tr>
<td>Western-East</td>
<td>75.5-95.0° E</td>
<td>36.0-43.0° N</td>
<td>Taklimakan</td>
</tr>
<tr>
<td>Eastern-East</td>
<td>98.0-117.0° E</td>
<td>36.0-49.0° N</td>
<td>Gobi</td>
</tr>
</tbody>
</table>

The FLOR Control simulation accurately captures the timing of the precipitation and evaporation peaks in both the East and West Deserts, including the lingering summer evaporation in the West Desert (Figure 2.4c,d). Notably, FLOR’s accuracy in simulating the extent and precipitation/evaporation climatology of these arid regions is a significant improvement over the previous generation model CM2.1 (not shown). Key features of FLOR versus CM2.1 which may be related to this improvement are increased atmospheric/land resolution and a more advanced version of GFDL’s land model which has deeper soil layers and more detailed vegetation.
Figure 2.5: Influence of the Tian Shan on seasonal cycles of different desert regions. Regional area average seasonal cycles of precipitation (first column) and evaporation (second column) are plotted with one standard deviation above and below shaded. Each row corresponds to a different region: the Tian Shan (a,b), the West Deserts (c,d), the East Deserts (e,f), the Western-East (g,h) and the Eastern-East (i,j). Control results are colored, and NoTianshan results are in black/grey. Averaging is done over grid cells that are desert (mean precipitation < 0.75 mm/day) in the Control run within the regions defined in Table 2.2 and shown in Figure 2.3c, except for the Tian Shan region where averaging is done over grid cells that are not desert (mean precipitation > 0.75 mm/day). Additionally, major inland lakes and seas (such as the Caspian and Aral Seas) are excluded by averaging only over places with elevation greater than 70 m.
2.5 Modeled Climatic Effects of the Tian Shan

The Tian Shan have by far their largest magnitude effects on the local climate of Asia, with farther remote effects being too small to have much climatic significance. The magnitude of Control-NoTianshan changes was found to be much greater than that of Control-NoTianshanDrag throughout Asia, suggesting that surface height rather than gravity wave drag and boundary layer roughness dominates the climatic influence of the Tian Shan. Given these observations, the rest of our analysis focuses on comparing the Control and NoTianshan simulations in Asia, particularly AEA. These results represent the full climatic effect of the Tian Shan on this region (including gravity wave drag and boundary layer roughness), but are dominated by the influence of surface height.

2.5.1 Precipitation in AEA

There are a few ways in which the Tian Shan have a dramatic influence on precipitation in AEA (Figures 2.6 and 2.7). First, while the Tian Shan have relatively high precipitation in Control such that there is an East-West break in the deserts, the flattened Tian Shan area is much drier, amounting to a >100%, up to 3 mm/day change in precipitation between the East and West deserts. This change at the Tian Shan is clearly attributable to the lack of the Tian Shan’s orographic precipitation in NoTianshan. This merges the East and West Deserts in the annual mean, creating a desert region in NoTianshan that appears relatively homogeneous in area extent. Next to the Tian Shan location itself, the second greatest change in desert area is north of the Tian Shan, which is relatively dry in Control, but significantly wetter in NoTianshan.

Focusing on the deserts themselves, the removal of the Tian Shan changes the West Deserts very little in extent or seasonality but exerts a strong influence on
Figure 2.6: Influence of the Tian Shan on seasonal mean precipitation of AEA. Precipitation is shaded for different seasonal means (rows) and FLOR runs (Control, left, and NoTianshan, right). The black contours designate the annual (not seasonal) mean desert (precipitation $<0.75$ mm/day) as defined for each FLOR run. The dark red contours designate places with elevation greater than 1700 m in each FLOR run’s boundary conditions. The blue contours designate lakes and coastlines.
precipitation in the East Deserts. Interestingly, this influence varies zonally, so to
describe this change, we divide the East Deserts further into a Western-East region
which includes the Taklimakan Desert and occupies the Tarim Basin, and an Eastern-
East region which includes the Gobi (Table 2.2, Figure 2.3c). The Western-East is
extremely dry all year round in Control; indeed, the Taklimakan is the driest portion
of AEA. In NoTianshan, this desert, while still extremely dry, receives more than twice
as much precipitation in all seasons other than summer. The Eastern-East region also
changes but somewhat less dramatically. In Control compared to NoTianshan, winter
precipitation in the Eastern-East is lower, while summer precipitation is higher. The
summer precipitation increase dominates slightly the annual mean change, as the
desert extends slightly less far to the east in Control versus NoTianshan.
Comparing area-average seasonal cycles of precipitation and evaporation in Control and NoTianshan highlights these changes (Figure 2.5). For the West Deserts, the seasonal cycles of precipitation and evaporation are almost indistinguishable in Control versus NoTianshan. The only slight change is less summer-fall precipitation and evaporation, presumably caused by Eastern summer moisture being blocked by the Tian Shan. In contrast, in the East Deserts there are clear changes throughout the year. The East Deserts’ summer precipitation peak is somewhat higher in Control compared to NoTianshan, while winter precipitation is lower. These changes are mirrored in evaporation, where summer evaporation is higher in Control compared to NoTianshan and winter evaporation is significantly lower. The East Deserts’ seasonality changes are magnified in the Western-East, where precipitation switches dramatically from a summer precipitation peak in Control, to a much higher fall and spring double peak in NoTianshan. In contrast, in the Eastern-East the change in the summer is greater than the change in the winter, and the timing of the precipitation peak (July) does not change.

The causes of fall to spring precipitation changes in the East Deserts appear to be primarily local effects. Drying by the Tian Shan is focused directly proximal to the Tian Shan in all seasons, suggesting the high Tian Shan block moisture fluxes from differing seasonal sources (Figure 2.7). In the fall to spring, meridionally averaged transects of humidity (not shown) show humidity collecting on the western side of the Tian Shan while the East shows a decrease in humidity, indicating that the Tian Shan block westerly moisture fluxes from reaching the East. Further, the seasonal progression of precipitation over the Tian Shan in Control is almost identical to that of the Western-East in NoTianshan, suggesting that much of this blocked moisture is rained out as orographic precipitation over the Tian Shan (Figure 2.5a,g). Orography can also generate drying through subsidence on its leeward side. Meridionally averaged transects of omega (not shown) indicate that the Tian Shan generate significant
subsidence over the Western-East in winter, hardly any in summer, and intermediate amounts in spring and fall. This seasonality is presumably because when zonal winds are stronger (as in winter), flow can go all the way up and over rather than divert around the Tian Shan. As a result of both these blocking and subsidence effects, in Control compared to NoTianshan three times less winter/spring precipitation occurs in the Western-East.

The implications of this winter/spring precipitation change in the Western-East are striking. Since the Western-East is extremely dry, even less than 0.5 mm/day of winter/spring precipitation is enough to completely change the seasonality of this region. As a result, in the absence of the Tian Shan, the Taklimakan is better characterized as a West winter/spring precipitation desert, rather than an East summer precipitation desert. In contrast, the Eastern-East region, including the Gobi, retains a summer peak of precipitation even in the absence of the Tian Shan. While AEA still has zonal variation in seasonality with or without the Tian Shan, the seasonality border of the West Deserts extends farther eastward when the Tian Shan are removed.

In addition to the winter-spring drying of the East Deserts, local orographic effects also explain the slight summer precipitation increase in the Western-East (Figure 2.5g). Meridionally averaged transects of humidity indicate that around summer (but not winter) humidity builds up east of the Tian Shan, indicating that significant easterly moisture fluxes reach the Tian Shan in this season. As a result, orographic precipitation on the eastern flank of the Tian Shan is greatest in the summer (Figure 2.7). This extension of orographic precipitation is primarily responsible for the slight increase in summer precipitation in the Western-East due to the Tian Shan.

In contrast to the Western-East, the Eastern-East is not directly adjacent to the Tian Shan and its larger summer increase in precipitation cannot be explained by orographic precipitation. Control-NoTianshan differences indicate that the Tian Shan
remotely generate a \( \sim 1 \) mm/day, 20-60\% increase in annual-mean precipitation across East Asia (around 95-135°E, 20-55°N). While this change is statistically significant in the annual mean, it occurs from spring through fall, and peaks during the summer monsoon season (Figure 2.7). This enhanced East Asia precipitation has a clear influence on AEA, both increasing the summer peak in precipitation in the Eastern-East, and also shortening AEA’s eastern extent. As a result, it is both interesting and important to deconstruct how the Tian Shan remotely enhance precipitation in East Asia.

**Understanding Remote Precipitation Change in East Asia**

A first step in understanding this East Asia precipitation enhancement is to complete a moisture budget analysis to understand whether dynamical or thermal effects drive this change. Summer change in precipitation minus evaporation \( (P - E) \) over this region due to the Tian Shan is positive (Figure 2.8a). \( P - E \) is balanced by the time-averaged, column-integrated moisture flux \( F \) as follows from Seager and Vecchi (2010) [200]:

\[
\rho_w g (P - E) = -\nabla \cdot F = - \int_{p_s}^{p_s} \nabla \cdot (\bar{u}\bar{q}) dp - \int_{p_s}^{p_s} \nabla \cdot (\bar{u}'q') dp - q_s \bar{u}_s \cdot \nabla p_s
\]  

(2.1)

Here \( u \) is the vector wind and \( q \) is the humidity, \( p \) is the pressure with \( p_s \) its surface value, \( g \) is acceleration due to gravity, and \( \rho_w \) is the density of water. The increase in \( P-E \) over East Asia indicates increased moisture convergence. Different possible sources of this moisture flux are decomposed in Figure 2.8b. Due to lack of 3-D high-frequency model data, the decomposition could only be completed with monthly data. Fortunately, the monthly change in moisture flux convergence from the Tian Shan \((- (\int_{p_s}^{p_s} \nabla \cdot (\bar{u}_{Cont}\bar{q}_{Cont}) dp - \int_{p_s}^{p_s} \nabla \cdot (\bar{u}_{NoT}\bar{q}_{NoT}) dp))\) accounts for the majority (about \( \frac{2}{3} \)) of the increased moisture flux, from which we infer that about \( \frac{1}{3} \) comes from transient ed-
dies. The monthly moisture flux convergence can be further separated into effects from changes in winds (dynamical effect: \(-\int_0^P \nabla \cdot (\bar{u}_{Cont} \bar{q}_{NoT}) \, dp - \int_0^P \nabla \cdot (\bar{u}_{NoT} \bar{q}_{NoT}) \, dp\)), changes in humidity (thermal effect: \(-\int_0^P \nabla \cdot (\bar{u}_{NoT} \bar{q}_{Cont}) \, dp - \int_0^P \nabla \cdot (\bar{u}_{NoT} \bar{q}_{NoT}) \, dp\)), and changes in correlations of the monthly wind and humidity changes (cross term: \(-\int_0^P \nabla \cdot ((\bar{u}_{Cont} - \bar{u}_{NoT})(\bar{q}_{Cont} - \bar{q}_{NoT})) \, dp\)). Here we calculated the cross term as a residual of the monthly total, dynamical, and thermal effects (cross term=[monthly total]-[monthly dynamical effect]-[monthly thermal effect]). This decomposition of monthly data indicates that dynamical effects of the Tian Shan, specifically changes in climatological mean winds and inferred changes in eddies, drive the summer moisture flux convergence over East Asia, with some divergence generated by the cross term and negligible contribution from the thermal effect.

This conclusion invites the question: how do the Tian Shan alter climatological mean winds to drive the majority of the increased moisture flux into East Asia? Examining Control-NoTianshan change in 850 mb moisture fluxes (\(\Delta u q\); Figure 2.9), two general flows of moisture into East Asia are apparent: 1) westerly across the Arabian Sea, India, and Bay of Bengal before veering southerly around the southeast edge of the Tibetan Plateau, and 2) southeasterly across southern Japan, before veering easterly, and then southerly once adjacent to the Tibetan Plateau. Explaining the precipitation enhancement over East Asia requires explaining how the Tian Shan alters atmospheric circulation to force these two somewhat distinct flows.

The most prominent circulation alteration by the Tian Shan in summer is an increase in geopotential height peaking at 200 mb and just north of the Tian Shan (Figure 2.10). This high is associated with a lower atmosphere decrease in geopotential height enveloping the Tian Shan and Tibetan Plateau, and a high geopotential extension farther south of this over India. Overall, this response to the Tian Shan is baroclinic throughout the atmosphere, with anticyclonic, divergent flow above and cyclonic, convergent flow below—circulation that is consistent with the response
Figure 2.8: Decomposition of moisture flux convergence due to the Tian Shan in East Asia. (a) shows summer (JJA) Control-NoTianshan change in moisture flux convergence \((P_{\text{Cont}}-E_{\text{Cont}})-(P_{\text{NoT}}-E_{\text{NoT}})\). The blue contour designates land, and the black contour designates desert. (b) shows components of summer moisture flux convergence averaged over the red box in (a). Note that monthly changes account for most of the moisture convergence due to the Tian Shan, and this moisture convergence is primarily caused by dynamical (wind) not thermal (humidity) changes.
to heating in the midlatitudes predicted from potential vorticity conservation. In the lower atmosphere, the low geopotential heights south of the Tibetan Plateau combined with high geopotential heights over India generate winds which align well with the first flow of moisture fluxes described in the previous paragraph (Figures 2.10b vs 2.9). Thus, it seems that the lower atmosphere cyclone associated with the Tian Shan’s forced upper atmosphere anticyclone is partially responsible for the precipitation enhancement in East Asia by the Tian Shan. It is worth noting here that certain details of the Tian Shan’s local influence on geopotential height are caused by adiabatic effects particular to the unique shape and location of the Tian Shan. For example, a particularly intense decrease in geopotential height is observed in the Tarim Basin (Figure 2.10), which appears related to the Tian Shan diverting westerly flow northward to flow through a corridor between the Tian Shan and Altai Mountains before entering the Tarim Basin (Figure 2.11). While these local circulation changes are certainly related to the significant precipitation changes of the Tarim Basin, the larger-scale baroclinic circulation response is more relevant to the remote precipitation enhancement across East Asia.

In addition to the baroclinic circulation change proximal to the Tibetan Plateau, examination of geopotential heights at a global scale indicates that the Tian Shan force a stationary wave which emanates eastward (Figure 2.12). In the summer this wave is more significant and compact than in the winter (not shown), creating a clear anticyclone-cyclone-anticyclone pattern with the first anticyclone just northeast of the Tian Shan, the cyclone centered over northeastern China, and the second anticyclone centered just east of Japan. Unlike the first anticyclone which is associated with a cyclone in the lower atmosphere, the circulation response associated with the cyclone and second anticyclone of the stationary wave is barotropic (not shown). Therefore, flow associated with this cyclone-anticyclone can explain the southeasterly moisture
In summary, two types of mean circulation changes forced by the Tian Shan are responsible for the remote enhancement of summer precipitation in East Asia: 1) a baroclinic response typical for midlatitude forcing that generates a lower atmosphere cyclone around the Tibetan Plateau and fluxes warm, moist air in from the southwest, and 2) a barotropic stationary wave response that creates a cyclone-anticyclone pair which flux warm, moist air in from the southeast. Mountains can force circulation changes either mechanically or thermally [82]. Mechanical forcing is simply the redirection of flows by the slope and elevation of the mountains. Thermal forcing is associated with orographic precipitation releasing latent heat and sensible heat flux from the elevated surface. Understanding whether the Tibetan Plateau and its constituent parts influence the Asian monsoons mechanically or thermally is a topic of extensive scientific debate [153]. While targeted experiments to address this question were outside the scope of this present work, it seems likely that the circulation and
Figure 2.10: The Tian Shan’s influence on geopotential height and wind in summer (JJA). Shown are anomalies (Control-NoTianshan) in geopotential height (m) zonally averaged over 65°E-100°E (a), and anomalies in 850 mb geopotential height overlaid with wind anomaly vectors (Δu; m/s) (b). All anomalies are contoured in black, but only significant anomalies are shaded, and places with only topography at the relevant pressure-level are masked in grey. Note the baroclinic structure in (a), and the correspondence south of the Tibetan Plateau between wind vectors and the zero-anomaly contour of geopotential height in (b) with moisture flux vectors shown in Figure 2.9.
remote precipitation responses to the Tian Shan are primarily driven by thermal forcing. First, regional model experiments in Tang et al. (2012) find that elevated heating of the Northern Tibetan Plateau, Tian Shan, and Altai Mountains, not mechanical forcing, causes most of the enhancement of the East Asian Summer Monsoon by this orography. Second, dominance of thermal forcing, which peaks in the summer, would be more clearly consistent with the stationary wave being strongest in the summer than dominance of mechanical forcing. These two lines of evidence suggest that the Tian Shan’s thermal forcing is more climatically influential at a large-scale than its mechanical forcing.
Here we have taken one approach to diagnosing how the Tian Shan enhances precipitation in the summer over East Asia, which is consistent with prior work examining the Tibetan Plateau influence on the East Asian Summer Monsoon. The upper atmosphere anticyclone and lower atmosphere cyclone around the Tibetan Plateau have been associated in prior work with forcing by the Northern Tibetan Plateau and related northern orography including the Tian Shan [220, 254, 134]. Additionally, the enhancement of the Western North Pacific subtropical high due to the Northern Tibetan Plateau is described in Zhang et al. (2012) [254]. The present study, which combines a GCM at high resolution with a specific focus on the Tian Shan, has allowed more clear association of these circulation effects with the Tian Shan in particular, including diagnosis of the enhanced Pacific high as part of a stationary wave.
It is worth noting that an alternative and perhaps complementary way of examining these circulation changes is in how the Tian Shan shift the westerlies and in turn how this affects the seasonality of the East Asian Summer Monsoon. Chiang et al. (2015) [36] suggests that when the westerlies shift north of the Tibetan Plateau earlier in the season, this results in longer and overall greater East Asian Summer Monsoon rains. Examination of the westerly jet and seasonality of East Asian Monsoon precipitation in the Control and NoTianshan runs (not shown) suggests that the Tian Shan may make the westerly jet extend farther north, and that the greatest enhancement of rainfall relative to the mean occurs over the farthest north portion of the monsoon. These results are suggestive of dynamics similar to those proposed in Chiang et al. (2015) [36]. Additionally, further focus on westerly shifts may help explain eastward extension of the Tian Shan’s enhancement of rainfall into the Pacific that echoes the Meiyu-Baiu rainband [Figure 2.7; 193]. However, fully understanding the Tian Shan’s influence in this alternative framework would require careful diagnosis of the East Asian Monsoon seasonality in FLOR, which we leave to future work.

2.5.2 Temperature in AEA

In addition to influencing precipitation, the Tian Shan also generate large local surface temperature changes. There is significant cooling over the Tian Shan of up to 32°C, which can be easily explained by adiabatic cooling due to the increase in elevation. More surprisingly, there is warming of up to 5°C in the rain shadow of the Tian Shan co-located with the peaks of the Altai and Kunlun Mountains (Figure 2.13a).

Close inspection indicates two possible causes for this warming, both related to the blocking of winter to spring moisture from the West by the Tian Shan. One possibility is that decreased snowfall over the Altai and Kunlun Mountains decreases the surface albedo and increases absorption of shortwave radiation. Snowfall does indeed decrease and absorbed shortwave radiation increases over the Altai and Kunlun
Figure 2.13: Remote warming by the Tian Shan and possible mechanisms. Shown are Control-NoTianshan changes in (a) surface temperature (°C), (b) snowfall (cm) and shortwave radiation reflected from the surface (purple contour= Δ <-10 W/m²), and (c) Bowen ratio. All shaded quantities are masked for significance. The Tian Shan are masked out in light grey to highlight effects remote from the Tian Shan. The black contour designates the Control desert, and the blue contours designate lakes/seas. Note that the greatest changes in each quantity are co-located with mountains east of the Tian Shan (Altai in the north and Kunlun in the south).
Mountains, consistent with this first explanation (Figure 2.13b). Another possibility is that decreased soil moisture over the Altai and Kunlun Mountains might decrease the potential latent heat flux and thus necessitate an increase in sensible heat flux and temperature to maintain energy balance. The Bowen Ratio (sensible heat flux divided by latent heat flux) does increase over these same mountains, seemingly consistent with the second explanation for the warming (Figure 2.13c).

To determine which of these two effects dominates, an energy balance decomposition was completed (Figure 2.14a and b). For Control-NoTianshan, the increases in absorbed shortwave radiation over the Altai and Kunlun mountains (+13.3 and +20 W/m² respectively) are many times greater than the decreases in latent heat flux (+2.2W/m² and +5.4W/m² respectively). Additionally, the magnitudes of the changes in sensible heat flux (-6.6W/m² and -12.6W/m²) are much greater than that of latent heat flux. In this circumstance, snow cover and albedo changes, which affect the shortwave radiation budget, drive the warming. The warming is maximized at the mountains in the winter because that is where and when snowfall is significant within this otherwise arid region. Somewhat counterintuitively, change in the Bowen Ratio here primarily reflects warming from snow/albedo changes driving sensible heat flux increase, rather than latent heat flux decrease necessitating sensible heat flux increase. Supporting this result, the remote warming has a clear seasonality peaking in winter, when snowfall and reduction in snowfall by the Tian Shan is greatest (not shown).

A contrasting case occurs in India, which warms slightly (up to 1°C) due to the Tian Shan. In this warm region where there is little snow, latent heat flux due to less precipitation does indeed drive the warming (Figure 2.14c). Apparently the background climate of a region (especially how much snow it receives) dictates the dominant mechanism through which drying generates warming (either decrease in
Figure 2.14: Control-NoTianshan changes in the surface energy balance for 3 different regions: (a) the Altai Mountains, defined as areas directly north of the Tian Shan that warm by more than 2°C, (b) the Kunlun Mountains, defined as areas directly south of the Tian Shan that warm by more than 2°C, and (c) places in India that warm by more than 0.4°C. “Cloud” is the change in surface radiative forcing (both shortwave and longwave) due to changes in clouds. Positive forcing implies greater energy into the surface while negative implies greater energy leaving the surface. All changes are in W m⁻². Note that clear-sky shortwave radiation dominates energy balance change in the mountains directly north and south of the Tian Shan, while latent heat flux dominates energy balance change in India.
snowpack and albedo as occurred in the Altai and Kunlun mountains, or decrease in latent heat flux and increase in sensible heat flux as occurred in India).

2.6 Summary & Discussion

This study sought to characterize the influence of the Tian Shan on Arid Extratropical Asia (AEA). In particular, we wanted to understand the extent to which the Tian Shan are responsible for a wet region bisecting AEA, and for the different precipitation seasonalities in the West versus East Deserts. To conduct this study, we employed a newly-developed high-resolution land, low-resolution ocean GFDL GCM called CM2.5-FLOR which skillfully represents both the area and seasonality gradient of AEA. This model was altered to assess the impacts of the Tian Shan through three different experiments: a Control run including the Tian Shan, a NoTianshan run with boundary conditions controlling surface height, gravity wave drag, and boundary layer roughness altered to remove the Tian Shan, and a NoTianshanDrag run with boundary conditions controlling only gravity wave drag and boundary layer roughness altered to remove the Tian Shan.

The Tian Shan were found to be fully responsible for the spatial divide between the annual-mean deserts, and influential in important details of the seasonality differentiation. The wet region dividing the West and East Deserts can be entirely attributed to orographic precipitation from the Tian Shan— the humidity in this region is likely too low for significant precipitation to occur without adiabatic lifting by the mountain slope and resulting cooling.

More interesting than the changes to desert area are the changes to desert precipitation seasonality. While the Tian Shan have negligible influence on the precipitation seasonality of the West Deserts, including the Kyzylkum and Karakum, the Tian Shan significantly alter the seasonality of precipitation in the East Deserts. Normally, the
driest portion of AEA known as the Taklimakan desert (and Western-East region in our study) has a weak summer peak in precipitation. When the Tian Shan are removed this region becomes much wetter, and the climatology completely switches to a fall and spring precipitation double peak due to three effects: 1) westerly-carried winter/spring precipitation no longer being blocked by the Tian Shan, 2) reduced drying winter subsidence over this region in the lee of the Tian Shan, 3) the absence of Tian Shan orographic precipitation bleeding into the region in the summer. Notably, this dramatic influence over the Western-East is consistent with paleoclimatic proxy evidence implicating the Tian Shan uplift in the formation of the Taklimakan desert \[258\].

The Gobi/Eastern-East also receives more winter precipitation and less summer precipitation in the absence of the Tian Shan, though the change is less significant as a summer precipitation peak is retained. The causes of the change in summer precipitation in this region are not immediately obvious as it is too far from the Tian Shan to be influenced by orographic precipitation. We found through moisture budget analysis that changes in seasonal mean winds are primarily responsible for the precipitation enhancement in East Asia by the Tian Shan. The relevant circulation changes appear to be an upper atmosphere anticyclone that is associated with a lower atmosphere cyclone around the Tibetan Plateau and a stationary wave, both which in turn increase moisture flux into East Asia from the west and east respectively. This change constitutes a significant enhancement of the spring to fall East Asian Monsoon, and corresponds with similar results found in prior studies examining the climatic influence of the Northern Tibetan Plateau, Tian Shan, and Altai together \[220\] \[254\] \[134\]. Interestingly, the timing of the Tian Shan’s monsoon enhancement is different from that of the Tibetan Plateau’s overall influence, which Liu and Yin (2002) \[135\] found to have a more significant effect on the winter than summer East Asian monsoon. Speculatively, it seems likely that these timing differences are related to the different
latitudes of the Tian Shan versus Tibetan Plateau paired with the seasonal meridional migration of the westerly jet.

In our simulations, the Tian Shan’s changes to precipitation were paired with a few temperature changes of note. The Tian Shan were found to remotely warm the Altai and Kunlun mountains to their east as follows: the Tian Shan block West winter moisture from this region, reducing orographic precipitation over the Altai and Kunlun, decreasing snowpack, decreasing surface albedo, and in turn allowing greater shortwave radiation to warm the surface. This is contrasted with slight remote warming over India also related to precipitation decreases, but caused proximally by Bowen Ratio increase (less latent and more sensible heat fluxes).

To summarize, even without the Tian Shan, AEA is still arid, consistent with Sato (2005) [195], and there is still a gradient in precipitation seasonality from the West to the East Deserts. This suggests that large-scale circulation, separate from the influence of the Tian Shan, drives the existence and precipitation/evaporation seasonality of AEA. However, the positioning of the seasonality border between the winter-spring dominated (West) and summer-dominated (East) deserts is strongly influenced by the Tian Shan. The Tian Shan block winter-spring precipitation from reaching the Taklimakan, leading it to exist in the present climate as a summer precipitation desert more similar in seasonality to the Gobi than the Kyzylkum and Karakum. The Tian Shan also remotely enhance the summer precipitation peak in the Gobi, and decrease its winter precipitation. This suggests that the climatological divide of the deserts is shifted farther west and made more distinct by the Tian Shan than it would be under the influence of moisture recycling limits alone.

There are a number of remaining questions in this study that merit further investigation. First, satellite and ground-based observations in this region that generate the gridded observational datasets are quite sparse. Comparison of the FLOR model runs to additional observational data, such as eddy flux tower and weather station
data not included in this paper’s analyzed datasets, could be useful in better understanding the biases of this model in simulating AEA. Second, vegetation is static in our simulations, when in reality it likely should change when the Tian Shan are removed. Changing the vegetation to reflect the surrounding lower-elevation landscape in the NoTianshan and NoTianshanDrag runs, or re-running these experiments with a dynamical vegetation model, would be useful additions to this work; indeed, modeling experiments by Liu et al. (2015) [134] suggest that climate feedbacks from Taklimakan desert formation had a comparable drying effect to the Northern Tibetan Plateau (including the Tian Shan) over the Tarim Basin. Additionally, in our experiments the Tian Shan create significant drying to their south and north that was not so relevant to the region of focus in this study (AEA) but may be interesting to deconstruct. Finally, how the Tian Shan forces its associated circulation changes (mechanically or thermally), and whether these changes are best considered through the frame of shifting the westerlies, are important questions that merit more targeted experiments and investigation.

In recent years, AEA has seen a number of significant hydrological trends. Over the past half century, the area of China covered in desert has expanded \( \sim 3000 \text{ km}^2/\text{yr} \), or \( \sim 30\% \) total [257], and the Aral Sea in Central Asia has desiccated to less than half its former size [205]. Alongside these present trends, there is little consensus regarding how AEA will be affected by projected global warming [216]. Future studies should work to discern to what degree proposed larger-scale climatological controls (i.e., monsoons, moisture recycling limits, the Tibetan plateau) are responsible for the existence and precipitation seasonality of AEA. Improved understanding of the basic climate of AEA will provide a foundation for understanding of past, present, and future hydrological trends in these environmentally sensitive arid regions, which is of primary societal significance.
2.7 Acknowledgements

Gabriel Vecchi is a co-author on the published version of this chapter in Journal of Climate and provided useful guidance throughout the project. This work was possible due to funding from a National Science Foundation Graduate Research Fellowship, the NOAA Climate Program Office, and a Princeton Centennial Fellowship. We are grateful for insightful comments from John Chiang and another anonymous reviewer during the Journal of Climate review process, and Tom Delworth, Isaac Held, Chris Milly, Sergey Malyshev, Elena Shevliakova, Xiaosong Yang, and Andrew Wittenberg for useful discussions earlier in the project. Seth Underwood and Zhi Liang provided critical technical support. The American Geophysical Union and Asia-Oceania Geosciences Society provided opportunities to present earlier versions of this work. CMAP, GPCP, and University of Delaware Precipitation data were provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their website at http://www.esrl.noaa.gov/psd/. University of East Anglia data was provided by their Climate Research Unit, from their website http://www.cru.uea.ac.uk/data.
Chapter 3

The Ocean-Mediated Influence of Asian Orography on Tropical Precipitation and Cyclones

3.1 Abstract

Prior Global Climate Model (GCM) experiments have shown that the Tibetan Plateau and related orography play a significant role in enhancing the Indian Monsoon, particularly during its onset, and the East Asian Monsoon. However, these experiments have been largely performed with atmosphere-only, lower-resolution GCMs that neglect the influence of atmosphere-ocean coupling, and do not resolve tropical cyclones (TCs). Here we explore the influence of Asian orography on tropical circulations in a Geophysical Fluid Dynamics Laboratory (GFDL) GCM at two different atmosphere/land resolutions (~50 and 200 km), and with or without atmosphere-ocean coupling. Atmosphere-ocean coupling is found to play a significant role in the precipitation response due to the Asian orography, enhancing the precipitation increase over the Western North Pacific (hereafter WNP), and drying
the Arabian Sea. In these same regions, the higher resolution model, which resolves TCs up to category 3, suggests that Asian orography has a significant influence on TCs, increasing TC frequency in the WNP, and decreasing it in the Arabian Sea. However, in contrast to precipitation, this TC response does not appear to be strongly affected by the atmosphere-ocean coupling. Connections between the direct atmospheric circulation response to the TP, ocean circulation changes, and these various effects on precipitation and tropical cyclones are analyzed and discussed.

3.2 Introduction

Precipitation in South and East Asia is dominated by the seasonal monsoons, which are more dramatic than anywhere else on the planet. The South Asian Monsoon is characterized by high moist entropy over South Asia especially the Bay of Bengal, seasonally reversing winds over the Arabian Sea, and summer rainfall across South Asia [153]. The East Asian Monsoon is composed of strong spring and summer rainfall over East China and along a band across Korea and Japan and into the WNP (the Meiyu-Baiu) [153]. The rainfall of both these summer monsoons is vital for agriculture— even small shifts in timing of the South Asian monsoon can be devastating for crop yields [65]. The rainfall can also be a hazard causing dramatic flooding [118]. Despite these significant impacts, the mechanisms driving these climatic phenomena are still a topic of debate. Clarifying understanding of Asian monsoon dynamics is critically important for better prediction of monsoonal rainfall in the present climate, and preparation for how these systems might change under increased atmospheric concentration of carbon dioxide. Climate projections in the broad Asian monsoon region remain highly uncertain [216], highlighting our still limited understanding of monsoon dynamics and the need for progress.
General circulation models (GCMs) of the earth’s atmosphere are capable of simulating the Asian monsoons, albeit with varying degrees of skill [20]. Thus, targeted experiments with GCMs can be used to disentangle the fundamental drivers of these monsoons. A suggested key factor for both the South and East Asian Monsoons is Asian orography. Including the Tibetan Plateau and Himalayas, these are the highest mountains on earth and stretch over a vast territory (Figure 3.1a). Experiments removing the Tibetan Plateau and related orography (compared to control simulations with full orography) were performed with some of the earliest GCMs by Hahn and Manabe (1975) [79]. They used an atmosphere-only GCM with prescribed SSTs and a resolution of about 270 km, and simulated less than a year focused on the summer months. Despite the relatively crude GCM and short simulation, they reached a number of conclusions that remain robust today. In particular, they found the Tibetan Plateau is associated with middle and upper atmosphere heating and high pressure, upward motion and surface low pressure over India, and northward extension of the South Asian monsoon rainfall.

Figure 3.1: Topographic boundary conditions for the GCM simulations. Surface height is shown for the Control (a,b,c) and FlatAsia (d,e) experiments. Observed 5’ resolution modern day topography (a; 51) is presented for comparison to FLOR (b) and LOAR (c) boundary conditions.
Since this pioneering study, numerous groups have adopted this GCM experiment design to further understand the related monsoon dynamics and other climatic influences of these mountains. Precipitation changes typical of many of these studies are summarized in Figure 3.2 which shows results from simulations with and without the Asian orography from the atmosphere-only 200 km resolution GCM GFDL-AM2.1. In addition to enhancing the South Asian Monsoon [122], the mountains dry extratropical Asia, and are fundamental to the existence of deserts such as the Gobi and Taklimakan [27, 13]. They also enhance the East Asian Monsoon, especially the Meiyu-Baiu, and are likely more essential to its existence than to the South Asian Monsoon [34, 153, 220, 193]. The heating of the middle atmosphere by monsoonal latent heat release, which is amplified by the mountains, can drive remote drying over the Mediterranean and the North African and Southwest Asian dry zones [188, 209]. The Tibetan Plateau is also found to shape the storm track over Asia in a variety of ways, including driving the midwinter suppression of the Pacific storm track activity [123]. Some of these studies have explored the impact of smaller portions of the Asian mountain system both to refine understanding and to simulate paleoclimatic periods [e.g., 220, 13, 204, 203]. These studies suggest that location can be just as important for climatic influence as size of mountains. For example, simulations indicate that the Mongolian Plateau, which lies north of the Tibetan Plateau, plays a bigger role in the atmospheric stationary wave pattern than the Tibetan Plateau, despite its smaller size [236].

A topic of significant current debate in the published literature is whether the Asian mountains enhance the monsoons through thermal or mechanical forcing. A number of studies argue that the high plateaus of Asia function as a “sensible heat pump” for the middle atmosphere, driving rising motion and near-surface low pressure which drives water vapor convergence into the monsoon region [251, 241]. These mechanisms are similar to the traditional argument that land-sea thermal contrasts
Figure 3.2: Influence of Asian orography on precipitation in an atmosphere-only model. Change in precipitation (AMIP Control-FlatAsia) is shaded and AMIP FlatAsia mean precipitation is contoured globally for the annual mean (a), and over the WNP and northern Indian Ocean for AMJ (b), and JAS (c). Anomalies are only shown where statistically significant at the 95% level based on a two-sided $t$-test.

Other studies argue that the Asian mountains enhance the South Asian Monsoon by insulating this region from cool, dry extratropical air, implying a critical role for the extremely tall, wall-like Himalayas [21, 22]. Going beyond total monsoon response to examine monsoon seasonality, Park et al. (2012) [165] find that the Tibetan Plateau significantly increases WNP precipitation during the monsoon onset period (AMJ), but only very weakly increases it during the monsoon peak (JAS). To explain this effect, they invoke mechanical influences of the southern Tibetan Plateau on the westerly jet which drive downstream convergence, and precipitation in a moist atmosphere. Another recent paper found that the Meiyu-Baiu’s convection, which dominates summer precipitation in the WNP, is driven primarily by meridional dry enthalpy advection associated with the Tibetan Plateau’s station-
ary wave pattern, but was agnostic as to whether this pattern is mechanically or thermally forced [34].

Most studies examining the influence of Asian orography have been performed with atmosphere-only GCMs with prescribed SSTs and typical GCM atmospheric and land resolution of about 2°/200 km. Due to lack of atmosphere-ocean coupling, such experiments do not capture the role of air-sea interaction in influencing monsoon precipitation. This is problematic given significant interaction between the monsoon winds and ocean current changes documented in prior work [e.g., 124]. In light of this, a few studies have performed topographic flattening experiments with atmosphere models coupled to slab ocean models [108, 165], and atmosphere models coupled to dynamical ocean models [110, 109, 111, 159, 107, 123]. These studies indicate that orographically driven atmospheric changes influence SSTs in the WNP, with warming between 0 and 20°N and cooling between about 20 and 50°N. The low-latitude SST warming enhances monsoonal precipitation [159]. These studies tend to focus on the WNP, with less attention given to changes in the Indian Ocean and adjoining seas. Questions also remain regarding the mechanisms of SST change, particularly the role of ocean transport versus changes to surface energy balance.

In this study we further explore the role of mountains in Asian summer monsoon precipitation by using a state-of-the-art high resolution atmosphere-ocean coupled GCM. GFDL CM2.5-FLOR, the GCM employed, has an approximately 50 km resolution atmosphere model coupled to a 1° fully resolved ocean model. We flatten topography across Asia, with the largest modification where topography is highest and broadest (i.e., the Himalayas and Tibetan Plateau). The high resolution atmosphere has a few advantages in studying precipitation around Asia. First, it captures with greater fidelity than lower resolution models the height of tall mountains critical for the monsoon circulation such as the Himalayas and lower mountains that shape local patterns of precipitation [102]. This leads to improved simulation of the Asian
monsoons [45]. Second, the high resolution of the atmosphere permits formation of tropical cyclones, or typhoons as they are called around Asia, which are responsible for significant seasonal and extreme rainfall [105]. While other studies have examined the influence of Asian mountains on winter storms [164, 123], to our knowledge this is the first set of simulations able to examine how tropical cyclones are influenced by Asian orography.

We performed additional experiments to isolate the role of high resolution and atmosphere-ocean coupling in our results. Regarding tropical cyclones, we employ a GCM identical to FLOR except with a lower atmospheric and land resolution (∼200 km), which limits their formation. Regarding SST changes, we run simulations of both FLOR and LOAR with SSTs nudged such that the mountain removal cannot influence SSTs except at very short timescales. This set-up is advantageous over simply prescribing SSTs as it allows high frequency air-sea interaction important for realistic simulation of tropical cyclones, and tropical rainfall and its variability [16]. The SST nudging process also produces metrics which allow us to distinguish the role of ocean transport versus changes in surface energy balance in the mountain-caused SST changes.

Section 3.3 describes the GCMs used in this study in more detail, the observations employed for model validation, and the analysis strategy. Section 3.4 provides results, describing changes in precipitation and tropical cyclones induced by the Asian mountains, and particularly the role of atmosphere-ocean coupling in these changes. Finally, Section 3.5 summarizes the results and provides conclusions.
3.3 Methods

3.3.1 Models

We utilize two Geophysical Fluid Dynamics Laboratory fully coupled atmosphere-ocean GCMs in this study. FLOR [228, 96], which is the Forecast-oriented Low Ocean Resolution derivative of CM2.5 [45], has a relatively high resolution $\sim 50$ km atmosphere and land, and a relatively lower resolution $\sim 1^\circ$ ocean. LOAR is identical to FLOR in every regard except for its atmosphere and land resolution, which is a more standard GCM resolution of $\sim 200$ km. The high resolution of FLOR allows it to simulate tropical cyclones up to Category 3 in strength, while LOAR does not simulate such circulation extremes. Additionally, FLOR resolves high and sharp topographic features, such as the Himalayas, more accurately than LOAR (Figure 3.1).

Both models employ the LM3 land model, which has options for static and dynamic vegetation [152]. Static vegetation keeps vegetation types ($C_3$ grass, $C_4$ grass, temperate deciduous tree, tropical tree, or cold evergreen tree) and phenology consistent with that in the observed modern climate, though biomass can vary. In contrast, dynamic vegetation allows vegetation type and phenology to adjust to be consistent with the simulated climate.

This family of models’ simulation of a variety of climatic phenomena has been examined and validated. Most relevant to the present work are prior studies utilizing these models’ simulation of Asian precipitation [13], extreme precipitation [225], and global and WNP TCs [228, 117, 255]. CM2.5, which has the same atmosphere as FLOR, exhibits a much improved simulation of monsoon precipitation compared to GFDL-CM2.1, which is similar to LOAR (see Figure 7 in Delworth et al. (2012) [45]).

To gain perspective on these GCMs’ simulation accuracy, we also use Coupled Model Intercomparison Project Phase 5 (CMIP5) pre-industrial control run data from
30 different GCMs [221]. The CMIP5 models utilized and their modeling centers are listed in Table 3.1.

### 3.3.2 Observational datasets

To validate the models' simulation of precipitation, we employ three observed precipitation datasets (TRMM, CMAP, and GPCP). TRMM stands for the “Tropical Rainfall Measuring Mission” and is a multisatellite-based precipitation product covering 50°S to 50°N across the globe and available at a 0.25° resolution [91]; data from January 2000 to September 2010 is used in this study. CMAP is a merger of five different satellite products spanning the entire globe [243], while GPCP is a merger of both satellite and ground-based observations [1]. Both are available at a 2.5° resolution, and data from 1979-2012 are used.

Additionally, for some nudged SST model experiments we employ a climatology derived from the Met Office Hadley Centre SST data [HADISST1.1, 183]. AM2.1 is forced with a climatology derived from years 1950-1998 of the Reynolds reconstructed SST dataset [185].

### 3.3.3 Experiments

For both FLOR and LOAR, experiments are run with two different topographic boundary conditions, which will be referred to as “Control” and “FlatAsia”. In Control, present-day topography is used as a boundary condition for the model. In FlatAsia, topography over most of Asia is flattened to the elevation of the surrounding landscape, with the most dramatic changes around the Tibetan Plateau and Himalaya where the present-day elevation is greatest (Figure 3.1). This alteration is performed in boundary conditions controlling surface height, gravity wave drag, and boundary layer roughness as in Baldwin and Vecchi (2016) [13]. Initializing FlatAsia simulations with extant atmospheric initial conditions adjusted to Control orography...
Table 3.1: CMIP5 GCMs used for validation of the FLOR and LOAR simulations, and the modeling centers that created each GCM. We use monthly precipitation data from each GCM’s pre-industrial control run.

<table>
<thead>
<tr>
<th>GCM</th>
<th>Modeling Center</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACCESS1-0</td>
<td>Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology</td>
</tr>
<tr>
<td>BCC-CSM1.1</td>
<td>Beijing Climate Center</td>
</tr>
<tr>
<td>BNU-ESM</td>
<td>College of Global Change and Earth System Science, Beijing Normal University</td>
</tr>
<tr>
<td>CanESM2</td>
<td>Canadian Centre for Climate Modelling and Analysis</td>
</tr>
<tr>
<td>CCSM4</td>
<td>National Center for Atmospheric Research</td>
</tr>
<tr>
<td>CMCC-CM</td>
<td>Euro-Mediterraneo sui Cambiamenti Climatici</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>Centre National de Recherches Meteorologiques / Centre European de Recherche et Formation Avancees en Calcul Scientifique</td>
</tr>
<tr>
<td>CSIRO-Mk3.6.0</td>
<td>Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence</td>
</tr>
<tr>
<td>FGOALS-g2</td>
<td>LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences; and CESS, Tsinghua University</td>
</tr>
<tr>
<td>FGOALS-s2</td>
<td>LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>NOAA Geophysical Fluid Dynamics Laboratory</td>
</tr>
<tr>
<td>GFDL-ESM2G</td>
<td></td>
</tr>
<tr>
<td>GFDL-ESM2M</td>
<td></td>
</tr>
<tr>
<td>GISS-E2-H</td>
<td>NASA Goddard Institute for Space Studies</td>
</tr>
<tr>
<td>HadGEM2-CC</td>
<td>Met Office Hadley Centre</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td></td>
</tr>
<tr>
<td>INM-CM4</td>
<td>Institute for Numerical Mathematics</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td></td>
</tr>
<tr>
<td>IPSL-CM5A-MR</td>
<td>Institut Pierre-Simon Laplace</td>
</tr>
<tr>
<td>IPSL-CM5B-LR</td>
<td></td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology</td>
</tr>
<tr>
<td>MIROC-ESM-CHEM</td>
<td></td>
</tr>
<tr>
<td>MIROC4h</td>
<td></td>
</tr>
<tr>
<td>MIROC5</td>
<td></td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Max Planck Institute for Meteorology</td>
</tr>
<tr>
<td>MPI-ESM-MR</td>
<td></td>
</tr>
<tr>
<td>MPI-ESM-P</td>
<td></td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>Meteorological Research Institute</td>
</tr>
<tr>
<td>NorESM1-M</td>
<td>Norwegian Climate Centre</td>
</tr>
<tr>
<td>NorESM1-ME</td>
<td></td>
</tr>
</tbody>
</table>
causes model instabilities. As a result, all experiments are run from a “cold” start, without atmospheric initial conditions, which allows the model to more robustly adjust to the presence or absence of Asian topography.

Since most prior modeling studies altering the Tibetan Plateau were not performed with atmosphere-ocean coupled GCMs, we perform an additional set of experiments to isolate the direct climatic influence of Asian orography from that mediated through changing SST. In these experiments (the “nudged SST” versions of both Control and FlatAsia) SSTs are restored to repeating monthly climatologies [154, 256]. We nudge to each model’s respective monthly climatology calculated from 100 years of Control run data using a 5-day restoring timescale, effectively removing the influence of flattening Asian topography on climatological SSTs in the FlatAsia experiment. In LOAR, we also ran a set of experiments nudged to the observed SST climatology from HADISST; in addition to removing low frequency atmosphere-ocean coupling, these experiments also eliminate model biases in SST. Notably, SST nudging still allows high frequency air-sea interaction important for TCs and tropical precipitation.

For each model setting described above, we have run simulations with static and dynamic vegetation. The dynamic option allows the vegetation to respond to the climatic changes associated with different topography. However, we found that employing static versus dynamic vegetation did not change the key results described in this study. Thus, for consistency, all results shown below are from simulations with static vegetation. One would also expect lakes and river flow in the hydrological portion of the land model to depend on topography; we do not alter these boundary conditions, but do not expect this to be a significant bias.

Table 3.2 provides a summary of all the GCM simulations examined for this study, other than the CMIP5 simulations used for model validation.
Table 3.2: GCM simulations employed in this study. Note that an additional set of simulations for the fully coupled model experiments was performed, identical in all respects to this except with dynamic rather than static vegetation.

<table>
<thead>
<tr>
<th>Experiment Name</th>
<th>Topography</th>
<th>Radiative Forcing Year</th>
<th>Vegetation</th>
<th>SSTs</th>
<th>GCMs Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMIP Control</td>
<td>Modern</td>
<td>1991-2000</td>
<td>Static</td>
<td>Forced with observed climatology</td>
<td>AM2.1</td>
</tr>
<tr>
<td>Control</td>
<td>Modern</td>
<td>1860</td>
<td>Static</td>
<td>Freely evolving</td>
<td>LOAR and FLOR</td>
</tr>
<tr>
<td>Nudged Control</td>
<td>Modern</td>
<td>1860</td>
<td>Static</td>
<td>Restored to Control climatology</td>
<td>LOAR and FLOR</td>
</tr>
<tr>
<td>Nudged2Obs Control</td>
<td>FlatAsia</td>
<td>1991-2000</td>
<td>Static</td>
<td>Forced with observed climatology</td>
<td>AM2.1</td>
</tr>
<tr>
<td>AMIP FlatAsia</td>
<td>Asia flat</td>
<td>1991-2000</td>
<td>Static</td>
<td>Freely evolving</td>
<td>LOAR and FLOR</td>
</tr>
<tr>
<td>FlatAsia</td>
<td>Asia flat</td>
<td>1860</td>
<td>Static</td>
<td>Restored to Control climatology</td>
<td>LOAR and FLOR</td>
</tr>
<tr>
<td>Nudged FlatAsia</td>
<td>Asia flat</td>
<td>1860</td>
<td>Static</td>
<td>Restored to observed climatology</td>
<td>LOAR and FLOR</td>
</tr>
<tr>
<td>Nudged2Obs FlatAsia</td>
<td>FlatAsia</td>
<td>1860</td>
<td>Static</td>
<td>Restored to observed climatology</td>
<td>LOAR and FLOR</td>
</tr>
</tbody>
</table>

3.3.4 Analysis strategy

The FLOR fully coupled Control experiment was run for 1000 years, and the FLOR fully coupled FlatAsia experiment was run for 100 years. Unless otherwise noted, we analyze years 31-100 of both to allow for some model spin-up. LOAR fully coupled experiments are run for 300 years each, since the low resolution makes this a more efficient and faster model to run, and we analyze years 201-300. FLOR and LOAR nudged experiments are initialized from year 100 of their associated fully coupled simulation, and run for 30 years. All 30 years are analyzed.
Prior work has suggested that the Tibetan Plateau exerts a significant influence on deep ocean circulation, in particular decreasing the Atlantic Meridional Overturning Circulation (AMOC) [55]. Due to the long timescales associated with these circulations, the ocean in the fully coupled FlatAsia simulations may not stabilize from the Control state it is initialized from for thousands of years. Due to computational limitations, we only run our simulations for hundreds of years, so the continued deep ocean adjustment will be ongoing over the period of analysis. However, we do not expect this to significantly bias results over the regions of interest for this study (i.e., the WNP and Arabian Sea).

Model-generated TCs are tracked using an algorithm developed by Harris et al. (2016) [80]. The algorithm primarily depends on 6-hourly instantaneous sea-level pressure, 10-meter winds, 850 hPa relative vorticity, and atmospheric temperature anomalies between 300 and 500 hPa. TC track density is determined by counting TC positions for each $1^\circ \times 1^\circ$ grid box, then smoothing this count using a 9-point moving average weighted by distance from the center of the grid box. These values are then integrated annually, so TC density results are presented in units of number of TCs per year.

Many result figures will be presented as Control minus FlatAsia (Control-FlatAsia), which can be imagined as the climatic effect of uplifting Asian orography. Statistical significance of most such results is determined using a two-sided $t$-test evaluated at a 95% level. The percent of change in a given quantity due to SST change induced by Asian mountains (i.e., the role of atmosphere-ocean coupling) can be quantified as: $\frac{(\text{Control-FlatAsia})-(\text{Nudged Control-FlatAsia})}{(\text{Control-FlatAsia})}\times 100$. 

56
3.4 Results

3.4.1 Model Validation

In general, mean and seasonal Asian precipitation and winds in LOAR are comparable to that of many CMIP5 GCMs, while FLOR tends to have improved performance especially over places with complex topography (not shown). Over the WNP, FLOR and LOAR both capture the general seasonal cycle of precipitation seen in the observations (Figure 3.3). Precipitation peaks in August in both the LOAR/FLOR and observations, but in LOAR/FLOR reaches a minimum one month late in March rather than February. Both models’ precipitation falls within the range of observations in the summer, but exhibits high biases in the winter typical of CMIP5 models. The LOAR nudged2obs simulation also exhibits this bias, albeit somewhat less so than the FLOR and LOAR simulations nudged to model climatology. This suggests that SST biases in the fully coupled simulations may contribute to the winter precipitation biases, but do not fully explain them.

Figure 3.3: Seasonal cycle of WNP precipitation in FLOR compared to observations and other models. Precipitation averaged over 0 to 40°N and 110 to 180°W is plotted for TRMM, GPCP, and CMAP observed data (black), CMIP5 models (grey), and LOAR and FLOR fully coupled (blue) and nudged simulations (red).
3.4.2 Precipitation

In the annual mean, Asian orography generally enhances precipitation over the Asian monsoon sectors and the WNP, but dries extratropical Asia and farther west into the Mediterranean and Sahel (Figure 3.4). These large-scale changes are similar to what is found with lower-resolution, atmosphere-only models (Figures 3.2). The precipitation response also appears to be quite similar between FLOR and LOAR. This is interesting because in FLOR Asian orography forces large changes in TCs not simulated in LOAR due to its low resolution. As discussed in detail in Section 3.4.3, TC density increases strongly in the WNP, and decreases in the Arabian Sea (Figure 3.5a). This suggests that the presence or absence of TCs does not affect the large-scale precipitation pattern, though it is possible it plays a more important role locally or in precipitation variance. In the following results, where data from only one of FLOR or LOAR is shown the results are qualitatively the same and quantitatively similar for both.

On a seasonal basis, key differences compared to prior studies emerge. Unlike Park et al. (2012) [165], Asian orography increases WNP precipitation throughout the entire summer monsoon season, including the onset (AMJ) and peak (JAS) (Figure 3.6). In AM2.1, the AMJ precipitation increase is focused around 30°N. In contrast, in LOAR (Figure 3.6a) and FLOR (not shown) the AMJ precipitation increase extends farther southward to about 10°N. The area-average AMJ precipitation increase also is approximately doubled in LOAR/FLOR compared to AM2.1 to a precipitation increase of about 20% (Figure 3.7).

As discussed in Section 3.2, atmosphere-only models including AM2.1 indicate that Asian orography does not enhance WNP precipitation during the monsoon peak. However, LOAR and FLOR exhibit significant increases in WNP precipitation during this season (Figure 3.6b). Asian orography forces an increase in precipitation centered over Japan, and another one centered around 15°N, which extends far into the
Figure 3.4: Annual mean precipitation changes induced by the Asian mountains. Annual mean change in precipitation (Control-FlatAsia) is shaded and FlatAsia mean precipitation is contoured for FLOR (a) and LOAR (b). Anomalies are only shown where statistically significant at the 95% level based on a two-sided $t$-test.
Figure 3.5: TC density changes induced by Asian orography. FLOR Control-FlatAsia TC changes are shaded, and Control TC density is contoured for the fully coupled runs (a) and nudged SST runs (b). For this analysis only, all available years (1000 total) of the fully coupled Control simulation are used, with years 1-30 still thrown out to allow for model spin-up. Anomalies are only shown where statistically significant at the 90% level based on a two-sided t-test. Note that the FLOR nudged simulations have only 30 years, which contributes to making those results less statistically significant.
Pacific. The area-average precipitation increase induced by Asian orography is not as large as in AMJ in both absolute and percent terms (<10%), however the anomaly importantly goes from zero or even negative to positive.

There are also strong Arabian Sea decreases in precipitation during the monsoon season not present in the AMIP simulations (Figure 3.2 vs 3.6). Decreases of more than 2 mm/day occur in places where mean precipitation is not much more than that. Additionally, the drying appears to extend over Southern India. The precipitation decreases are stronger during the monsoon peak (JAS) than the monsoon onset (AMJ), suggesting an inverse link to monsoon circulations.

Figure 3.6: Seasonal precipitation changes induced by the Asian mountains and role of atmosphere-ocean coupling. Change in precipitation (Control-FlatAsia) is shaded and FlatAsia mean precipitation is contoured for LOAR AMJ (a) and JAS mean (b). The percent of precipitation change due to SST changes induced by the Asian mountains is shaded for AMJ (a) and JAS (b) by comparing the fully coupled and nudged SST LOAR simulations (see Section 3.3). Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test.

It is natural to ask the reasons behind these seasonal differences: are these due to the increased spatial resolution in FLOR or to air-sea coupling missing in previous studies? Because these WNP and Arabian Sea changes are found in both FLOR
Figure 3.7: WNP precipitation climatology changes due to Asian orography for different GCMs. Results for AM2.1 (a,b), FLOR (c,d), and LOAR (e,f) are compared. In the left panels (a,c,e), precipitation climatology is averaged over the WNP (0-40°N, 110-180 °W) and plotted for Control (black) and FlatAsia (blue) runs, with one standard deviation above and below shaded. In the right panels (b,d,f), absolute (thick dash) and percent (thin dash) differences between Control and FlatAsia climatologies are plotted, showing results for the standard settings for each model in black (atmosphere-only for AM2.1, fully coupled for FLOR and LOAR), in red for simulations nudged to model SST climatology, and in blue for simulations nudged to observed SST climatology, where those simulations are available.
and LOAR, we conclude that increased spatial resolution and resulting TCs are not driving the differences in precipitation response between this study and prior studies. However, allowing the presence or absence of Asian orography to influence SSTs (via atmosphere-ocean coupling) does drive much of these differences. The enhancement of southern WNP precipitation and Arabian Sea drying are both more than doubled in many places due to atmosphere-ocean coupling (Figures 3.6d and 3.7). In contrast, the northern WNP precipitation increase in JAS found in our simulations but not in Park et al. (2012) [165] is not due to coupling. This change likely results from model differences not examined in this work, or possibly differences in where topography was flattened.

While not the focus of this work, the WNP winter precipitation changes tell an interesting and contrasting story to the summer results. Significant precipitation increases in the winter are found in the fully coupled and nudged runs, but not in the nudged2obs or AMIP runs (Figures 3.7). This suggests that the winter precipitation increase may be the result of model SST biases and is spurious. This is distinctly different from the summer precipitation change, in which the AMIP, nudged, and nudged2obs results are consistently less than the fully coupled results, and so atmosphere-ocean coupling clearly enhances the precipitation increase due to Asian mountains.

**Related SST changes**

Asian orography drives strong SST changes in the WNP and Arabian Sea responsible for much of the precipitation change in these regions (Figure 3.8). The WNP mostly warms between 0 and 30°N and cools from 30 to 60°N, consistent with prior work [159, 123]. The Arabian Sea also generally cools. This is consistent with enhanced precipitation in the southern WNP and drying of the Arabian Sea,
as positive(negative) SST anomalies decrease(increase) static stability, and so increase(decrease) convection.

Figure 3.8: SST changes induced by the Asian mountains. Shaded are annual mean Control-FlatAsia differences in SST from LOAR, with FlatAsia SST contoured. Anomalies are only shown where statistically significant at the 95% level based on a two-sided $t$-test. The blue and red dashed shapes demarcate the WNP regions of cooling and warming averaged over for Figure 3.10.

Based on the SST nudging, the model outputs metrics that can be used to quantify how much of the SST difference from the target SST is due to the energy transfer with the atmosphere versus ocean transport. The equation that governs SST in a nudged simulation can be summarized as follows:

$$
\frac{\delta SST}{\delta t} = ADV + MIX + HFLUX + \frac{1}{\tau}(SST^* - SST)
$$

(3.1)

, where $ADV$ and $MIX$ represent fluxes from the ocean to the surface through advection and diffusion/mixing, respectively, $HFLUX$ represents net heat fluxes between the atmosphere and the ocean surface (comprising longwave and shortwave radiation, and latent and sensible heat fluxes), $\tau$ represents the relaxation timescale for the nudging (5 days in our simulations), and $SST^*$ represents the target SST being nudged to (in this study, Control simulation climatology or observed climatology),
and $SST$ represents the model’s SST. $HFLUX$ and $\frac{1}{\tau}(SST^* - SST)$ are diagnostics output by the model. These can be used to determine the energy transfer from ocean transport as follows. Assuming $SST$ is in steady state so $\frac{\delta SST}{\delta t} = 0$, and grouping the terms associated with heat fluxes from the ocean ($OCEAN = ADV + MIX$), Equation 3.4.2 can be rearranged to:

$$OCEAN = -HFLUX - \frac{1}{\tau}(SST^* - SST)$$ (3.2)

In our simulations, comparing $HFLUX$ and $OCEAN$ indicates that the dipole of SST change in the WNP is due to energy transfer with the atmosphere, while the Arabian Sea cooling is due to ocean circulation changes (Figure 3.9).

To further examine the WNP SST changes, we decompose the fluxes of energy between the atmosphere and ocean surface (Figure 3.10). In the south, the warming is driven primarily by decreased latent heat fluxes. In the north, the cooling is driven by increased sensible heat fluxes, decreased shortwave radiation reaching the surface from cloud changes, and a smaller contribution from increased latent heat fluxes. Across the northern WNP region, increases in cloud cover occur at all levels, but most coherently at low and mid-levels (Figure 3.11).

In the south, decreased latent heat fluxes occur due to decreased wind speed. Asian orography generates a stationary wave [89], which includes a high-low-high geopotential height pattern emanating in a south-eastward direction from the Tibetan Plateau (Figure 3.12). The first low and second high intersect around 120-180°W and 15-30°N depending on the pressure level, generating southwesterlies in this region. For all seasons other than JAS, there are mean easterlies in this region, thus the southwesterlies decrease wind speed and turbulent fluxes. The SST warming lags the wind speed changes such that warming is present throughout the year, as described
Figure 3.9: Ocean versus atmospheric drivers of SST change. Shaded is Control-FlatAsia change in energy transfer from the atmosphere to the surface \((HFLUX; a)\) and change in ocean heat transport \((OCEAN; b)\). Data is from LOAR, and these metrics are calculated as part of the SST nudging in the GCM. Anomalies are only shown where statistically significant at the 95\% level based on a two-sided \(t\)-test.
Figure 3.10: WNP surface energy balance changes. Nudged Control-FlatAsia change in different components of the surface energy balance is calculated from LOAR. Averages are calculated over the northern blue box (a) and southern blue box (b) shown in Figure 3.8. The nudged simulation data is used because it shows the initial atmospheric forcing on the ocean surface from Asian orography that drives the SST changes. The fully coupled simulation data is equilibrated with the surface already and so is less informative.
Cloud changes induced by the Asian mountains. Nudged LOAR Control-FlatAsia change in total cloud amount (a) and change at low (b), mid (c), and high (d) levels in the atmosphere. The location of modified topography is contoured green and the regions of WNP SST cooling and warming are boxed blue and red respectively. Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test. Nudged simulation data is used to highlight that these changes are directly driven by atmospheric circulation changes without SST response to the orography. However, results from the fully coupled runs are largely similar.

Thus, even though wind speed is not lessened over JAS, SSTs are still warmer and precipitation is increased.

In the north, the energy balance changes are driven by Asian orography enhancing the East Asian Winter and Summer Monsoons [36, 135]. In the winter, the enhanced Tibetan high (Figure 3.12) generates northerly wind anomalies in northeastern Asia (Figure 3.13 [123]). These northerlies advect cold, polar air southward, where it is carried along the mean westerlies across the northern WNP. The increased surface-air temperature gradient increases both sensible and latent heat fluxes, cooling the northern WNP. Latent heat fluxes increase less than sensible because this region is cold, and because there are some compensating humidity increases. The cooling is stronger at low levels in the atmosphere (not shown), which increases static stability. In the northern WNP, increasing static stability increases low and mid-level stra-
Figure 3.12: Stationary wave pattern induced by the Asian mountains. Annual mean Control-FlatAsia differences in geopotential height with the zonal mean removed at 200 mb (a) and 850 mb (b). Green contours designate the region of topographic modification and grey shading shows where Control topography is higher then the relevant pressure level. Anomalies are only shown where statistically significant at the 95% level based on a two-sided t-test.
tus clouds, a result that has also been shown in other observational and modeling studies [112, 157, 37]. These clouds further exaggerate the initial cooling by decreasing shortwave radiation reaching the surface. In the summer months, prior studies demonstrate that the Tibetan Plateau leads to warm air advection across this region, fueling convection of the Meiyu-Baiu. Two mechanisms for this warm air advection have been proposed: 1) the enhanced Tibetan high leads the westerly jet to advect higher temperatures across China and Japan into the West Pacific [193], and 2) the Tibetan Plateau’s stationary wave pattern generates southerlies in the WNP which advect warm air into the Meiyu-Baiu region [34]. Moist static energy budget analysis of AM2.1 simulations indicates that the latter mechanism is the primary driver [34]. Either way, the clouds associated with the Meiyu-Baiu further cool the northern WNP by reflecting shortwave radiation. In summary, Asian orography cools the northern WNP throughout the year, but via different mechanisms depending on the season.

The Arabian Sea SST cooling again is not driven through surface energy balance changes, but rather through ocean circulation changes. By blocking cool, dry extratropical air, the Himalayas increase moist entropy in South Asia and the Bay of Bengal, leading to off-equatorial maxima [21]. This drives a longitudinally localized cross-equatorial overturning circulation [86, 24]. At low-levels, northward flow in the northern hemisphere needs to be balanced by friction on westerly winds. Thus, the orography enhances summer low-level southwesterlies across the Arabian Sea known as the Findlater jet (Figure 3.13), an effect shown in prior work such as [79]. The associated southwesterly wind stresses along the land-sea boundary of Oman and Somalia induce coastal upwelling (Figure 3.14). The upwelling of deeper, cold water cools the Arabian Sea surface, and reduces local precipitation.
Figure 3.13: Seasonal changes in winds and wind speed induced by Asian mountains. Shaded nudged Control-FlatAsia differences in surface wind magnitude; nudged FlatAsia and nudged Control-FlatAsia 850 mb wind vectors are plotted in grey and black, respectively. Seasonal averages for AMJ, JAS, OND, and JFM are shown in panels a, b, c, and d, respectively. Green contours designate the region of topographic modification. Anomalies are only shown where statistically significant at the 95% level based on a two-sided $t$-test. Nudged simulation data is used to highlight that these changes are directly driven by atmospheric circulation changes without SST response to the orography. However, results from the fully coupled runs are largely similar.

### 3.4.3 Tropical cyclones

While found to be unimportant for the precipitation changes, the TC response to Asian orography is interesting in and of itself. It is also unexplored in prior work due to lack of TC-permitting GCMs. Asian orography yields a dramatic increase in TC density in the southern portion of the WNP, reaching 60% of the mean TC density (Figure 3.5a). In contrast, in the Arabian Sea, Asian orography strongly suppresses the development of TCs. In the present very few TCs form in the Arabian Sea; it appears that this is largely due to the presence of Asian orography.
Figure 3.14: Seasonal 50-m depth ocean upwelling changes induced by the Asian mountains. LOAR change in upwelling is shown for JFM (a), AMJ (b), JAS (c), and OND (d) seasonal means. Anomalies are only shown where statistically significant at the 95% level based on a two-sided $t$-test.

TC density change in a given location can occur due to alteration of TC genesis or tracks. To test whether genesis can plausibly explain the density changes, we calculate a genesis potential (GP) index developed by Kerry Emanuel and used in [29]:

$$GP = |10^5\eta|^{3/2}\left(\frac{\mathcal{H}}{50}\right)^{3}\left(\frac{V_{pot}}{70}\right)^{3}(1 + 0.1V_{shear})^{-2}$$  \hspace{1cm} (3.3)

where $\eta$ is the absolute vorticity at 850 hPa, $\mathcal{H}$ is the relative humidity at 600 hPa in percent, $V_{pot}$ is the potential intensity (in $\text{m s}^{-1}$), and $V_{shear}$ is the magnitude of the vertical wind shear between 850 hPa and 200 hPa (in $\text{m s}^{-1}$). High values of GP reflect climatic conditions favorable for TC genesis. The Control-FlatAsia GP change
exhibits a similar spatial pattern to the TC density changes (Figure 3.15a), with a strong decrease in the Arabian Sea, strong increase in the WNP, and some increase in the East Pacific. This suggests that the TC density changes due to Asian orography can largely be understood as the result of changes in TC genesis.

We examine percent changes in the components of TC genesis to further disentangle the mechanisms through which Asian orography influences TC density (Figure 3.16). All the components other than vorticity exhibit spatial patterns of change largely similar to the TC density changes. 600 mb relative humidity and potential intensity exhibit the greatest magnitude of change, implying that these components drive the TC density changes.

We employ the nudged SST simulations to further probe the TC changes. In these runs the pattern and magnitude of TC density change is quite similar to the fully coupled runs (Figure 3.5b), despite the fact that there are very limited SST changes and so potential intensity changes are smaller (Figure 3.16). It is worth noting that with nudging there is still some muted potential intensity increase in
Figure 3.16: TC GP component changes due to Asian orography. Shown are changes in components for 600 mb relative humidity (a,b), potential intensity (c,d), vertical wind shear (d,e), and 850 mb absolute vorticity (f,g), from the fully coupled (a,c,e,g), and nudged (b,d,f,h) FLOR simulations. Each plot represents % change of the relevant component in Equation 3.4.3 including the factors (e.g., the wind shear term is differences in $(1 + 0.1V_{shear})^{-2}$ so positive implies a positive contribution to GP).
the southern WNP and decrease in the Arabian Sea. This suggests that changes in other quantities used to calculate potential intensity, such as upper tropospheric temperature and specific humidity, also enhance this TC changes. Nonetheless, due to the similarity between the nudged and fully coupled TC changes, we conclude that Asian orography’s influence on potential intensity is not critical to the TC change, and differences in relative humidity are the primary cause of TC increase in the WNP and decrease in the Arabian Sea.

Different circulation features drive the local relative humidity changes in the WNP and Arabian Sea. In the WNP, the intersection of the Asian mountains’ stationary wave first low and second high drive southwesterlies (Figure 3.17), and upward motion (not shown; [39]). Acting on the vertical and meridional moisture gradients, both of these flows increase relative humidity. In the Arabian Sea, the Asian monsoon’s diabatic heating creates low pressure and cyclonic circulation, in accord with Gill (1980) [67]. This advects in dry air from the arid north and west (i.e., the Sahara and Mediterranean), which decreases relative humidity (Figure 3.17). An additional contributing factor is the drying subsidence over the Kyzylkum desert north of the Arabian Sea, which is a remote response to the monsoon heating [188]. Asian orography suppresses TC activity in the Arabian Sea from May through November (not shown), spanning most times of year when TCs occur occasionally over this region in the present climate [54].

It is worth noting that there is consistency between the regions of relative humidity, precipitation, and SST increases and decreases over the WNP and Arabian Sea, respectively. This suggests that even though the SST changes are not the main driver of the TC density changes, the precipitation and SST changes positively feed back on the changes in relative humidity that are the primary drivers.
Figure 3.17: Annual mean wind changes induced by the Asian mountains overlaying mean specific humidity. Control-FlatAsia change data is from the nudged FLOR runs, and specific humidity is from the nudged FLOR FlatAsia run. Anomalies are only shown where statistically significant at the 95% level based on a two-sided $t$-test. Nudged simulation data is used to highlight that these changes are directly driven by atmospheric circulation changes without SST response to the orography. However, results from the fully coupled runs are largely similar.

3.5 Summary & Discussion

In our simulations, Asian orography impacts monsoonal precipitation both directly through altering the atmospheric circulation, and indirectly through the atmosphere’s impact on the ocean. This is shown by comparing the fully coupled and SST nudged simulations, in which the mountains’ low-frequency impact on SST is removed. Over the WNP, the mountains drive a dipole of SST change with warming to the south and cooling to the north, modulated by changes to the surface energy balance. This in turn increases the mountains’ enhancement of WNP precipitation during monsoon onset (AMJ), and drives precipitation increase during the monsoon peak, a period when the mountains play little role in the atmosphere-only simulations of Park et al. (2012) [165]. Over the Arabian Sea, the mountains’ enhancement of low-level southwesterlies drives coastal upwelling, SST cooling, and significantly enhances the
drying over this region. Overall, the Asian mountains play a significantly larger role in monsoonal precipitation when atmosphere-ocean coupling is allowed.

While precipitation changes over land were not the focus of this work, it is interesting to note that our simulations find a dipole of precipitation change over India due to Asian orography. Precipitation increases in northern India, especially close to the Himalayas, and decreases over southern India (Figures 3.4 and 3.6). To the authors’ knowledge this drying over southern India has not been emphasized in prior work, and is not clear in the AM2.1 simulations (Figure 3.2). The coupled response over the Arabian Sea causing cooling and drying likely bleeds into southern India, flowing along monsoonal southwesterlies, driving or at least enhancing the drying. Importantly, while Asian orography overall enhances the monsoon circulations over South Asia, such as the Findlater Jet, this does not translate to precipitation increases across all of South Asia.

Our study also presents the first examination of the climatic influence of Asian orography with TC-permitting simulations. The mountains are found to have a large influence on the spatial distribution of TCs, increasing TC density up to 60% in the WNP, and eliminating most TCs in the Arabian Sea. Interestingly, while these are hotspots of the role of atmosphere-ocean coupling for precipitation, change in SSTs may enhance but do not seem to be the primary driver of the TC changes. Over the southern WNP, upward motion associated with the Asian mountains’ stationary wave pattern increases mid-level relative humidity and in turn increases TC genesis. Over the Arabian Sea, a Gill-type cyclonic circulation response to the Asian mountains fluxes in dry air from the deserts to the west and north. Combined with remote subsidence also driven by the monsoon heating, mid-level relative humidity in this region significantly decreases, in turn suppressing TC genesis. The climatology of the few Arabian Sea TCs in the present climate has maxima in June and November. We find that Asian orography suppresses TCs over this region from May to November,
including preventing almost any TC occurrence in the peak monsoon season of JAS. However, the Arabian Sea TC climatology still exhibits the double peak even in the absence of Asian orography. This seems consistent with a weaker monsoon circulation still existing, and suppressing some summer TCs, in the FlatAsia experiments.

Overall, these regional TC changes provide new perspective on the drivers of the present pattern of TCs across the Asian sector. The WNP has some of the highest density of tropical cyclones across the globe, and while it might seem straightforward to attribute this high density to the high SSTs in this region, our results suggest a significant role for the relative humidity changes driven by the orographic landmass over Asia. The sparsity of tropical cyclones in the Arabian Sea in the present climate also seems largely attributable to the presence of Asian mountains.

This study performed an idealized topographic perturbation over a very large area, presenting results useful for understanding the basic climate of Asia. One limitation of this work is that we explored means but not climatic variability. While the tropical cyclone changes did not significantly alter the precipitation response to Asian orography on an annual mean or seasonal basis, it is very plausible that they alter the variance of precipitation. Another limitation is that we only experimented with one set of flattened topography boundary conditions. Our results should not necessarily be interpreted as primarily due to the Tibetan Plateau, as particular orographic sections such as the Mongolian Plateau and the Himalayas have an outsized impact on the winter stationary wave and the monsoon circulation respectively [236, 21].

In reality, different parts of the Tibetan Plateau and related orography formed successively in different past time periods [220]. Doing further experiments with smaller, more precise topographic regions flattened would be useful for putting these results in a clearer paleoclimatic context and also clarifying the dynamical mechanisms at play. That said, finding proxy records of past climate to compare to such simulations would be a challenge. The uplift of the Tibetan Plateau and Himalayas occurred over
the course of millions of years \cite{153}, and the current best proxy records of monsoonal precipitation are only reliable over the past few hundred thousand years \cite{235}. Proxy records of TCs are even harder to come by, as they represent rare extremes of rainfall and winds. For comparison to proxy records of precipitation and tropical cyclones, it would be useful to develop simulations of more recent past paleoclimatic periods, such as changes in orbital configuration and solar insolation on the timescale of tens of thousands of years \cite{189}. It would also be interesting to employ the framework used in this study to explore the impact of topography already theorized or observed to be of key importance for TCs. For example, inspired by observational studies \cite{214, 253}, ongoing work is already employing the framework used in this study to examine the impact of the Papagayo and Tehuantepec gaps in Central America on TCs.

### 3.6 Acknowledgements

Gabriel Vecchi and Simona Bordoni are secondary authors on the submitted version of this chapter and provided feedback and direction throughout the project. Funding for this research was generously provided by a National Science Foundation Graduate Research Fellowship and the NOAA Climate Program Office. The AM2.1 simulation data was supplied by Ho-Hsuan Wei. The calculation of tropical cyclone genesis potential was significantly aided by scripts provided by Hiroyuki Murakami, for which the fortran subroutine made available online by Kerry Emanuel was used (see https://emanuel.mit.edu/products). Hiroyuki Murakami, Tom Delworth, Isaac Held, Chris Milly, Bill Boos, and Kerry Emanuel provided useful feedback at various stages of the project, and Seth Underwood, William Cooke, and Sergey Malyshev provided critical technical support. We acknowledge the World Climate Research Programme’s Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the participating climate modeling groups for producing and making
available their model output. For CMIP the U.S. Department of Energy’s Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. Earlier versions of this work were presented at the American Geophysical Union Fall Meeting, American Meteorological Society Annual Meeting, and the Northeast Tropical Meteorology Workshop.
Chapter 4

Temporally Compound Heat Wave Events and Global Warming: An Emerging Risk

4.1 Abstract

The temporal structure of heat waves having substantial human impact varies widely, with many featuring a compound structure of hot days interspersed with cooler breaks. In contrast, many heat wave definitions employed by meteorologists include a continuous threshold-exceedance duration criterion. This study establishes a framework to examine the impact, vulnerability, and adaptation implications of these temporal features of extreme heat. We redefine heat waves to include those periods with additional hot days following short breaks in heat wave duration. We apply these definitions to analyze daily temperature data from observations, NOAA Geophysical Fluid Dynamics Laboratory global climate model simulations of the past and projected climate, and synthetically generated time series. We demonstrate that hot days that closely follow prior hot days or heat waves will constitute a greater pro-
portion of heat wave hazard as the climate warms, and suggest an explanation for this phenomenon. This result implies that in order to limit heat-related mortality and morbidity as the climate warms, there is a need to consider added vulnerability caused by the sequencing of extremely hot days.

4.2 Introduction

Heat waves—multiple, consecutive, hot temperature days—present a significant threat to human health. Studies for individual regions or cities have demonstrated that heat waves result in elevated mortality \[e.g., 212, 150\] and morbidity \[e.g., 132, 64\]. Of the eleven most deadly natural hazards in the continental United States, heat waves (here including those coupled with drought) constitute a plurality (\(~20\%)\) of the mortality \[23\]. Heat stress is often exacerbated by electric power disruptions, which interrupt air conditioning \[A/C; 226, 2\]. Extremely high temperatures decrease yields of major crops such as corn, soybean, and cotton \[199\] and dairy cow production \[100\]. Despite these impacts, heat waves often do not receive significant media attention, possibly because they are not visually spectacular and also because they tend to affect underserved members of the population such as elderly, racially marginalized, sick, and/or socially isolated individuals \[113, 103\]. Ongoing sociological trends are expected to increase populations vulnerable to heat waves: for example, especially in developed countries, populations are aging and individuals are increasingly isolated from close family or friends \[113, 103\].

The severe impacts of heat waves have motivated research to characterize, understand, and predict them. Major heat waves in the midlatitudes typically result from blocking highs (quasi-stationary anticyclones) further amplified via moisture deficit \[17, 58, 197\]. Over continental regions in the northern hemisphere, 80\% of warm temperature extremes are associated with these atmospheric blocking pat-
terns [174]. Diverse modes of variability of the climate system, such as the El Niño-Southern Oscillation and the North Atlantic Oscillation, modulate these synoptic patterns and in turn influence heat waves [104, 75, 90]. Additionally, heat waves are exacerbated over populous regions due to urban heat island effects [182].

Global warming from increasing greenhouse gases (GHGs) has and will continue to increase heat wave hazard. Increases in heat wave frequency, duration, and intensity have already been observed [170], and numerous attribution studies demonstrate that global warming has increased the probability of recent major heat waves [e.g., 217, 149, 94]. As an example, the summer 2010 Russian heat wave was reportedly responsible for $\sim$56,000 deaths [77, 180]; the July monthly temperature record associated with this event is estimated to be five times more likely due to the warming trend [180, 162]. By the end of this century, following the RCP8.5 emissions scenario (“business-as-usual”), heat waves with duration and temperature anomaly magnitude comparable to this event are expected to occur every few years in many regions across the globe [191].

Both changes to the mean and higher order moments of temperature distributions can influence heat wave hazard. Trends in higher order moments (such as variance) might result from interplay between the radiative effects of increased CO$_2$, circulation changes, and land-atmosphere interactions. In places with moderate levels of soil moisture, projected summertime drying is expected to increase surface temperature response to circulation anomalies, and in turn likelihood of heat events [e.g., 201, 47]. Trends also may exist in the blocking events and other circulation anomalies associated with heat waves [175, 87, 173, 41, 40]. However, these trends remain speculative as the observed period is short and climate model results are inconsistent [85]. Overall, diverse phenomena might make temperature variability change alongside mean warming, but how and why is still highly uncertain.
A necessary first step and complication in studying heat waves is defining them. Common to most definitions is the choice of a threshold above which a day’s temperature, or a thermal stress metric, is considered hot. If a minimum number of hot days occur in a row, then a heat wave is said to have occurred. One definition measuring heat wave duration is the Warm Spell Duration Index (WSDI), which uses a seasonally varying 90th percentile temperature threshold, and requires at least six threshold-exceeding days in a row (see Section 4.3). For the rest of this paper we refer to days that exceed a temperature threshold, such as the WSDI’s seasonally varying one, as “hot days”, and a set of hot days occurring close in time meeting certain duration requirements as a “heat wave”.

Temperature time series for major historical heat waves are compared to the corresponding local WSDI threshold in Figure 4.1. According to our review of the existing literature, these are the four deadliest heat waves in Europe and the USA respectively since 1980— mortality associated with each of the heat waves shown in Figure 4.1 is shown in Table 4.1. Of the eight events, only Western Europe in 2003 and Russia in 2010 clearly meet the WSDI, and these were indeed associated with the first and second highest mortality among the eight. Chicago in 1995 just misses the duration requirement, with 5 threshold-exceeding hot days. The other deadly heat waves included in Figure 4.1 exhibit more exotic temporal structures that do not appear to be well described by the continuous hot days requirement of WSDI, with temperature dipping below the threshold multiple times (Belgium in 1994 is a particularly striking example). This suggests that temperature extremes that occur close in time with short break periods of cooler days in between might compound together to create impacts similar to more consistent hot periods recognized by standard heat wave duration definitions. This variable temporal structure resulting in high mortality also may point to heightened vulnerability to subsequent temperature extremes after
an initial heat wave (see Oppenheimer et al. (2014) for definitions of hazard, vulnerability, exposure, and risk used in this paper).

Figure 4.1: Past heat waves that resulted in high mortality. MERRA2 daily minimum temperature (black) and the corresponding seasonally varying thresholds (red) are averaged over regions and plotted against summer days. The location name, latitude-longitude range, and year of each heat wave are listed at the bottom of each panel. These heat waves were chosen to illustrate temperature time series for the four most deadly heat waves in Europe and the USA respectively since 1980 (see Table 4.1 for mortality estimates). These events were initially selected by aggregating information from various sources.

Here we characterize heat waves with intermittent temporal structures as a type of compound extreme event (Figure 4.2 gives a cartoon example of this type of event to build intuition). Broadly, a compound extreme event is a combination of climatic events that together constitute an extreme event in terms of the associated climatic anomaly or impacts. Even though many past climate-related natural disasters are best characterized as compound extreme events, such events are relatively understudied. Recent work has made some advances in this area, including joint
Table 4.1: Mortality estimates associated with the four most deadly heat waves in Europe and the USA respectively since 1980 as determined by a review of the existing literature. Note that the size of the region affected and the methods for estimating mortality differ.

<table>
<thead>
<tr>
<th>Location</th>
<th>Year</th>
<th>Estimated Excess Deaths</th>
</tr>
</thead>
<tbody>
<tr>
<td>Western Europe</td>
<td>2003</td>
<td>~70,000 [43]</td>
</tr>
<tr>
<td>Russia</td>
<td>2010</td>
<td>~15,000 [15]</td>
</tr>
<tr>
<td>Paris, France</td>
<td>2006</td>
<td>2,065 [63]</td>
</tr>
<tr>
<td>Brussels, Belgium</td>
<td>1994</td>
<td>1,226 [194]</td>
</tr>
<tr>
<td>The Midwest, USA</td>
<td>1980</td>
<td>~10,000 [137]</td>
</tr>
<tr>
<td>The Midwest, USA</td>
<td>1988</td>
<td>5,000-10,000 [137]</td>
</tr>
<tr>
<td>Chicago, USA</td>
<td>1995</td>
<td>739 [238]</td>
</tr>
<tr>
<td>East Coast, USA</td>
<td>1999</td>
<td>502 [137]</td>
</tr>
</tbody>
</table>

projections of temperature and humidity [59], storm surge associated with tropical cyclones combined with sea level rise to predict extremes of high water [133], extreme storm surge and precipitation events [230], the possibility of disasters occurring in multiple bread baskets at once and affecting world food supply [140], and clustered outbreaks of tornadoes [222]. In this paper we focus on temporally compound heat wave events, i.e., multiple heat extremes occurring in sequence in a particular location with intermittent short breaks. Our aim is to establish a framework to explore the implications of compounding for heat wave impacts and adaptation. While some studies use more flexible heat wave definitions that can allow for short breaks of cooler days within the event [e.g., 149, 120, 121, 146], these have not focused on the temporal structure of extreme heat events.

In Section 4.3 we present our heat wave definitions and the temperature data utilized; Section 4.4 explores compound heat wave events in the present and their projected change; finally, Section 4.5 discusses the results in the context of prior analysis of temperature extremes, examines relevance for heat wave impacts and policy, and suggests directions for future work.
Figure 4.2: Schematic temperature time series to build intuition regarding the heat wave definitions. Cartoon temperature (black) and a seasonally varying threshold (red) are plotted against time. At the top of the figure, threshold-exceeding hot days are marked with red H’s while below threshold cooler days are marked with black minus signs. According to prior heat wave definitions [i.e.,169] this would constitute two three-day-long heat waves. In this paper we count this event as having a total duration of seven days, composed of an initial three-day long heat wave with four additional hot days compounded onto it.

4.3 Methods

4.3.1 Compound heat wave definition

Many heat wave definitions exist; these are distinguished by different minimum duration and sometimes additional aspects such as temperature anomaly magnitude or spatial extent [171]. This number of required subsequent hot days is typically either arbitrarily selected or based on a limited view of impacts—for example, it might be determined from statistical analyses relating time series of temperature and mortality. To allow easier comparison between studies, the Expert Team on Climate Change Detection and Indices (ETCCDI) synthesized prior work to codify a set of standard extreme climatic event definitions [172]. The standard ETCCDI heat wave duration definition (the “Warm Spell Duration Index”, WSDI) is defined as follows [207]:

- The hot day threshold is the 90th percentile of daily minimum or maximum temperature determined for each day of the year from a 15-day window across
30 years of temperature data. For example, the threshold for June 8th might be derived from June 1st through 15th from years 1961 through 1990. The threshold has one point for each day of the year and is seasonally varying.

- At least six hot (i.e., threshold-exceeding) days must occur in a row to constitute a heat wave.

Given our focus on heat wave temporal structure, we adapt existing heat wave definitions that measure heat wave duration. While much prior heat wave research has used absolute thresholds that are the same throughout the year (i.e., 90°F), seasonally varying thresholds locally defined, such as the WSDI, are now common in climate studies of heat waves [e.g., 60]. Studies also recommend various minimum duration requirements. For example, Perkins et al. (2012) [169] found that the 6 hot days requirement of WSDI results in no heat waves in some locations, and suggest that a 3 consecutive hot days requirement might be more practical.

Our definition uses the same threshold as WSDI but modifies the requirement of consecutive days via additional parameters. The condition of a minimum number of hot days occurring in a row to constitute a heat wave is instead replaced with: 1) a minimum number of hot days occurring consecutively to start a heat wave, 2) a maximum number of cooler (below threshold) days that can occur consecutively for the heat wave to continue, and 3) a minimum number of hot days occurring consecutively that can add onto a heat wave after a break. Multiple breaks are allowed in a single heat wave provided the additional days follow conditions 2 and 3 above. For quick reference, we denote a temporal structure definition with three numbers, for example 321 where 3 indicates a minimum initial event length of three hot days, 2 indicates a maximum break length of two cooler days, and 1 indicates a minimum length of a set of consecutive hot days that can compound on after a break.

This new definition includes parameters unconstrained by prior work. These could be constrained by drawing correlations with an impact of interest, such as morbidity,
or seeking to generate meteorological events of a certain rarity. Given the dearth of work on temporal structure of heat waves and their compounding, we instead vary the parameters and report conclusions that are robust to that parameter range. All the definition parameters that we vary are summarized in Table 4.2. In addition to the temporal structure parameters described in the prior paragraph, we also test using daily minimum versus daily maximum temperature data, and different percentile threshold levels.

Table 4.2: Options for the temporally flexible heat wave definition used in this study. We test definitions using all combinations of the parameter options shown here. Note that we refer to days that exceed the threshold as hot days, and a set of consecutive hot days plus hot days separated by short breaks as a heat wave.

<table>
<thead>
<tr>
<th>Definition Parameter</th>
<th>Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>temperature data</td>
<td>daily minimum, daily maximum</td>
</tr>
<tr>
<td>threshold percentile</td>
<td>90th, 95th</td>
</tr>
<tr>
<td>minimum initial heat event duration</td>
<td>1, 3, or 6 days</td>
</tr>
<tr>
<td>maximum break duration</td>
<td>1, 2, or 3 days</td>
</tr>
<tr>
<td>minimum subsequent heat event duration</td>
<td>1, 3, or 6 days</td>
</tr>
</tbody>
</table>

Once we find hot days in events meeting our definition, we calculate two quantities: the cumulative total number of hot days occurring in heat waves each year (hereafter “heat wave days”), and the number of these hot days that occur in subsequent events that add onto prior heat waves after short breaks, which we will refer to as “compound days” (Figure 4.2). The quantity of interest here is the cumulative annual compound days as a proportion of total heat wave days (hereafter “compound proportion”). This represents the proportion of heat wave risk subject to vulnerability from prior hot days separated by cooler breaks.

We only calculate these quantities from the summer months (May-September in the Northern hemisphere, November-March in the Southern hemisphere) to simplify the meteorological interpretation and because heat-related morbidity and mortality
are the primary impacts of interest. As a result, the maximum length of a heat wave in our study is the entire summer (153 days). We use the seasonally varying threshold to be consistent with recent studies of heat wave duration, but expect that a threshold defined as constant throughout the entire year would yield qualitatively similar results. We calculate these metrics over land points, excluding ocean points in regional averaging.

4.3.2 Temperature data

In this study we apply our heat wave definitions to three types of data: Global Climate Model (GCM) output, observationally-derived reanalysis to validate the GCM’s simulation of heat wave statistics, and synthetic time series generated from statistical models to help interpret results from the GCM data. These are described below.

Climate model simulations

The GCM used for this study is CM2.5-FLOR (hereafter FLOR), which is the Forecast-oriented Low Ocean Resolution derivative of CM2.5 [45]. It has a relatively high resolution ~50 km atmosphere and land, and a relatively low resolution ~1° ocean [227, 97]. The relatively high land/atmosphere resolution of FLOR allows it to simulate finer spatial and temporal scales of temperature variability [97]. However, urban heat island effects are not captured. This family of models’ simulation of a variety of climatic phenomena has been examined and validated. Most relevant are prior studies using these models to examine the heat waves in 2006 and 2012 over the contiguous USA and their climatic drivers [95], the predictability of temperature and precipitation over land [97], and precipitation extremes over land [225].

Two sets of experiments are used in this study. The first is a 5-member ensemble initialized in year 1861 and simulating through 2100 following the Representative Concentration Pathway (RCP) 4.5 Scenario from year 2006 onward [95]. This en-
semble is employed to validate FLOR’s simulation of heat wave events. The second are two idealized radiative forcing simulations [81]: “Control”, in which atmospheric levels of CO$_2$ are kept constant at year 1990 levels, and “2xCO$_2$”, in which CO$_2$ is increased to twice 1990 levels and then held constant.

For the ensemble, the threshold is calculated from each individual ensemble member, and for the idealized simulations the threshold is calculated from Control and applied to both Control and 2xCO$_2$. The ensemble hot day thresholds are calculated from years 1981-2010 of each individual ensemble member (consistent with MERRA2). If the model is unbiased the observations of heat wave events should roughly fall within the range of internal variability represented by the ensemble. Regarding the idealized simulations, 2xCO$_2$ is initialized from year 101 of Control, and atmospheric levels of CO$_2$ increase 1% annually to reach twice 1990 levels by year 171, after which CO$_2$ levels are held constant. Years 401 to 495 of each simulation are compared, and the threshold is calculated from years 401 to 430 of the Control simulation and applied to both the Control and 2xCO$_2$ simulations.

FLOR employs the LM3 land model, which has options for static and dynamic vegetation [152]. Static vegetation keeps vegetation types (C$_3$ grass, C$_4$ grass, temperate deciduous tree, tropical tree, or cold evergreen tree) and phenology consistent with that in the observed modern climate, though the amount of biomass can vary. In contrast, dynamic vegetation allows vegetation type and phenology to adjust to be consistent with the simulated climate. Dynamic vegetation is employed for the 5-member ensemble, and static vegetation is used for the Control and 2xCO$_2$ simulations.

Observationally-derived datasets

To validate FLOR’s simulation of temperature extremes, we use NASA’s MERRA2 reanalysis, which provides daily maximum and minimum temperature computed on
the model time step at a 0.625° by 0.5° resolution from 1980 to the present [70]. Data from years 1981-2010 (same years as the FLOR ensemble) is used to calculate the MERRA2 hot day threshold.

**Synthetic time series**

One type of synthetic time series that incorporates memory is the autoregressive (AR) family of models, the simplest of which is the AR1. AR1 defines subsequent points from the prior point in a time series as follows:

\[ T_{n+1} = \mu + \Phi (T_n - \mu) + \epsilon_n \]  

, where \( T_n \) is the present point in time, \( T_{n+1} \) is the subsequent point, \( \mu \) is the mean of the time series, \( \Phi \) is the lag 1-day autocorrelation, and \( \epsilon_n \) is some random innovation determined at each point in time. We choose a random innovation drawn from a Normal distribution, defined by a mean of 0 and a specified variance. Analogous temperature time series to the Control and 2xCO₂ simulations are created by shifting the mean of the AR1 synthetic time series. The AR1 time series are generated for the same temporal length, range of autocorrelation, and range of variance normalized by mean shift as the FLOR data, then analyzed using our heat wave definitions. The daily seasonal cycle of the model data is removed before its autocorrelation is calculated, while in the AR1 this is not necessary as there is no seasonal cycle. The threshold for the AR1 is also not seasonally varying it is simply calculated as a percentile of the entire synthetic temperature time series.

### 4.4 Results

We present the following analyses on compound heat waves: a) validation of GCM simulation, b) projections from GCM data, c) synthetic data analysis to aid un-
derstanding, and d) projections from observed data. When only results from one definition are shown, that definition is 311 temporal structure derived from daily minimum temperature data with a 90th percentile threshold. However, the qualitative conclusions discussed are robust to the range of definition parameter settings shown in Table 4.2.

4.4.1 GCM validation

To validate FLOR’s simulation of compound heat waves, we compare output from the 5-member ensemble of FLOR to MERRA2. The FLOR and MERRA2 daily minimum temperature data for summer months are analyzed using our heat wave definitions with a 90th percentile threshold for three different temporal structure settings (311, 333, and 621). We first examine regional average time series of compound proportion over Europe, the USA, and Asia (Figure 4.3). Over Europe and the USA, the ensemble encompasses MERRA2 most of the time, suggesting the model’s simulation of these heat wave metrics is reasonably accurate. However, in the USA, especially from 2000-2015, the model is biased high compared to MERRA2, and in Asia the model is biased high over much of the period.

To more thoroughly examine these biases, we calculate the mean and trend of all heat wave days, compound days, and compound proportion at all land locations for MERRA2 and the ensemble members. This analysis is done for years 1980 to 2015 (when MERRA2 data is available). Where MERRA2 deviates from the ensemble envelope is shaded in (Figure 4.4). Where the model is biased, it is generally biased high for both means and trends for all tested temporal structures (333 and 621 not shown). Notable exceptions are where the autocorrelation is biased low (Figure 4.5), in which case, especially for definitions requiring longer initial or compounded events such as 621 and 333, the model is biased low in its simulation of heat wave day means and trends due to not sustaining long heat waves. The biases in compound
days are more limited, and compound proportion means and trends are simulated well for most locations. The model’s high bias in heat wave days may be partially attributable to a failure of the model to capture the well-documented “global warming hiatus” beginning around 2000 [216], which appears to have at least in part been driven by decadal variations in the tropical Pacific [115, 53]. In some locations, high autocorrelation biases of the model contribute to this high bias in heat wave metrics

Figure 4.3: Regional average comparison of reanalysis and GCM results. Summer compound proportion is determined using daily minimum temperature and three different temporal structure definitions, using MERRA2 reanalysis (red) and FLOR ensemble members (grey). These values are then averaged over land points in Western Europe (a,b,c; -10 to 40°E, 40 to 60°N), the USA (d,e,f; -125 to 65°E, 20 to 50°N), and Asia (g,h,i; 70 to 140°E, 0 to 60°N) and plotted against time in years. The mean of FLOR’s ensemble members is also plotted (black).
Figure 4.4: Reanalysis versus GCM results across locations. Comparison between MERRA2 and the FLOR ensemble over 1980-2015 for means (a,c,e) and trends (b,d,f) of all heat wave days (a,b), compound days (c,d), and compound proportion (e,f). For the heat wave definition daily minimum temperature, a 90th percentile threshold, and the temporal structure 311 are used. All values over bodies of water are masked white, and over land places where the MERRA2 value falls within the range of the FLOR ensemble are masked white. Places where the MERRA2 value falls outside the range of the ensemble are shaded with the percent deviation compared to the ensemble mean for the mean bias (a,c,e) and percent deviation compared to the ensemble range for the trend bias (b,d,f). Positive values and red colors show a high bias of the model, while negative values and blue colors show a low bias of the model.
Figure 4.5: FLOR Control versus MERRA2 summer temperature standard deviation and autocorrelation. Standard deviation (a) and lag 1-day autocorrelation (b) are calculated from daily minimum temperature, and only summer months for each hemisphere. The log of the Control versus MERRA2 ratio is taken such that places where FLOR Control variance is greater are positive, and where MERRA2 variance is greater are negative. Bodies of water are masked out.
as well. It is also possible that the reanalysis itself is biased in locations with limited station data.

Overall, FLOR simulates mean heat wave days and trends in the US and Western Europe quite well, but has high biases outside of these regions. It is difficult to disentangle whether the differences between the reanalysis and model data result from model biases, reanalysis biases, or MERRA2 representing only one realization of internal variability compared to the average of many realizations in the model ensemble. Fortunately, the bias in the metric of most interest, compound proportion, is generally small. We move forward using FLOR as an initial examination of compound heat wave events, but given these biases acknowledge the need for further verification of our results with other models and observations.

4.4.2 GCM sensitivity

In Control, the heat wave days are relatively few (only about 10 days per summer) (Figure 4.6a), and only about 1 of these days (10%) is compounded onto prior hot days (Figure 4.6b). This is similar to the compound days and proportion found over the observed period using MERRA2 (Figure 4.7). In contrast, in 2xCO₂, there are on average about seven times as many heat wave days each summer as in Control. This increase in heat wave days is expected given that the temperature threshold computed from Control is applied to both Control and the much warmer 2xCO₂ simulation. The greatest increase in heat wave days occurs in the tropics, consistent with prior studies [208]. The tropics have low variance in temperature relative to the extratropics, thus an increase in mean temperature approaches the limit of moving the entire temperature time series above the hot day threshold.

In addition to the higher total number of heat wave days in 2xCO₂, the proportion of hot days compounded onto prior heat waves is also higher—global-time mean of 25% in 2xCO₂ versus 10% in Control (Figure 4.6c). As with the total number
Figure 4.6: FLOR output heat wave hazard and compound proportion. Control (a,b) and 2xCO₂ (c,d) total summer heat wave days (a,c) and proportion of those heat wave days that are compounded in percent terms (b,d), calculated from all 100 years of the model daily minimum temperature data. Temporal structure definition is 311 and threshold is the seasonally varying 90\textsuperscript{th} percentile calculated from years 1981-2010. Global means are noted on each panel.

of heat wave days, the greatest increases in compound proportion tend to occur in the tropics (Figure 4.9a). The increase in compound proportion is also robust across all tested definition parameter values (Figure 4.8). The trend across definition parameter variations (Figure 4.8) appears to be composed of two sub-trends: 1) definitions which have a relatively lower proportion of compound heat wave days in the present also have a relatively lower proportion in the future, and 2) using daily minimum temperature results in a greater increase of compound heat wave days compared to daily maximum temperature. This second trend is apparent in Figure 4.8 in that for the same threshold (star/circle) and compounding definition (numbers), the blue, daily minimum temperature points on the figure generally lie
Figure 4.7: MERRA2 reanalysis heat wave hazard and compound proportion. Total heat wave days on average over the summer months (May-September) (a) and compound proportion of those days in percent terms (b) for MERRA2 1980-2015 daily minimum temperature data. Temporal structure definition is 311 and the threshold is the seasonally varying 90\textsuperscript{th} percentile calculated from years 1981-2010. Spatial means over all locations with data are listed on each panel; note that this is not the full globe as in maps of FLOR data due to MERRA data availability.

above their corresponding red, daily maximum temperature points. This result is consistent with larger changes in daily minimum temperature documented in prior work [e.g., 216, 208].

4.4.3 Understanding the increase in compound proportion

In seeking to explain these behaviors we consider both the physical characteristics of the system and the statistical properties of temperature time series. Observed temperature trends over the past few decades are primarily explained by a shift in the mean, though limited change in higher order moments of temperature has occurred as well [147]. Simply increasing the mean of a temperature time series, such as those in Figure 4.1, results in more exceedances above the threshold (hot days) with those hot days occurring closer together, increasing the proportion of compound days. Another possible explanation is that changes in higher-order moments of the temperature time
series lead the hot days to be clustered closer together, increasing the proportion of compound days.

To test these potential explanations, we shift the mean of Control temperature to equal the mean of 2xCO₂ temperature, and compare the mean shifted Control to 2xCO₂ heat wave results. We calculated the mean shift (i.e., 2xCO₂-Control for daily minimum or maximum temperature) in a few different ways: 1) global-time mean, 2) time mean spatially varying, and 3) spatially varying daily climatology. In all cases we calculate the mean shift over land locations excluding the ocean. We only found minor improvements with the more complex methods of calculating the mean shift (not shown), so will focus on results from adding the global-time mean difference between 2xCO₂ and Control to Control (hereafter Control+ΔGMT where GMT = global mean temperature).

Figure 4.8: Compound proportion across definitions. Control versus 2xCO₂ summer, global mean compound proportion is plotted in percent terms. The black line is a one-to-one line to highlight that the compound proportion is higher in the 2xCO₂ simulation across definitions. Colors, symbols, and numbers note daily minimum versus maximum temperature, threshold percentile, and allowed temporal structure, respectively (as shown in the key to the right).
We find that spatial variations of compound proportion change for 2xCO₂-Control are well-approximated by (Control+ΔGMT)-Control (Figure 4.9 and 4.10). Across the globe and various versions of the heat wave definition, the pattern correlation is quite high—close to 0.8. For particular regions, the pattern correlation and thus success of the mean shifting approximation varies. The approximation is quite accurate over most highly populated regions and especially over the USA and Australia (correlation ~0.9). In contrast, Greenland has a negative pattern correlation for many definitions. We hypothesize this arises from Greenland’s ice melting with warming, an effect not captured with our simple approximation. India presents a particularly
interesting response, with a high correlation for daily maximum temperature (∼0.8), but a low correlation for daily minimum temperature (∼0.4). We suggest that the strong seasonality of cloudiness and rainfall due to the South Asian Monsoon could be responsible for this effect. Acknowledging these biases, shifting the mean of the temperature data reasonably captures the sign, magnitude, and pattern of change in compound proportion with increasing atmospheric CO₂.

Figure 4.10: Spatial correlation of 2xCO₂-Control and (Control+∆GMT)-Control over the globe and various smaller regions. The regions that the spatial correlation is calculated over are shown in Figure 4.9. The grey bars designate the spatial correlation calculated for the definition used in Figure 4.9 (daily minimum temperature, 90th percentile threshold, 311), and the markers represent spatial correlations calculated for the full range of definition variants. Blue and red designate daily minimum and maximum temperature, and stars and circles designate 90th and 95th percentile thresholds, respectively; temporal structures are not noted but include the full parameter space of Table 4.2.
This suggests that spatial variations in daily temperature variability (i.e., weather) drive the spatial variation in compound proportion change with warming, while weather changes and the pattern of mean warming are of secondary importance. We hypothesized that the spatial structure of the temperature time series memory and variance might essentially describe the relevant local weather. To test this hypothesis, we use the synthetic AR1 time series. We find there are some key similarities in the relationship between variance, autocorrelation, and change in compound proportion for the AR1 and FLOR data. Change in compound proportion is generally greatest at the low autocorrelation, low variance limit, decreasing as variance and autocorrelation increase (Figure 4.11). With low variance, excursions of the time series over any individual day are small; with low autocorrelation, the same is true for series of days. Mean shifts then easily approach the limit of moving the whole temperature time series above the threshold with warming, generating large changes in heat wave days and compound proportion. This is consistent with the highest changes in compound proportion occurring in the tropics (Figure 4.9), where the synoptic variability of the atmosphere is low.

Altogether, in the present climate when a heat wave occurs it likely requires a system with some memory (i.e., blocking high) to create an increase in temperature sufficiently large and long-lasting (Figure 4.12a). In contrast, in the future warmed climate, the mean is sufficiently close to the threshold that typical weather variations can result in threshold exceedances, and in turn a greater proportion of compound days (Figure 4.12b). In other words, given there are more hot days, those hot days occur closer together in time and are more likely to compound.

4.4.4 Projections from observationally-derived data

The main cause of spatial variation in compound proportion change is spatial structure of temperature time series variability. This suggests we may estimate future
Figure 4.11: Influence of autocorrelation and variance on change in compound proportion. Change in compound proportion with warming is shaded and plotted against lag 1-day autocorrelation and standard deviation normalized by mean warming. For the GCM, i.e., FLOR, data (a,b,c), lag 1-day autocorrelation and standard deviation are calculated from the Control simulation at each location. For the AR1 synthetic data, standard deviation and mean warming are assigned to be consistent with the GCM data, while autocorrelation is varied across the full possible range (0-1). Three temporal definitions are used: 311 (a,d), 333 (b,e), and 621 (c,f). For the 621 definition, some of the AR1 synthetic time series at lower autocorrelations are not able to generate long enough periods of hot days to meet the definition event duration requirements particularly for the “Control” climate; where this occurs, the shaded compound proportion is colored grey.

change in compound proportion simply by shifting the mean of observed temperature data. Projected changes in compound proportion applying a mean shift to the MERRA2 temperature data are shown in Figure 4.13.

The mean temperature shifts examined include targets of the United Nations Framework Convention on Climate Change (UNFCCC; 1.5 and 2°C; [92]) and the ΔGMT found for CO₂ doubling in FLOR (2.7°C). The UNFCCC targets are intended for means of daily average temperature over the entire globe, however the data relevant for our heat wave calculation is daily minimum or maximum temperature over land. We scale the shifts applied to the MERRA2 data to reflect this. Land warms
Figure 4.12: Mechanism for change in proportion of compound days. Cartoon temperature time series and threshold prior in original (e.g., pre-industrial) climate (a), and after increase in CO$_2$ (b). To reasonable approximation, the change in the proportion of compound days can be understood as the result of the mean shift of a time series resulting in more threshold exceedances, and hence those threshold exceedances occurring closer together. Faster than ocean, and theoretical constraints point to a ratio of about 1.4 [28], which is similar to the land versus warming ocean contrast from FLOR. Models generally find that daily minimum temperature warms more than daily maximum temperature, though disagree on how much more [126, 129]. The daily minimum versus maximum warming ratio from FLOR over land is about $\sim 1.17$. We scale the GMT shifts using these two ratios and approximating daily average temperature as the mean of daily minimum and maximum temperature.

The FLOR Control versus 2xCO$_2$ analysis of compound proportion change (Figure 4.9) and this analysis have complementary limitations. The FLOR analysis is biased in its underlying temperature time series (i.e., weather), while this MERRA2 analysis has a simplified warming. Thus, comparing Figure 4.9b and 4.13 provides a range of estimates applying different methodologies for compound proportion change.

CO$_2$ doubling in FLOR and 1.5 and 2°C of GMT warming of MERRA2 exhibit large changes in compound proportion in the tropics, and smaller changes towards the poles. However, for the $\Delta$GMT equivalent to a doubling of CO$_2$ in FLOR, MERRA2 counterintuitively exhibits a decrease in compound proportion in the tropics. We
Figure 4.13: Change in compound proportion for MERRA2 with different amounts of warming. Temperature at all locations is increased by the estimated daily minimum temperature warming over land corresponding to global average near-surface warming of 1.5°C (a), 2°C (b), or that from the FLOR 2xCO₂ compared to its Control (∼ 2.7°C; c), and then compared to the original MERRA2 data with no warming. Spatial means over locations with data are listed in each panel. The heat wave definition is the same as in prior figures.
illustrate the reason for this compound proportion decrease by shifting temperature time series from an extratropical location (Chicago, USA) and a tropical location (Manaus, Brazil) (Figure 4.14). When every day in the summer is hot, there are no cooler breaks, so no compound days and the compound proportion is zero. For an extratropical location like Chicago, the temperature variance is high, thus even for very large warming values (we tested up to $6^\circ C$) temperature dips below the threshold many days in the summer and the compound proportion still increases with warming. However, for a low variance location like Manaus the limit where every day in the summer is hot is rapidly reached, and the compound proportion starts to decrease with even $1.7^\circ C$ warming. This compound proportion decrease is not found in FLOR until higher levels of warming (Figure 4.9 and 4.14c,d) because FLOR’s tropical temperature variance is biased high compared to MERRA2 (Figure 4.5).

4.5 Discussion

We demonstrate that the proportion of heat wave days that occur as hot days following short cooler breaks will increase in a warming climate. This is a robust result that can be understood from a simple shift of the mean of a time series characterized by some memory and noise. Prior modeling [120, 121] and observational studies [180, 93, 147] have shown that changes in other characteristics of temperature extremes are largely explained by mean shifting without change in higher order moments. This is true even though GCMs have significant biases in their simulation of meteorological events that influence temperature extremes [7,30]. Notably, mean shifting does not explain precipitation changes: in Europe, wet day clustering, not total number, drives recent wet/dry period changes [260].
Figure 4.14: Heat wave metrics for example cities under different levels of warming. MERRA2 and FLOR Control daily minimum temperature data from Manaus, Brazil and Chicago, USA are analyzed under a range of warming values (0-6°C). Plotted are all heat wave days (blue solid line), compound days (blue dashed line), percent of summer that is a heat wave day (red dotted), and compound proportion of all heat wave days (red dashed). The standard deviation of summer daily minimum temperature is labeled for each location and dataset. Manaus is chosen to represent a typical tropical location with low temperature variance, and Chicago is chosen to represent a typical extratropical location with high temperature variance.

The uncertainty in future temperature extremes is typically quantified via a suite of different GCM projections, which capture relevant dynamic climate effects such as land-atmosphere interactions and changes in blocking [62]. However, for the GCM used in this study these nonlinear changes in temperature with global warming are of secondary importance in setting the spatial pattern of changes in compound proportion. More important appears to be the structure of the local temperature time series in the present climate, which can be assumed to shift warmer with increased CO$_2$. An alternative method then of determining temperature extreme change uncertainty would be to take an observed or reanalysis temperature time series from the present, shift its mean across the distribution of GMT sensitivities to increasing
CO$_2$, then calculate the heat wave statistics. Indeed, this method is plausibly more accurate than, or at least complementary to, using the raw GCM projections which have biases in their daily temperature time series structure.

We have provided this alternative projection of change in compound proportion by shifting the mean of the MERRA2 reanalysis data (Figure 4.13). For low levels of warming, the tropics exhibit greater increases in compound proportion than the extratropics, as was found for the GCM data. However, for higher levels of warming (between $\sim 1.5$-$3.5^\circ$C depending on location) this analysis suggests there will be a regime change in tropical locations, at which point every day in the summer will be hot and compound proportion will tend to zero due to the lack of breaks. In contrast, compound proportion continues to increase in the extratropics for the foreseeable future. This tropical-extratropical difference is rooted in the lower temperature variance in the tropics.

For the 311 definition, we project that compound proportion will more than double for 1-3$^\circ$C of warming, to compose $\sim 25\%$ of heat wave risk under doubled CO$_2$; changes are larger for definition parameter values that allow longer breaks or shorter duration compounded events. This suggests that with global warming it is increasingly important to consider vulnerability from prior heat waves when characterizing heat wave risk. Vulnerability from prior heat waves may come from a few different sources:

- dehydration—when under thermal stress the human body sweats more and can lose water at rates of 1-1.5 litres per hour [163, 42];

- building thermal inertia—without A/C, building interior temperature often exceeds and has smaller diurnal cycles than outdoor temperature, and after heat waves its cooling can lag that of the outdoors by a few days [237, 182, 178]; also those most vulnerable (the elderly and sick) often do not leave buildings or have A/C during heat waves [119];
• limited social system capacity—during severe heat waves emergency response time increases due to too many calls, and hospital emergency wards and morgues fill up, struggling to treat patients and process bodies in a timely manner [113, 103];

• power system disruptions—extensive A/C use during heat waves causes excessive electricity demand and resulting outages in pole-top and substation transformers [2]; inland bodies of water used for power plant cooling are hotter during and presumably shortly after heat waves causing reduced power plant efficiency [226];

• transportation delays—low air density from very high temperatures makes airplanes unable to take off without weight reductions [38], causing disruptions with ripple impacts for days [239]; overheated overhead electric train lines sag and sometimes collapse, causing travel delays and cancellations and sometimes taking days to repair [e.g., 190].

All these sources of vulnerability are not immediately remedied during a short break of cooler days, making compound days likely more impactful than hot days occurring long after a prior heat wave.

Prior work quantifying such vulnerability is limited. One reason for sparsity of the relevant literature is that temporally compound heat wave events have historically been uncommon (Figure 4.7), and thus not a significant public health concern. However, the increasing proportion of heat wave hazard from compound days motivates careful consideration of resulting vulnerability. Prior studies of mortality-health relationships provide some insights: for many different locations mortality has significant relationships with temperature more than one day prior [72]. A study examining mortality-temperature relationships across many countries uses a statistical model that examines temperature for 21 days prior to any given day [66]. The source of
these lagged relationships cannot be discerned from such statistical analyses, but they nonetheless suggest that vulnerability from prior heat waves, even after a break of cooler days, may be significant.

There are many avenues in which people may adapt to the increasing hazard from compound heat waves, including improved heat wave warning systems [144], resilient building design and materials [61], and power and medical system emergency preparedness [63, 18, 2]. To facilitate such adaptation, we encourage rigorous quantification of the impacts associated with compound days as a topic for future work. A challenge in doing such a study for mortality is the fact that mortality can be displaced by heat waves, meaning that those vulnerable to heat waves perish in an initial heat wave, and thus reduce the pool vulnerable to subsequent events [148]. This effect might make mortality from compound days lower than that of heat wave days occurring long after prior events. Morbidity (e.g., emergency room visits) or occupational health hazards are less subject to displacement effects and so may relate more clearly to compound days [64].

This work presents a first look at temporally compound heat wave events, leaving various ways this analysis might be refined. Some possible directions include: redoing this analysis using a combined temperature-humidity metric such as wet bulb temperature that directly reflects heat stress [145, 202]; adding a spatial extent requirement when identifying heat wave events [215, 146]; using other GCMs which present a range of projections for changes in temperature extremes and presumably compound heat waves [73, 208]; utilizing a regional climate model with resolution ~1 km over an urban metropolis to see how urban heat island effects influence projected change in compound proportion [e.g., 181]; and more fully characterizing the relevant components of temperature time series using the Matern statistical models which allow a wide range of correlation structures [158, 219].
4.6 Acknowledgements

There are three secondary authors in the submitted paper based on this chapter: Jay Dessy made substantial strides in the preliminary analysis for this chapter as part of his senior thesis in Geosciences at Princeton University, and Michael Oppenheimer and Gabriel Vecchi both helped conceive of and guide the project throughout. The Princeton Environmental Institute-Science Technology Environmental Policy Perkins Fellowship provided funding that made pursuit of this project possible. We thank Sarah Perkins-Kirkpatrick and Tammas Loughran from the University of New South Wales for providing heat wave definition scripts instrumental to this work and Bob Kopp, Radley Horton, Gregory Garner, Frederik Simons, Jorge Gonzalez, Prathap Ramamurthy, Maya Buchanan, D.J. Rasmussen, and John Lanzante for useful discussions. The American Meteorological Society, American Geophysical Union, and International Society of Biometeorology provided opportunities to present earlier versions of this work at academic conferences.
Chapter 5

Summary

This dissertation is comprised of three distinct research projects. As described in the Introduction (Chapter 1), Chapters 2 and 3 are studies of fundamental climate dynamics, seeking to understand how orography shapes the spatial and temporal distribution of precipitation in and around Asia. Chapter 4 presents a more applied study of climate extremes that is primarily relevant for policy and risk analysis, examining the temporal compounding of heat waves. Summaries of the methodology and main results of each chapter are presented below.

5.1 Chapter 2: Influence of the Tian Shan on Arid Extratropical Asia

Chapter 2 examines the vast arid regions of Asia (hereafter AEA for Arid Extratropical Asia), which are zonally bisected at the Tian Shan mountain range. According to both observed precipitation datasets and GCMs, east of the Tian Shan, precipitation peaks in the summer, while in the west precipitation peaks in the late winter/early spring. To examine the role of the Tian Shan in this differentiation, we employ the GCM FLOR, which has a relatively high resolution, tropical cyclone-permitting 50
km atmosphere and a lower resolution 1° ocean. Additionally, FLOR reasonably accurately simulates the spatial distribution and precipitation climatology of the deserts. FLOR is run in three configurations (Control, NoTianshan, and NoTianshanDrag) to test the climatic impact of the Tian Shan. The Control simulation employs boundary conditions with full modern-day topography. NoTianshan employs boundary conditions with the Tian Shan flattened in surface height, boundary layer roughness, and gravity wave drag. NoTianshanDrag flattens the Tian Shan in just boundary layer roughness and gravity wave drag, retaining full surface height. By examining differences between the Control and NoTianshan simulations, the Tian Shan’s climatic influence is isolated. Surface height changes are found to be far more influential than those of boundary layer roughness and gravity wave drag. Thus, our analysis focuses on the results of Control minus NoTianshan.

The Tian Shan’s orographic precipitation is found to be fully responsible for the spatial division of the East and West deserts. The Tian Shan also enhance the precipitation gradient across these deserts, by blocking the flow of moisture along the westerlies in the winter, and enhancing moisture inflow into East Asia in the summer through altering the mean winds. The Tian Shan negligibly impact the west deserts, and even in the absence of the Tian Shan some precipitation gradient remains. This suggests that other larger-scale circulation features help shape the zonal variation across this region. The Tian Shan’s enhancement of precipitation in East Asia is consistent with prior work with regional climate models (RCMs). These studies demonstrate that the northern Tibetan Plateau has a disproportionate impact on the East Asian Monsoon. Mechanisms for this enhancement of the East Asian Monsoon posited before include the Tian Shan’s alteration of the north-south shifting of the westerly jet [36], and westerly anomalies south of the Tibetan Plateau that bring moisture across India and into East Asia [220, 254, 134]. We additionally find that the Tian Shan’s stationary wave pattern over the Pacific plays a key role in the East
Asian Monsoon enhancement by advecting moisture over the West Pacific in from the south.

The Tian Shan’s hydroclimatic effects are also found to remotely warm some surrounding regions via two different mechanisms. The blocking of westerly-carried winter moisture decreases snowfall on the Altai and Kunlun mountains to the east, thus decreasing snowfall, decreasing albedo, increasing incoming shortwave radiation to the surface, and increasing surface temperature. In contrast, drying over India decreases latent heat fluxes, and drives increases in temperature to increase sensible heat fluxes and maintain the surface energy balance.

5.2 Chapter 3: The Ocean-Mediated Influence of Asian Orography on Tropical Precipitation and Cyclones

Chapter 3 explores the influence of all Asian orography, especially the Tibetan Plateau, on tropical precipitation and cyclones. Much prior work has investigated the role of the Tibetan Plateau and related orography in driving the Asian monsoons using atmosphere-only, relatively low-resolution GCMs [e.g.,79]. Chapter 3 examines this question using a higher resolution, fully coupled atmosphere and ocean GCM (i.e., FLOR). FLOR has a more accurate simulation of the Asian monsoons, and also allows assessment of the orographic impact on tropical cyclones (TCs). The experimental set-up is similar to Chapter 2 in that GCM experiments are run with the boundary conditions for surface height, gravity wave drag, and boundary layer roughness altered. Control experiments have modern day topography, and FlatAsia experiments have orography across most of Asia flattened. In addition to FLOR, experiments are run with a lower 200 km atmosphere/land resolution GCM called
LOAR, which does not permit the simulation of TCs. Comparing FLOR with LOAR results helps clarify the role of TCs. All experiments are also run with SSTs nudged to the Control simulation annually repeating climatology. This nudging process prevents the removal of Asian topography from altering SSTs at low frequencies. As a result, comparing fully coupled and nudged SST results isolates the role of atmosphere-ocean coupling in a given climatic response.

Prior studies indicate that Asian orography strongly increases Western North Pacific (WNP) precipitation during the monsoon onset but increases it only very weakly during the monsoon peak [165]. In contrast, our simulations show that Asian orography enhances monsoonal precipitation through the entire summer monsoon season. Climatological changes in precipitation are similar between LOAR and FLOR, suggesting that higher model resolution, and the simulation of TCs, is not responsible for this change. Instead, comparison with the nudged SST simulations suggests that orographic influence on SSTs is responsible for enhancement of monsoon peak precipitation, and also strong drying over the Arabian Sea.

Asian orography creates a dipole of warming over the WNP (cool to the north, warm to the south), with the warming coincident with precipitation increase. This change is modulated through alteration of the surface energy balance. In the northern WNP, Asian orography advects cold air in from the north in the winter, cooling through increased sensible heat fluxes and related increases in low and mid-level clouds. Over the summer in this same region, Asian orography enhances the Meiyu-Baiu through advecting in warm air from the south and west, increasing convection and cloud cover and cooling the surface through decreased shortwave radiation. In the southern WNP, the stationary wave of the Asian mountains drives westerly anomalies which increase wind speed in seasons outside the summer, increasing latent and sensible heat fluxes and resulting in cooler SSTs year-round. In contrast, drying over the Arabian Sea is driven by SST cooling from ocean heat transport changes. Asian orog-
raphy enhances the Findlater Jet, which drives coastal upwelling along the western margin of the Arabian Sea and resultant SST cooling.

Asian orography is also found to exert a strong influence on the spatial distribution of TCs, an effect unexplored in prior studies due to modeling limitations. In our simulations, orography significantly increases TC density in the WNP (up to 60%) but decreases TCs in the Arabian Sea. As a result, in the modern climate the WNP has some of the highest density of TCs in the world and formation of Arabian Sea TCs is very rare. Spatial changes in a TC genesis potential index (GP) are very similar to the density changes, suggesting that changes in TC genesis not tracks are behind the density differences. Mid-troposphere relative humidity differences are responsible for most of the change in GP over both the WNP and Arabian Sea. Over the WNP, the orographically generated stationary wave pattern increases upward motion and mid-troposphere relative humidity, enhancing TC formation. Over the Arabian Sea, the mountains’ enhancement of monsoonal diabatic heating drives anomalous cyclonic motion, which advects in dry air from the Middle East, Sahara, and Mediterranean, suppressing formation of TCs. This monsoonal heating also forces remote subsidence to their west which likely further contributes to this drying [188].

5.3 Chapter 4: Temporally Compound Heat Wave Events and Global Warming: An Emerging Risk

Chapter 4 examines the risk associated with the temporal compounding of heat waves. Much prior work has quantified the hazard of heat waves in the present climate, and the expected change with global warming. Almost all of these studies define a heat wave as a certain number of threshold-exceeding hot days occurring in a row. Examin-
ing the most deadly heat waves over Europe and the USA since 1980, we demonstrate that heat waves associated with high mortality often exhibit more variable temporal structures, having hot days interspersed with cooler days. This suggests that heat waves or even individual hot days can compound onto one another in time, such that vulnerability to future hot days is higher following a heat wave. Reasons this might occur include but are not limited to building thermal inertia and social system inertia. Regarding building thermal inertia, interior temperatures are higher than and lag outdoor temperatures in the absence of robust air conditioning [182]. Regarding social system inertia, during prior major heat waves hospitals, emergency responders, and even morgues reached capacity, taking days to deal with the backlog of people [113, 103].

In light of the likely importance of heat wave compounding for health and other impacts, we explore the historical hazard of heat wave compounding, and projected change with global warming. New heat wave definitions are developed from the commonly used Warm Spell Duration Index (WSDI) allowing short below-threshold breaks of cooler days. These definitions are used to compute compound proportion—the proportion of heat wave hazard coming from hot days that shortly follow prior heat waves. Given uncertainty regarding the appropriate values for the definition parameters, a range of parameter values are assessed, and results are reported that are robust to this range.

These definitions are used to analyze a variety of daily minimum and maximum temperature datasets: MERRA2 reanalyzed observations, a FLOR ensemble simulating 1941-2050 along RCP 4.5, idealized 1990 Control and 2xCO₂ simulations of FLOR with constant radiative forcing, and synthetic AR1 time series. MERRA2 time mean and trends of compound proportion are within the ensemble range in most locations globally, suggesting that the GCM’s simulation of compound proportion is reasonably accurate. Comparing the idealized radiative forcing scenarios
(2xCO₂ minus Control) demonstrates that compound proportion robustly increases with global warming. Compound proportion is on average 10% in Control, but 25% in 2xCO₂, with increase in compound proportion generally higher at lower latitudes. This result, including its broad spatial variations, can be recovered by substituting the 2xCO₂ simulation with a mean-shifted version of the Control data. This suggests that changes in the mean, not high order moments in temperature, drive the change in compound proportion with increasing CO₂. Mean shifting AR1 time series also recovers this increase in compound proportion, demonstrating that the underlying time series attributes necessary to recover this trend are simply some memory and noise. Additionally, lower variance AR1 time series exhibit greater increases in compound proportion, because with lower variance the limit is rapidly reached of shifting the whole temperature time series above the hot day threshold. This explains the greater increase in compound proportion in the tropics, which have lower temperature variance than the extratropics.

Our results demonstrate that the reasons for the increase in compound proportion with rising atmospheric CO₂ are relatively simple. With warming, more days exceed the threshold and are considered hot. As a result, heat waves and hot days occur closer together and are more likely to compound. Given the simplicity of the mechanism, mean shifting observed data provides an alternative and possibly more accurate method for heat wave projection compared to computationally intensive GCM simulations. Chapter 4 includes a compound proportion projection with MERRA2 data using this method.

From a broader risk management perspective, the increase in compound proportion found in this study suggests that warning systems should consider recent past heat waves in the determination of heat wave risk. To support this policy change, future research should quantify the added vulnerability from prior heat waves. Understanding this vulnerability for diverse sectors, including human health, food produc-
tion, energy systems, and transportation, will be increasingly important with global warming.


[70] Global Modeling and Assimilation Office (GMAO). statD_2d_slv_nx: MERRA-2 2d, Meteorology Aggregated Daily (p-coord, 0.625x0.5l42), version 5.12.4. Greenbelt, MD, USA: Goddard Space Flight Center Distributed Active Archive Center (GSFC DAAC), 2015.


[142] Jeff Masters. Earth’s 5th Deadliest Heat Wave in Recorded History Kills 1,826 in India | Category 6, 2015.


[163] Randall Packer. How Long Can the Average Person Survive Without Water?


135


