Factors influencing rainfall over the Congo

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FACTORS INFLUENCING RAINFALL OVER THE CONGO

by

Ajay Raghavendra

A Dissertation
Submitted to the University at Albany, State University of New York
in Partial Fulfillment of
the Requirements for the Degree of
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ABSTRACT
The hydrological cycle over tropical rainforests includes some of the most intense thunderstorms and rainfall totals. The energy associated with this convective activity plays an important role in the Earth’s weather and climate system. Therefore, the interannual variability, trends, and future climate projections of the hydrological cycle over tropical rainforests are important topics for research. The Congo rainforest situated over equatorial Africa is the second largest rainforest in the world, and recent studies have documented a >30-year large-scale and long-term drying trend over the Congo since the late-1970s. However, unlike the Amazon rainforest in South America, the Congo rainforest is relatively understudied. The challenges associated with meteorological research over the Congo basin is also exacerbated by the declining trend in surface observations (e.g., rain gauges) and the complex topography surrounding the Congo basin. In this dissertation, rainfall variability and trends over the Congo basin are explored by analyzing satellite and surface observations, global atmospheric reanalysis data, sub-seasonal/seasonal teleconnection indices, and convection-allowing simulations from a mesoscale numerical model. Since there is a strong relationship between rainfall and convective activity over the tropical latitudes, trends in thunderstorm activity was explored. Next, convectively coupled atmospheric equatorial waves (CCAEW) and the Madden Julian oscillations (MJO) were investigated as a possible mechanism to explain thunderstorm activity. The relationship between the MJO and rainfall over the Congo basin was investigated in more detail to clarify the method-dependent findings reported in previous works. Finally, the interaction of precipitation with orography was studied by perturbing orography by using a high-resolution, convection allowing, mesoscale numerical model. The findings presented in this work include the following:
1. The areal extent and intensity of thunderstorms have increased from 1982–2016, particularly over the Northern Congo Basin. Reanalysis data suggests a moister upper troposphere and drier lower troposphere.

2. The tropical frequency-wavenumber power spectrum shows CCAEW activity in the low-frequency part of the spectrum (e.g., Madden–Julian oscillation and equatorial Rossby wave) to have a weakening trend characterized by high interannual variability. In contrast, CCAEW activity occurring in the high-frequency part of the spectrum (e.g., Kelvin waves, mixed Rossby–gravity waves, and tropical disturbance–like wave) shows an increasing trend with relatively low interannual variability.

3. An investigation on the relationship between rainfall and the MJO shows a significant correlation between the number of wet and dry MJO days, and rainfall enhancement and suppression over the Congo. There exists a significant increase in the number of dry MJO days (3.47 days decade$^{-1}$), which tends to intensify the large-scale drying trend over the Congo during October–March. The increasing trend in the number of dry MJO days is likely enhancing the net drying trend by 13.6% over the Congo.

4. The direct dynamical impact of the East African highlands includes blocking of the tropical easterlies, increasing the mid/lower tropospheric windshear, and intensifying the meridional channeled flow around the mountain. The weaker zonal wind and enhanced meridional wind convergence over the Congo basin produces slower propagating and intense mesoscale convective systems with enhanced rainfall.
ACKNOWLEDGMENTS

I am graced with doctor’s name thanks to the strong mentorship and support I have received ever since I was a child. Since birth, I have had very supportive parents (Suma Prakash and Bungale M. Prakash) who have often been tested by my career and life choices. For instance, at the ripe age of seventeen, I had once proudly told my mother that I have no interest in going to college. I look back and smile for not getting away with that decision. My parents unwavering support forms the bedrock for my personal success. The advice from my extended family, teachers, and mentors including B. Mukund Begur, Prashanth P. Bungale, Sharada C. Rao, S.R. Swarum, Arvind Sharma, and Y.N. Vaidyanath helped me succeed at Embry-Riddle Aeronautical University (ERAU), FL between August 2011 and May 2015.

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In August 2016, I arrived in Albany, NY to pursue my PhD under the advisement and guidance of Prof. Liming Zhou. While I could write pages in praise of Liming and his mentorship in this section, I’ll stick to a few important points. Liming is a fantastic advisor because he clearly detailed his expectations, objectives and milestones on *day one*! His expectations helped me stay focused despite my many distractions which included numerous other research projects, scientific workshops, and student government. Liming has also been a very kind and compassionate advisor who gave me sufficient freedom to grow as a researcher. His honest critique of my work also helped me improve my research skills. Liming always put his students’ first and would often prioritize my work (e.g., paper revisions, recommendation letters, etc.) over his own work. His commitment to student success and mentorship has played a significant role in my research and professional success.

My PhD advisor Prof. Liming Zhou along with Profs. Aiguo Dai, Brian E. J. Rose, and Paul E. Roundy graciously agreed to serve on my PhD committee. I completed a majority (7/11) of my graduate level courses thought by members of my PhD committee. The scientific knowledge, insights, and understanding I have gained from each member of my PhD committee has profoundly impacted my learning, and influenced the work presented in the PhD dissertation. I would like to thank each member of my committee for diligently working with me, pointing out my deficiencies, and helping me become a better scientist and researcher.

I met numerous fellow students and professionals during my four-year tenure as a graduate student. Some of these students and professionals became close friends over time. While it is difficult to name all my friends and colleagues who have helped me succeed as a graduate student,
I would like to extend a sincere thanks to Kathrin Alber, Tomer Burg, Dylan R. Card, Yan Jiang, M. Cameron Rencurrel, Nicholas J. Schiraldi, Stephen L. Solimine, Alexander M. Tomoff, Matthew T. Vaughan, and Geng Xia. Numerous professional societies and organizations also helped enhance my graduate school experience and helped me financially. I would especially like to thank the AMS and AMS Policy Program, International Center for Theoretical Physics (ICTP) Summer School, National Science Foundation (NSF AGS-1535426 and AGS-1854486), and NCAR ASP Summer Colloquium. Finally, I would like to extend a special thanks to my loving girlfriend and colleague Heather S. Sussman for helping me navigate this challenging journey.
Statement of Publication/Contribution of Authors

I hereby state that the three of my previous published articles listed below are reprinted in this dissertation with permission from the publisher. Only minor changes were made to ensure formatting and continuity throughout the thesis. These works are included because they are part of the programmatic line of research which resulted in this dissertation.


LIST OF FIGURES

Figure 2.1: a) An example of a satellite image obtained by Meteosat–7 on 1500 UTC 9 August 2015 and made available via GIBBS. The domain of interest in this study is depicted using a red box. b) An idealized thunderstorm cell showing clouds contoured at different $T_b$. C-1, C-2, C-3, and C-4 represent different temperature thresholds at which contours were drawn.

Figure 2.2: a) Interannual variations in the AMJ mean pixel count for thunderstorm defined based on four different $T_b$ threshold ranges for the period 1982-2016 over the Congo. As a reference, an illustration of the satellites used over the study region (Table 1) is shown in the background. b) Interannual variations in the mean $T_b$ of thunderstorm cloud tops at four different $T_b$ thresholds. The climatological mean temperature (m) and the linear trend ($\alpha$) are shown in the box for each panel. All the trends in both panels are statistically significant at $p < 0.01$.

Figure 2.3: Interannual variations in the number (top), mean size (middle), and total area (top; i.e., number $\times$ mean size) of thunderstorms over Northern Congo (left columns) and Southern Congo (right columns) for the period 1982-2016 during AMJ. The mean (m) and the linear trend ($\alpha$), and the p-value (p) of the trend are shown in the box for each panel.

Figure 2.4: Spatial patterns of the mean (left columns) and trends (right columns) in $T_b$ (top two rows in K and Kyr$^{-1}$) and OLR (bottom two rows in Wm$^{-2}$ and Wm$^{-2}$yr$^{-1}$) from 1984–2009 during AMJ. Trends significant at $p<0.05$ are shown using the ‘+’ symbol.
Figure 2.5: a) Trends in AMJ OLR (shaded in Wm⁻²yr⁻¹) calculated from 1982–2017 using interpolated and uninterpolated data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA (available at www.esrl.noaa.gov/psd/). Trends significant at p<0.05 are shown using the ‘+’ symbol. Interannual variations in the regional mean OLR (red curve; left axis) and the daily mean number of pixels (right axis) for OLR<200 Wm⁻² are shown for b) Northern Congo, and c) Southern Congo. The linear trend (α) and its p-value (p) are shown in this panel. Note: The uninterpolated OLR data was interpolated following the techniques highlighted in Liebmann and Smith (1996) prior to being analyzed.

Figure 2.6: Trends in AMJ vertical velocity (shaded in × 1/4 Pa s⁻¹yr⁻¹) for (a) 200–250 hPa and (c) 875–825 hPa, and trends in AMJ specific humidity for (b) 200–250 hPa (× 10⁻³ g kg⁻¹yr⁻¹) and (d) 875–825 hPa (g kg⁻¹yr⁻¹) calculated from ERA-Interim. Trends significant at p<0.05 are shown using the ‘+’ symbol.

Figure 2.7: An illustration of changes observed over the Congo from 1982–2016. Trends include larger and more intense thunderstorms over Northern Congo, increase (decrease) in the mean size of thunderstorm at lower (higher) Tbk, a drier (wetter) lower (upper) troposphere, and weaker ascent at both the lower and upper troposphere, and an overall reduction in soil moisture. These changes were found to be associated with a significant decrease in AMJ precipitation over the Congo during the same period.

Figure 3.1: Global tropical convection (15°N–15°S) from 1979–2016 using NOAA’s daily Interpolated OLR dataset (Liebmann and Smith 1996). a) Daily mean OLR, b) the difference in OLR between 1979–1987 and 2008–2016, and c) linear trends in OLR
obtained after removing the seasonal cycle from the OLR dataset. The black dots indicate trends that are statistically significant (p-value<0.1).

**Figure 3.2:** The frequency-wavenumber power spectrum diagram normalized by the smoothened background spectrum similar to the technique developed by WK99. The individual panels represent the antisymmetric power spectrum using the a) OLR and c) \( T_b \) datasets, and symmetric power spectrum using the b) OLR and d) \( T_b \) datasets.

**Figure 3.3:** Observed shift in the \( \log_e \) spectral power calculated by taking the difference between the mean normalized power for 2008–2016 and 1979–1987 (for OLR dataset)/1982–1990 (for \( T_b \) dataset). The individual panels represent the antisymmetric power spectrum using the a) OLR and c) \( T_b \) datasets, and symmetric power spectrum using the b) OLR and d) \( T_b \) datasets. A two-sample t-test applied to the two pairs of populations proved that the power for 2008–2016 is significantly different from the power for 1979–1987 at the 1% significance level.

**Figure 3.4:** Linear trends in the \( \log_e \) spectral power (\( \times 10^{-3} \)) from 1979–2016 for the OLR dataset and 1982–2016 for the \( T_b \) dataset. The individual panels represent the antisymmetric power spectrum using the a) OLR and c) \( T_b \) datasets, and symmetric power spectrum using the b) OLR and d) \( T_b \) datasets. The black dots indicate trends that are statistically significant (p-value<0.1).

**Figure 3.5:** Interannual variations in the regional (see Fig. 3.2 for domain) mean \( \log_e \) power spectrum (red for antisymmetric part, and blue for symmetric part) corresponding to different wave types in the WK99 frequency-power spectrum diagram using the OLR (left column), and \( T_b \) (right column) datasets. The slope, and the p-value (p-val) of the linear trend lines are shown in the box embedded in each panel.
Figure 3.6: A Monte Carlo analysis carried out by randomly rearranging the data points for each interannual variability curve 1,000 times in Fig. 3.5 without repetition in order to quantify uncertainties in the slope ($\text{units: } \times 10^{-2} \log_e(P) \text{ year}^{-1}$) of the linear trend line shown in Fig. 3.5. The upper (95th percentile) and lower (5th percentile) limits of the uncertainty is represented by the top and bottom whiskers respectively, and the slope values for the symmetric (S) and antisymmetric (A) components from Fig. 3.5 are represented using five symbols for each type of disturbance using both the OLR and $T_b$ datasets.

Figure 3.7: Trends in OLR variance calculated by squaring the spectrally filtered OLR anomaly for (a) the MJO, (b) ERW, (c) KWs, (d) MRG, and (e) TD from 1979 to 2016. The black dots indicate trends that are statistically significant ($p$ value < 0.1).

Figure 3.8: The spatial structure corresponding to the leading EOF for a) the MJO, b) ERW, c) KWs, d) MRG, and e) TD obtained by first filtering the daily OLR anomaly data from 1979–2016 for the five different wave bands, and then applying an EOF analysis. The percentage variance explained by the leading EOF are show in each panel.

Figure 3.9: Interannual variability of the variance corresponding to first PC of the band filtered daily OLR anomaly data from 1979–2016 (blue line) for a) the MJO, b) ERW, c) KWs, d) MRG, and e) TD. The slope, and the p-value ($p$-val) of the linear trend lines (red line), and the result and p-value from the Mann-Kendall trend test are shown in the box embedded in each panel. The spatial structure corresponding to the leading EOF for each wave is shown in Fig. 3.8.

Figure 3.10: The mean number, and duration of events corresponding to (a–b) the MJO, (c–d) ERW, (e–f) KWs, (g–h) MRG, and (i–j) TD from 1979–2016 using daily OLR
anomalies. The mean frequency and duration of events was calculated by applying a spectral filter for different wave types, and then using the negative OLR anomaly time series at each grid point to generate the necessary statistics. A linear regression and t-test was applied to determine regions showing significant (p<0.1) increasing (black dot) and decreasing (white cross) trends.

**Figure 3.11:** Difference in P constructed using NOAA’s OLR dataset for each ENSO state for the antisymmetric and symmetric parts of the spectrum (a–f) relative to the mean power spectrum in Fig. 3.2. A two-sample t-tests shows significantly differences at the 1% level between panels a–f. g) The Niño 3.4 index derived from ERSSTv5. The blue and green lines represent the ±0.75 and ±0.25 thresholds used to segregate the time windows to obtain a composite spectrum for a particular ENSO state. The number of time windows in each ENSO state is shown in bold numbers.

**Figure 4.1:** a) Seasonal cycle of rainfall over the Congo using daily CPC rainfall data (see plot legend for details). b) Boxplot showing the average seasonal rainfall by MJO category. c) Mean and d) anomalous rainfall (shaded in mm day$^{-1}$) for each month and RMM phase. In b), non-overlapping notches indicate that the true medians differ at the 95% confidence level, and the top and bottom whiskers indicate the maximum and minimum values. Days with an RMM amplitude < 1 are omitted in b–d.

**Figure 4.2:** CPC daily rainfall anomaly, ERA-I 850 hPa divergence (dotted red), convergence (dotted green) and vector wind anomalies for a wet MJO days, and b dry MJO days during Oct–Mar from 1979–2018. Wind vectors are shown only when significantly different from the Oct–Mar climatology at the 10% level using
bootstrapping. The domain representative of the Congo rainforest is shown in dashed green in panel b.

**Figure 4.3:** Stacked area plot showing the Oct–Mar raw and percentage based interannual variability decomposed by MJO category for a, c MJO days, and b, d rainfall. The solid line represents the categorically integrated climatological mean. The trend in total seasonal rainfall amount is depicted using a dotted red line in b.

**Figure 4.4:** Scatter plot showing the relationship between the Oct–Mar mean rainfall anomaly and a number of wet MJO days, b number of dry MJO days, and c difference between the number of wet and dry MJO days normalized by the number of RMM phases chosen for wet and dry RMM phases from 1979–2018. The linear regression line (red line), correlation coefficient (R) with significance level (p value in parentheses), and ±25% of the regression prediction interval (gray shading) are displayed in each panel.

**Figure 4.5:** a) Interannual variability in the number of MJO wet (blue), dry (red), and wet–dry days (grey bar) normalized by the number of RMM phases used. Precipitation anomaly (PR; mm day$^{-1}$; blue circles) from 1979–2018 is displayed against the right vertical axis. The slope of the trend line and p value (in parentheses) are displayed in the legend. b) Interannual variability and trend of MJO days by category. The slope (bold indicates significant trend as per the MK-test) and p value for trend lines are displayed next to b.

**Figure 4.6:** Interannual variability and linear trend in the Oct–Mar mean rainfall (black line) with a) wet day, b) dry days, c inactive days, and d) other MJO days categorically removed from the overall timeseries (blue line). The slope for trend lines are displayed.
within each panel. The title in a–d also shows the % contribution (ct) to the overall rainfall trend for each MJO category removed from the reconstruction.

**Figure 4.7:** Interannual variability and linear trend in the Oct–Mar areal extent of cold cloud cover (black line) with a wet day, b dry days, c inactive days, and d other MJO days categorically removed from the overall timeseries (blue line). The slope for trend lines are displayed within each panel. The title in a–d also shows the % contribution (ct) to the total cold cloud cover trend for each MJO category removed from the reconstruction.

**Figure 5.1:** Topographical input data used in the a) WRF CTL run presented in this study, b) a typical GCM (e.g., CMIP5 models), and c) a higher-resolution GCM.

**Figure 5.2:** The evolution of MCSs diagnosed using cold cloud top $T_b$ over equatorial Africa shown every 6-h from 12:00 UTC on 05-Nov to 12:00 UTC on 06-Nov 2014 from GridSat-B1, and CTL, $TOPO_{50\%}$ and $TOPO_{150\%}$ runs. Zonal and meridional wind vectors from ERA-I ($800 \text{ to } 500 \text{ hPa}$ layer mean for OBS) and the WRF model ($2 \text{ to } 5 \text{ km}$ layer mean) are also displayed. Color bars for orography (in meters) and brightness temperature (in °C) are displayed below the figure.

**Figure 5.3:** Hovmöller diagrams showing the longitude-time evolution of $T_b$ from a) GridSat-B1 and b) OLR from the CTL run, rainfall from c) IMERG, d) CTL run, e) CTL run − IMERG, f) $TOPO_{50\%} − CTL$ run, and g) $TOPO_{150\%} − CTL$ run. h) Spatial extent of cold clouds. All data was spatially averaged between 5°N/S and 12 to 28°.

**Figure 5.4:** Longitude-height cross section along the equator showing the rain/ice particle number concentration (shaded), specific humidity ($g \text{ kg}^{-1}$; grey contour), zonal
and vertical wind (× 10) vector, the freezing level (dotted blue line), and rainfall (mm; blue bars along the x-axis) for the CTL, \(TOPO_{50\%}\), and \(TOPO_{150\%}\) runs.

**Figure 5.5:** a) Hourly and b) accumulated rainfall, c–d) Zonal and e–f) meridional wind at \(\sim5\) km and 2 km, g) wind magnitude at 5 km (solid line) and 2 km (dashed line), and h) windshear. Data was spatially averaged between \(5^\circ N/S\) and 12 to 28\(^\circ E\) and shown from 00:00 UTC on 05-Nov to 00:00 UTC on 07-Nov-2014.

**Figure 5.6:** Hourly rainfall from five extreme MCS events over the Congo basin from the CTL and \(TOPO_{50\%}\) runs. The data was spatially averaged between \(5^\circ N/S\) and 12 to 28\(^\circ E\). The WRF model simulation were initialized three days prior to the day of the event in a manner identical to the primary case study analyzed in this article (see section 2).
### LIST OF TABLES

<table>
<thead>
<tr>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Table 2.1:</strong> A list of geostationary satellites used from 1982–present that were used to provide coverage over the Congo basin (adapted from NOAA’s ISCCP B1 Satellite Information webpage available at <a href="http://www.ncdc.noaa.gov/gridsat/inde2.php">www.ncdc.noaa.gov/gridsat/inde2.php</a>).</td>
</tr>
<tr>
<td><strong>Table 2.2:</strong> A list of satellite datasets used in this study with the corresponding reference, spatio temporal resolution, and data availability.</td>
</tr>
</tbody>
</table>
## TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABSTRACT</td>
<td>ii</td>
</tr>
<tr>
<td>ACKNOWLEDGEMENTS</td>
<td>iv</td>
</tr>
<tr>
<td>Statement of Publication/Contribution of Authors</td>
<td>vii</td>
</tr>
<tr>
<td>List of Figures</td>
<td>viii</td>
</tr>
<tr>
<td>List of Tables</td>
<td>xvi</td>
</tr>
<tr>
<td>Chapter 1: Introduction and Hypotheses</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Introduction</td>
<td>4</td>
</tr>
<tr>
<td>1.2 Hypotheses</td>
<td>4</td>
</tr>
<tr>
<td>Chapter 2: Increasing Extent and Intensity of Thunderstorms</td>
<td>12</td>
</tr>
<tr>
<td>Observed Over the Congo Basin from 1982–2016</td>
<td></td>
</tr>
<tr>
<td>2.1 Introduction</td>
<td>12</td>
</tr>
<tr>
<td>2.2 Data</td>
<td>14</td>
</tr>
<tr>
<td>2.3 Methods</td>
<td>16</td>
</tr>
<tr>
<td>2.4 Results</td>
<td>21</td>
</tr>
<tr>
<td>2.4 Concluding remarks</td>
<td>33</td>
</tr>
<tr>
<td>Chapter 3: Trends in Tropical Wave Activity from the 1980s</td>
<td>38</td>
</tr>
<tr>
<td>to 2016</td>
<td></td>
</tr>
<tr>
<td>3.1 Introduction</td>
<td>38</td>
</tr>
<tr>
<td>3.2 Satellite Data</td>
<td>42</td>
</tr>
<tr>
<td>3.3 Methods</td>
<td>44</td>
</tr>
<tr>
<td>3.4 Results</td>
<td>48</td>
</tr>
</tbody>
</table>
3.5 Conclusions and remarks 65

**Chapter 4: The MJO’s impact on rainfall trends over the Congo rainforest**

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1 Introduction</td>
<td>69</td>
</tr>
<tr>
<td>4.2 Data</td>
<td>72</td>
</tr>
<tr>
<td>4.3 Methods</td>
<td>77</td>
</tr>
<tr>
<td>4.4 Results</td>
<td>79</td>
</tr>
<tr>
<td>4.5 Concluding remarks</td>
<td>90</td>
</tr>
</tbody>
</table>

**Chapter 5: Dynamic Aspects of Orographic Enhancement of Rainfall Over the Congo Basin**

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1 Introduction</td>
<td>93</td>
</tr>
<tr>
<td>5.2 Model setup</td>
<td>96</td>
</tr>
<tr>
<td>5.3 Model validation</td>
<td>98</td>
</tr>
<tr>
<td>5.4 Results</td>
<td>103</td>
</tr>
<tr>
<td>5.5 Discussion and Conclusions</td>
<td>109</td>
</tr>
</tbody>
</table>

**Chapter 6: Concluding remarks**

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Copyright Clearance/Permission to Use Published Works</td>
<td>122</td>
</tr>
<tr>
<td>BIBLIOGRAPHY</td>
<td>125</td>
</tr>
</tbody>
</table>
Chapter 1: Introduction and Hypotheses

1.1 Introduction

Water is often cited as the most important compound for the existence and proliferation of life, and is the cause for the existence of tropical rainforests over parts of the world which receive the largest amounts of surface rainfall. Tropical rainforests play an important role in regulating the Earth’s climate system. For example, rainforests help mitigate human caused global warming by acting as a global carbon sink (e.g., Lewis 2006; Lewis et al. 2009). Rainforests also act as a biodiversity hotspot that boast a rich variety of flora and fauna. The destruction of tropical rainforests may result not only in the loss of biodiversity but could potentially result in the acceleration of global warming via a net increase in carbon in the atmosphere. Additionally, due to the amplified diurnal cycle over land when compared to the oceans, tropical rainforests also play an important role in the general circulation of the atmosphere by acting as a hotspot for thunderstorms and a source for large-scale ascent in the atmosphere (e.g., Zipser et al. 2006; Malhi et al. 2013).

Regions characterized by high rainfall amounts include the tropical and subtropical latitudes where the Intertropical Convergence Zone (ITCZ), tropical rainbelt, or monsoon circulation drive rainfall. The orographic enhancement of precipitation (e.g., Andes mountains, and Western Ghats) also play an important role to increase regional rainfall amounts. Vegetation growth and sustainability rely on both water availability and sunlight for photosynthesis. Over tropical rainforests such as the Amazon, persistent cloudiness may hinder plant growth by limiting the amount of sunlight reaching the surface. Therefore, both water and sunlight availability dictate
the sustainability and growth of vegetation. In other words, tropical rainforests may be both water and light limited (Guam et al. 2015; Zhou et al. 2014). Changes in the spatio-temporal coverage of clouds and shortwave radiation absorbed by the surface may also result in significant impacts on the surface temperature, latent and sensible heat fluxes, and the atmospheric diurnal cycle. Understanding mechanisms leading to such changes and associated atmosphere-land surface/vegetation feedbacks are crucial for future climate assessments.

While there has been considerable recent works to understand climate change and variability over the Amazon rainforest, the Congo rainforest, which is the second largest rainforest in the world covering over 3.8 million km² (i.e., area enclosed within 8°N-8°S and 12°E-32°E) has received relatively little attention. In fact, a recent review paper by Alsdorf et al. (2016) presents the lack of fundamental research (e.g., significantly fewer research papers pertaining to the Congo when compared to the Amazon) and avenues to improve our understanding of the hydrological processes over the Congo. While regions surrounding the Congo, e.g., Sahel, East Africa, and South Africa are relatively better researched, the Congo basin is often excluded due to its complex land surface and atmospheric dynamics. Given the important role played by rainforests in the Earth’s weather and climate system, it is crucial to improve our understanding of changes observed over the Congo, especially in regard to the hydrological cycle since some of the most intense thunderstorms and rainfall totals occur in this region (e.g., Zipser et al. 2006).

In a recent study, Zhou et al. (2014) found that the vegetation greenness during April–June (AMJ) rainfall transition season has decreased substantially over the Congo. The loss of vegetation was linked to a long-term decline in rainfall. Jiang et al. (2019) found that the dry season length
measured using vegetation and rainfall indices has significantly increased over the Congo during the months of June–August (JJA). The vegetation loss during JJA is likely linked to the rainfall losses during AMJ that subsequently limits water availability during the dry season attributed to the poor replenishment of soil moisture during the rainy seasons. A reduction in AMJ rainfall has resulted in an earlier onset of the dry season, and thus contributes to an overall increase in the dry season length.

In an ideal scenario, an accurate, well-established, long-term record of high-resolution rainfall data over the Congo region would prove useful to understand the impacts of natural variability and anthropogenically forced climate change on rainfall and vegetation. A confident understanding of the complex land-atmosphere feedback mechanism over the Congo would help provide accurate projections for future climate scenarios. However, there appears to be large uncertainties and biases in observational records (Washington et al. 2013) and climate models over the Congo region (e.g., Creece and Washington 2018). Some of the key findings reported in Washington et al. (2013) include a substantial drop in the number of rain gauges from ~60 per year in the 1980s to ~5 per year towards the late 1990s and into the 21st century, and a large spread in rainfall estimates from observations (including satellite and surface), reanalysis, and climate model datasets. Issues pertaining to consistency in rainfall estimates between different observations and reanalysis products was also explored by Lee and Biasutti (2014) and reported poor correlation between datasets over the Congo. In term of climate model projections, some limitations include seasonal and spatial biases in rainfall over the Congo (Creece and Washington 2018) and the large spread in historical and future climate estimates for rainfall over the Congo basin (Haensler et al. 2013).
The significant uncertainties in observations, reanalysis data, and climate models over Africa provides motivation to investigate fundamental processes such as tropical convection and rain-bearing thunderstorms, how atmospheric equatorial waves that are generally convectively coupled modulate rainfall characteristics over the Congo, and the interaction of precipitation with orography. Broadly speaking, this dissertation seeks to answer the following questions:

**Question #1**: Are thunderstorms increasing or decreasing over the Congo basin, and can the interannual variability and trends in thunderstorm activity explain the observed rainfall variability and trend over the Congo?

**Question #2**: Are atmospheric equatorial wave a potential modulator of thunderstorm activity over the Congo? And are there significant relationships between equatorial wave activity and rainfall over the Congo basin?

**Question #3**: Since orography is poorly represented in climate models, is there added value in improving the representation and interactions between the atmosphere and orography? What role does the orographic features surrounding the Congo basin have on thunderstorms and rainfall activity over the Congo basin?

1.2 Hypotheses

Often, researchers have the luxury of incorporating a large volume of previous research work into their research to further the scientific knowledge on a particular topic. The key findings
from past and on-going research allows scientists to carefully construct a hypothesis and lay-out numerous related hypotheses in-sequence. Often, the process of defining multiple relatable hypotheses is completed in advance of starting the research work and act to narrow the scope of a research project. Over the Congo however, the lack of basic and fundamental scientific knowledge creates some of the most unique challenges and opportunities. Therefore, the hypotheses and scientific questions answered in this work are relatively broad in order to expand our understanding on some factors influencing rainfall variability and trends over the Congo.

1.2.1 Thunderstorms over the Congo Basin

Over the tropical latitudes, majority of rainfall stems from thunderstorms (Dai 2006) and the seasonal cycle of rainfall is attributed to the migration of the tropical rainbelt (Nicholson 2018). Over the Congo which is located in equatorial Africa, this trend is observed and there exists a bimodal structure in the seasonal cycle for thunderstorm activity and precipitation (e.g., Washington et al. 2013). However, most of the rainfall over the Congo are linked not to ordinary thunderstorms, but to organized convective systems known as mesoscale convective systems (MCSs) and changes in MCS characteristics will strongly impact the rainfall, vegetation, and hydrological cycle over the Congo (Jackson et al. 2009; Taylor et al. 2018). Investigating trends in MCS activity and possible physical mechanisms controlling MCS activity will help us better assess water availability over the Congo. Over the Sahel for instance, Taylor et al. (2017) found a tripling in convective activity over the past three decades and attributed this increase in thunderstorm activity and rainfall to the recent greening of the Sahel.
Furthermore, central Africa is one of the most convective regions characterized by intense thunderstorm activity (Zipser et al. 2006). As thunderstorms are convective systems accompanied by the occurrence of lightning, the Democratic Republic of Congo in Central Africa is known as the thunderstorm and lightning capital of the world (Cecil et al. 2015). Large changes in atmospheric convection activities are expected to have significant impacts on rainfall patterns over this region. Understanding such changes could provide insights into observed variations in rainfall characteristics and future rainfall trends in a warming climate over Africa, one of the most vulnerable continents to climate change and climate variability (Maidment et al. 2015).

**Hypothesis #1:** The long-term significant decrease in rainfall observed during AMJ and associated decline in vegetation may be attributable to a decrease in thunderstorm activity. This decrease in thunderstorms results in lesser surface rainfall.

### 1.2.2 Atmospheric Equatorial Waves

One of the most intriguing phenomena observed over the tropical latitudes includes the presence of a wide spectrum of tropical waves. Holton and Hakim (2013) elegantly stated the necessity to study the tropics separately from the mid-latitudes given the complexity of dynamics making up the tropical circulation. Unlike the mid-latitudes that are mostly dominated by Rossby wave dynamics, the tropical latitudes house many different disturbances such as equatorial Rossby (ER) waves, Kelvin waves, mixed Rossby gravity (MRG) waves, Madden–Julian oscillation (MJO; Madden and Julian 1971, 1972), and tropical depression-type disturbances (TDs). Furthermore, the mid-latitude dynamics are relatively better understood and explained by using models such as the quasi-geostrophic framework, but a similar parallel and concise dynamic–
thermodynamic framework to understand tropical dynamics does not exist yet. Since these waves are strongly linked to the dynamics observed in the Earth’s atmosphere, understanding how these waves may have/continue to change will help us better understand atmospheric convection, precipitation characteristics, and energy redistribution.

From the standpoint of climate change and variability, it is also critical to improve our understanding and prediction of the change of the Earth’s climate system. For instance, some studies have explored changes and long-term trends in the ITCZ using observations and modeling experiments and have concluded that the ITCZ may be intensifying and narrowing in a warming climate (e.g., Byrne and Schneider 2016). If this is true, the ITCZ may more readily breakdown and result in an increased occurrence of tropical disturbances (e.g., Raghavendra and Guinn 2016).

The robust wave activity observed in the tropical atmosphere include fast eastward, or westward propagating disturbances such as the Kelvin wave and mixed Rossby gravity wave, and slower moving disturbances such as the eastward propagating MJO, and westward propagating equatorial Rossby wave. These waves interact with each other and produce a wide range of precipitation characteristics i.e., the frequency, intensity, and duration of precipitation. The governing mechanisms responsible for the genesis and maintenance of tropical waves are still ripe for research work, and how tropical waves influence rainfall over equatorial Africa is not well understood.
Hypothesis #2a: Interannual variability and trends in the frequency, intensity, and duration of CCEW and the MJO play an important role in determining the enhancement and suppression of thunderstorm activity and rainfall over the Congo.

Hypothesis #2b: A decreased occurrence of MJO wet phases and an increased occurrence of MJO dry phases over the Congo enhances the drying trend over the Congo.

1.2.3 The Role of Africa’s Orography

Land–atmosphere interaction is an important interdisciplinary subset in the atmospheric science community. Land–atmosphere interactions are perhaps most easily observable when we study the effect of a mountain on the general circulation of the atmosphere, and atmospheric precipitation characteristics. For instance, flow over a mountain may result in atmospheric wave activity, assist in cyclogenesis, and enhance, or suppress precipitation. There are also other important implications aside from flow regimes that encourage the study of orography. For instance, some studies such as Motzer (2005) illustrate micrometeorological constraints such as sunlight availability for photosynthesis for plants growing over mountainous regions.

Given the complex interactions between the land surface and atmosphere, it is important to better understand and represent land-surface processes in both weather and climate models. Over the Congo for instance, there is still some debate on what role topographical features such as the Ethiopian highlands, Turkana channel, and East African Highlands play in order to channel moisture advection from the Indian ocean into the Congo (e.g., Dyer et al. 2017; Sorí et al. 2017). Also, the orographic structure of the Congo may be represented as an approximate reverse “C-
shape”, and the impact of this shape on the rainfall regime is not well understood. Furthermore, while some research work (e.g., Shi and Durran 2015) has been carried out to assess the impact of climate change on precipitation over a mid-latitude mountain, a similar analysis is to my knowledge is absent over the tropical latitudes, especially to understand orographic impacts on the hydrological cycle of the Congo.

Not surprisingly, the complex orographic features surrounding the Congo basin have been speculated to play an important role in modulating thunderstorm and MCS activity (Jackson et al. 2009). However, as expected with an understudied location, notwithstanding speculation and some evidence from reanalysis datasets on the role of orography in influencing thunderstorms and rainfall over the Congo, very little work has been conducted to document the impacts of orography on precipitation over the Congo region. Also, an in-depth analysis of how the orographic features surrounding the Congo impact vegetation and rainfall has not been previously studied. While large-scale influences of Africa’s orography have been previously studied to assess its importance on the south east Asian Monsoon (Wei and Bordoni 2016) and the influence of the east African highlands on the atmospheric circulation, and temperature and rainfall over Africa have been evaluated using GCMs (e.g., Slingo et al. 2005), there exists many unanswered questions pertaining to mechanisms regulating rainfall over equatorial Africa. These questions range from sub-grid scale processes that may warrant the use of dynamic downscaling, or large-scale forcings on atmospheric equatorial waves and tropical circulation.
**Hypothesis #3:** The Congo rainforest is surrounded by complex orographic features. The orographic modification of the atmospheric flow plays a critical role in producing an environment conducive for MCS development over the Congo.

In summary, this PhD dissertation focuses on three important questions that will help us better understand convection, rainfall, atmospheric flow regimes, and orographic interactions over the Congo. The three processes to be studied include thunderstorm activity, atmospheric equatorial waves (especially the MJO), and orographic influences on thunderstorm activity. While serving the common theme of this dissertation, these three processes may be studied individually and in conjunction with each other in order to improve our understanding of rainfall generating mechanisms over the Congo. For instance, African orography may influence atmospheric waves that may in-turn enhance or suppress thunderstorm activity. Diurnal processes associated with orographic features (e.g., upslope/downslope winds) appear to influence thunderstorm genesis and intensification. Also, variability in tropical convection including the MJO and ENSO strongly impact thunderstorm and rainfall over the Congo. Finally, the energy released by large convective events which are likely enhanced by Africa’s orography may generate high-frequency disturbances in the tropical atmospheric flow/circulation.

In this work, satellite data was used in conjunction with reanalysis and other datasets (e.g., precipitation, climate/teleconnection indices) to identify atmospheric convection, and atmospheric flow patterns across scales associated with wet and dry periods over the Congo. The technique of compositing different reanalysis variables is also incorporated in this research. Large-scale flow patterns (including atmospheric equatorial waves) that are better represented in relatively coarser
resolution climate models can then be studied to better estimate future climate rainfall and vegetation projections over Africa. Finally, this work also seeks to shed light on the influence of Africa’s orography across many scales of motion including the large-scale circulation, MCS initiation and development, and precipitation over the Congo. In this dissertation, thunderstorm activity over the Congo basin is investigated in Chapter 2, global trends in CCAEW are explored in Chapter 3, the impact of the MJO on rainfall over the Congo is presented in Chapter 4, and results from an orographic perturbation experiment using a mesoscale convection-allowing numerical model is presented in Chapter 5. Concluding remarks are presented in the last chapter of this dissertation i.e., Chapter 6.
Chapter 2: Increasing Extent and Intensity of Thunderstorms Observed Over the Congo Basin from 1982–2016

Abstract

Recent studies found a long-term drought and resulting declines in vegetation greenness and canopy water content over the Congo Basin, the second largest rainforest in the world after the Amazon. Since most precipitation in tropical latitudes stems from convection, this chapter analyzed 35 years of high-resolution (8 km spatial resolution and 3 h temporal resolution) satellite data to document the long-term trends in the number, size and intensity of thunderstorms activity over the Congo Basin during April, May, and June (AMJ) for the period 1982–2016. Changes in the magnitude and area of cold cloud top brightness temperatures ($T_b$) at different thresholds were used as a proxy to quantify the number and size of individual thunderstorms at different intensities. We found that the areal extent and intensity of thunderstorms increased over the past 35 years, particularly over Northern Congo Basin, and these changes are consistent with other satellite datasets. Combined with a reanalysis dataset, our work suggests that thunderstorms over the Congo Basin are becoming taller and wider, and likely resulting in a moister upper troposphere and drier lower troposphere.

2.1 Introduction

Central Africa is one of the most convective regions characterized by intense thunderstorm activity (Zipser et al. 2006). As thunderstorms are convective systems accompanied by the occurrence of lightning, Democratic Republic of Congo in Central Africa is known as the thunderstorm and lightning capital of the world (Cecil et al. 2015). Because most of the
accumulated rainfall in tropical latitudes originates from convective type precipitation (Dai 2006), large changes in atmospheric convection activities are expected to have significant impacts on rainfall patterns over this region. Understanding such changes could provide insights into observed variations in rainfall characteristics and future rainfall trends in a warming climate over Africa, one of the most vulnerable continents to climate change and climate variability (Maidment et al., 2015).

Possible physical mechanisms responsible for this drying trend over the Congo were explored by Hua et al. (2016, 2018). Based on analyses of multiple reanalysis datasets, and climate modeling experiments, Hua et al. (2016, 2018) linked the drying trend to tropical sea surface temperature (SST) anomalies and associated changes in the tropical Walker circulation. While a significant relationship between the anomalies in the Congo precipitation and large-scale atmospheric circulation was identified, we do not fully understand how convection, which is responsible to generating the majority of precipitation in tropical latitudes (Dai 2006), has changed over the Congo. Furthermore, it is difficult to study precipitation and thunderstorm trends using coarse resolution data (e.g., reanalysis, weather, and climate models) given their inability to accurately capture the diurnal cycle, frequency, and rain rate when compared to observations (Dai 2006). Therefore, satellite datasets are perhaps the best and most reliable observational platforms to study thunderstorms and convection over Central Africa.

Satellite products have been used to understand convection over Central Africa. Hodges and Thorncroft (1997) presented a short 8-year satellite-derived storm track and thunderstorm climatology for Africa, and Futyan et al. (2007) examined convection and storm tracks over the
tropical Atlantic Ocean and Africa using four months of satellite data. Several studies (e.g., Laing and Fritsch 1993; Petersen and Rutledge 2001; Yang and Slingo 2001) explored MCS activity, atmospheric convection, and precipitation over Africa using satellite data over a period of 2–4 years. However, a comprehensive satellite-based climatology and variability of convection activity over the Congo do not exist. In more recent years, Taylor et al. (2017) found a tripling in thunderstorm activity and a proportionally large increase in rainfall during the months of June, July, and August (JJA) over the Sahel using satellite data, but paid little attention to the Congo. This implies that the changes in the number, intensity, and size of thunderstorm activity over the Congo have not been documented nor well understood. Motivated by this knowledge vacuum, here we seek to shed light on the long-term trends in convection over the Congo by using 35-years of high-resolution satellite data.

The chapter is organized as follows. Section 2 provides a brief description of datasets and methods used. Results pertaining to the long-term trends in the number, intensity, and size of thunderstorms are presented in section 3. Major conclusions and possible physical mechanisms are discussed in section 4.

2.2 Data

2.2.1. Satellite Datasets

We used the gridded infrared (IR) channel brightness temperature ($T_b$) dataset (GridSat-B1; Knapp 2008; Knapp et al. 2011) sampled by the European Meteosat (MET) series of geostationary satellites (MET 2–10; Table 1) for 35 years (1982–2016). GridSat-B1 obtained the data from the International Satellite Cloud Climatology Project (ISCCP; Schiffer and Rossow...
1983), mapped them on a 0.07-degree latitude equal-angle grid at a 3-hour temporal resolution, and applied a view zenith angle correction (Joyce et al. 2001). It contained the data for visible (VIS; 0.7μm), IR (11.0μm), and water vapor (WV; 7.7μm) channels, but only the IR window channel data was used since the other channels were not considered to be of Climate Data Record (CDR) program quality (NRC 2004). While the frequency of missing data is relatively higher from 1982–1985 when compared to the long-term record, we alleviated issues pertaining to missing data by calculating the mean thunderstorm activity by season (i.e., AMJ which consist of 91 days)

2.2.2. Other Datasets

It is impossible to study thunderstorms or MCSs given the relatively poor spatio-temporal resolutions of most datasets (e.g., global reanalyses). However, it may be possible to trace significant changes observed in the mesoscale activities (e.g., thunderstorms) projecting on to, and influencing some variables in the larger scale circulation and dynamics. Here we examined outgoing longwave radiation (OLR), vertical motion (vertical velocity ‘w’), and moisture fields (specific humidity ‘q’) using three different datasets:

- European Centre for Medium-Range Weather Forecast (ECMWF) interim reanalysis (ERA-Interim; Dee et al. 2011)
- National Oceanic and Atmospheric Administration (NOAA) OLR–Daily CDR (Lee et al. 2014)
- NOAA’s Interpolated OLR (Liebmann and Smith 1996).

GridSat-B1 dataset was obtained from geostationary satellites whereas the two NOAA’s OLR datasets were produced from polar orbiting satellites. In addition, the $T_b$ dataset from the
CLoud Archive User Service (CLAUS; Hodges et al. 2000) was also used. In this study, an intercomparison between four different satellite derived products (i.e., two \(T_b\) datasets from GridSat-B1 and CLAUS, and two OLR data datasets from NOAA) was carried out to ensure confidence in the major results presented in the chapter using the GridSat-B1 \(T_b\) dataset.

Table 2.1: A list of geostationary satellites used from 1982–present that were used to provide coverage over the Congo basin (adapted from NOAA’s ISCCP B1 Satellite Information webpage available at [www.ncdc.noaa.gov/gridsat/inde2.php](http://www.ncdc.noaa.gov/gridsat/inde2.php)).

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Launch Date</th>
<th>Period of Record</th>
</tr>
</thead>
<tbody>
<tr>
<td>MET-05</td>
<td>02-Mar-1991</td>
<td>01-Jan-1994 01-Feb-1997</td>
</tr>
<tr>
<td>MET-07</td>
<td>02-Sep-1997</td>
<td>31-May-1998 01-Jan-2005</td>
</tr>
<tr>
<td>MET-09</td>
<td>21-Dec-2005</td>
<td>10-May-2007 20-Jan-2013</td>
</tr>
<tr>
<td>MET-10</td>
<td>05-Jul-2012</td>
<td>20-Jan-2013 present</td>
</tr>
</tbody>
</table>

2.3 Methods

Our study region is limited to the Congo rainforest that lies on the Equator, defined as the area enclosed by 8°N–8°S and 12.5°E–32.5°E (1778 km × 2222 km near equator), and covers
an area of approximately 3.9 million km². This constitutes a total of 65,208 pixels in the GridSat-B1 dataset. The Congo rainforest has a complicated seasonality of precipitation that is closely linked with the seasonal passage of the *rainbelt* that migrates *north* and *south* across the equator throughout the course of the year (e.g., Nicholson 2014). The causal factors governing the characteristics of the rainfall regime and its interannual variability, including atmospheric circulation, sea surface temperature, moisture flux, and convective activity, differ markedly by season within equatorial Africa and the Congo Basin (e.g., Dezfuli and Nicholson 2013; Nicholson and Dezfuli 2013; Nicholson 2014). These factors can interact nonlinearly to enhance and weaken their individual contributions at different months and seasons, making it difficult to detect long-term climate signals. To minimize seasonal variations of such interactions, here we focus on the three-month period of April, May, and June (AMJ) given the strong seasonality in moisture source (Dyer et al. 2017) and precipitation over the Congo (Washington et al. 2013), and to effectively compare our results to existing literature where a strong drying trend was documented during AMJ (e.g., Zhou et al. 2014; Hua et al. 2016, 2018). Although AMJ represents the transition period from precipitation maxima in April to drier conditions in June (Washington et al., 2013), it corresponds to one of two peak growing seasons for the rainforests.

The equator passes through the Congo. This implies that the tropical diurnal and season cycles strongly influence convection and precipitation over the Congo. The tropical diurnal cycle (e.g., Yang and Slingo 2001) plays an important role in regulating convection over our study region. The diurnal cycle observed in the GridSat-B1 dataset (not shown) was quite typical for convection over land in tropical latitudes i.e., peak in convective activity observed around 15–18 local standard time (LST; e.g., Yang and Slingo 2001; Nesbitt and Zipser 2003). Also, our analysis
does not filter for the time of peak convection activity (e.g., 1800LST in Taylor et al. 2017) since we are able to document significant trends in thunderstorm activity using data from all times of the day.

\( T_b \) has been used as an alternate to radiance to detect clouds and quantify cloud top temperatures (Schmetz et al. 1997). Thermal infrared radiation in the atmospheric window is sensitive to both surface temperature and cloud cover, especially deep convective clouds (thunderstorms). Over tropical rainforests, the diurnal and seasonal variations in surface temperature are much smaller than other ecosystems (e.g., Mildrexler et al. 2011), but the presence of convective clouds will largely modify the satellite measured radiance due to the pronounced contrast of temperatures between warm surfaces and very cold cloud tops. Different \( T_b \) thresholds are often used to measure deep convective clouds and quantify thunderstorm systems: the deeper the convection, the stronger the intensity, and the lower the \( T_b \) value. In other word, changes in the magnitude and area of very low \( T_b \) at different thresholds can be used as a proxy to quantify the number and size of thunderstorms at different intensities (e.g., Maidment et al. 2014).

The MET satellites are centered along the prime meridian and provide excellent coverage over Central Africa, which includes our domain of interest. The GridSat-B1 dataset has the best inter-calibrated IR window channel and is well-suited for analyzing the horizontal structure of thunderstorms over the Congo (Knapp 2012). For illustrative purposes, an image from the Global ISCCP B1 Browse System (GIBBS; available online at [www.ncdc.noaa.gov/gibbs/](http://www.ncdc.noaa.gov/gibbs/)) archive was obtained to provide an example of IR \( T_b \) associated with thunderstorms over the Congo (Fig. 2.1a). In Fig. 2.1a we observed a line of convection in the eastern part of the domain, and a cluster of
thunderstorms near the middle of the domain. Some intense convection characterized by very low $T_b$ (i.e., $T_b < -60^\circ C$) was present over Sudan and Chad (north east with respect to our study region).

At each three-hourly time step, the gridded IR $T_b$ data over the study region was obtained and contours of $T_b$ less than or equal to a given prescribed $T_b$ threshold were drawn. Figure 2.1b presents a thunderstorm cell in an idealized framework to help illustrate the vertical structure of individual convective towers. An enclosed contour represents a thunderstorm cell for a given $T_b$ threshold and some deep convective thunderstorms may overlap with shallow convective systems at different $T_b$ thresholds. For instance, the contour C-1 in Fig. 2.1b depicted in black delineates lowest clouds with highest $T_b$, but it also includes the middle cloud contours C-2 (blue) and C-3 (orange) with intermediate $T_b$ and the high cloud contour C-3 in red with lowest $T_b$. The number of thunderstorms, the mean size (or area) of each thunderstorm, and the mean $T_b$ value (or intensity) of each thunderstorm were documented by searching for the contours containing a specified $T_b$ threshold and drawing $T_b$ contours of temperatures less than or equal to the prescribed $T_b$ threshold. While $T_b$ based contours were drawn using multiple $T_b$ thresholds, for the sake of clarity and to avoid cluttering the figures only the results from the thresholds of $-40^\circ C$, $-50^\circ C$, $-60^\circ C$, and $-70^\circ C$ $T_b$ are shown in this chapter. The $-40$ to $-70^\circ C$ temperature range is representative of thunderstorms and deep convection in tropical latitudes (e.g., Taylor et al. 2017). This procedure helped us obtain the total number of thunderstorms, and the mean size and intensity of individual thunderstorm cells at four different $T_b$ thresholds over the study region eight times per day. We also validated the correctness of our computing algorithm by independently verifying the findings of Taylor et al. (2017) and found a similar tripling in MCS activity over the Sahel.
Finally, linear trend analysis based on least squares regression was employed to quantify long-term changes in thunderstorm characteristics (i.e., number, size, and total areal extent) in the GridSat-B1 dataset at both the grid and regional level. Linear trend analysis was also used to document changes in OLR, vertical velocity, and moisture from other coarser resolution datasets. The statistical significance level or the $P$ value, is estimated by the two-tailed student’s test to quantify whether the trend is statistically significant rather than an artifact of random noise.
Figure 2.1: a) An example of a satellite image obtained by Meteosat–7 on 1500 UTC 9 August 2015 and made available via GIBBS. The domain of interest in this study is depicted using a red box. b) An idealized thunderstorm cell showing clouds contoured at different \( T_b \). C-1, C-2, C-3, and C-4 represent different temperature thresholds at which contours were drawn.

2.4 Results

2.4.1 Areal extent and intensity of thunderstorm
Understanding trends in the total number of pixels across different \( T_b \) thresholds acted as a primer and provided motivation to further explore thunderstorm activity over the Congo. This was achieved by simply counting the number of pixels satisfying the \( T_b \) thresholds range for each image and then calculating the mean by season. From Fig. 2.2a, we observed a significant increase of 3.4–1.4 pixels yr\(^{-1}\) (\( p<0.01 \)) in the mean pixel count across four relatively very cold \( T_b \) ranges, i.e., \(-85^\circ \text{C}\) to \(-70^\circ \text{C}\), likely attributed to an increase in intense thunderstorm activity. Notwithstanding variability in the interannual timescale, this serves as direct evidence that the areal extent of very cold \( T_b \) corresponding to thunderstorms have increasing for the past 35 years. Figure 2.2a also showcases the MET series satellites being used over the Congo in constructing the long-term record (Table 1) in the figure background to easily identify any sharp changes in pixel count to changes in satellites used in constructing the dataset. There is no evidence to suggest that the trends obtained from the GridSat-B1 dataset are an artifact of changes in satellites across the 35-year study period (e.g., Maidment et al. 2014). Further, the dataset has already been calibrated and verified by Knapp (2008; 2012). Figure 2.2b shows a steady decrease of 0.018–0.032°C yr\(^{-1}\) (\( p<0.01 \)) in the mean cold cloud top \( T_b \) across a relatively large range of cold \( T_b \) thresholds, i.e., \(-70^\circ \text{C}\) to \(-40^\circ \text{C}\), indicating that the mean intensity (height) of thunderstorm has increased. This panel was generated by calculating the mean of the mean \( T_b \) within each \( T_b \) threshold contour for each image and then calculating the mean by season.

### 2.4.2 Total number and mean size of thunderstorms

The above results show that the presence of cold cloud top \( T_b \) has increased. Next we investigated if this increase was attributed to an increase in the thunderstorm number, and/or thunderstorm size. AMJ is a transitioning season characterized by a precipitation maximum during
April and a minimum around June. Also, there lies strong evidence to suggest intensification of thunderstorms towards Northern Congo (Fig. 2.3) where the mean position of the inter-tropical convergence zone (ITCZ\textsuperscript{1}) is also collocated during AMJ. Since we choose to analyze a transitioning season for precipitation (i.e., AMJ) over the Congo, the volume of convection closely followed the predominant position of the ITCZ (Fig. 2.4). Furthermore, opposite trends were observed in the spatial pattern of temperature over the Northern and Southern Congo (Fig. 2.4; more details in section 3.3), we quantify the trends in the number, mean size, and total area of thunderstorms for four different $T_b$ thresholds separately over Northern and Southern halves of the Congo (Fig. 2.3).

The mean number of thunderstorms significantly increased (39–21% change; $p<0.1$) across all four $T_b$ thresholds throughout our study region and Northern Congo accounted for $>55\%$ of the observed increase (Fig. 2.3a–b). While the difference in the number of individual thunderstorm cells between Northern and Southern Congo was relatively small, thunderstorms over Northern Congo appear to be on average 1.2–1.5 times larger when compared to ones over Southern Congo across the four $T_b$ thresholds (Fig. 2.3c–d). Such regional differences in the observed characteristics and trends in thunderstorms are likely a consequence of a narrowing ITCZ (e.g., Byrne and Schneider 2016) resulting in more intense and robust thunderstorm activity over Northern Congo than Southern Congo.

\textsuperscript{1} While it may be technically incorrect to refer to the equatorial convergence zone (ECZ) over Africa as an ITCZ (Nicholson et al. 2018), the term ITCZ will be used in this manuscript to describe the seasonal mean location of peak convection activity.
Figure 2.3c–d shows trends in the mean size (or area) of individual thunderstorm cells per image for four $T_b$ thresholds. This panel shows a decrease at the rate of approximately $9–24$ km$^2$yr$^{-1}$ in the mean areal extent of thunderstorm size contoured at $-40^\circ$C and $-50^\circ$C, and an increase of $9–29$ km$^2$yr$^{-1}$ contoured at $-60^\circ$C and $-70^\circ$C. While the number of thunderstorms has increased at all $T_b$, the mean area of thunderstorms shows a relatively weak decreasing trend at higher $T_b$ ($-40^\circ$C and $-50^\circ$C) and an increasing trend at lower $T_b$ ($-60^\circ$C and $-70^\circ$C). The viewing angle of the satellite which is perpendicular to the surface results in lower clouds being shadowed by higher clouds (e.g., contour C-2 in Fig. 2.1b). Therefore, it was difficult to conclude if the horizontal extents of thunderstorm cells have physically decreased at higher $T_b$ (i.e., $-40^\circ$C to $-50^\circ$C). We are confident in the increasing trend in the mean areal extent of thunderstorm tops at lower $T_b$ (i.e., $-60^\circ$C to $-70^\circ$C). Since the mean cold cloud top $T_b$ has also been steadily decreased and resulting in lower $T_b$ (Fig. 2.2b), we can conclude with reasonable confidence that thunderstorms have increased in size (i.e., both the width and height of thunderstorms have increased) for the past 35 years. This upward trend may be attributed to an increasing trend in the number density of thunderstorms over the Congo (Fig. 2.3a–b) that may favor convection aggregation (Muller and Bony 2015), and intensity of thunderstorms (Fig. 2.2).
Figure 2.2: a) Interannual variations in the AMJ mean pixel count for thunderstorm defined based on four different $T_b$ threshold ranges for the period 1982-2016 over the Congo. As a reference, an illustration of the satellites used over the study region (Table 1) is shown in the background. b) Interannual variations in the mean $T_b$ of thunderstorm cloud tops at four different $T_b$ thresholds. The climatological mean temperature ($m$) and the linear trend ($\alpha$) are shown in the box for each panel. All the trends in both panels are statistically significant at $p < 0.01$.

These results indicate that the number of thunderstorm cells has increased over the Congo and the mean areal extent of thunderstorms at higher (lower) $T_b$ has decreased (increased).
However, the total areal extent at different $T_b$ thresholds attributed to the combined effects of the change in number and size of thunderstorms was unanswered. Since trends in the number of thunderstorms were stronger when compared to the mean area of thunderstorms at all four $T_b$ thresholds, it was found that the total areal extent of thunderstorm cloud cover (i.e., multiplying the mean number and mean area of thunderstorms i.e., Fig. 2.3a–b with Fig. 2.3c–d) increased (significantly at $-60^\circ$C and $-70^\circ$C) at all $T_b$ thresholds (Fig. 2.3e–f). This increase was stronger over Northern Congo than its Southern counterpart. In fact, no significant trends in the total areal extent of thunderstorm cloud cover were found over Southern Congo at $-40$ and $-50^\circ$C $T_b$ thresholds (Fig. 2.3f).
Figure 2.3: Interannual variations in the number (top), mean size (middle), and total area (top; i.e., number × mean size) of thunderstorms over Northern Congo (left columns) and Southern Congo (right columns) for the period 1982-2016 during AMJ. The mean (m) and the linear trend (\( \propto \)), and the p-value (p) of the trend are shown in the box for each panel.

2.4.3 Consistency with other coarser resolution datasets
We found agreement in the AMJ spatial trends among the GridSat-B1 $T_b$, CLAUS $T_b$, and the two NOAA’s OLR datasets for the common period ranging from 1984–2009 (see Fig. 2.4 and Table 2). All four datasets show orographic enhancement of thunderstorm activity over eastern Congo (e.g., Soula et al. 2017), and similar spatial features in both the seasonal mean and trend. Consistent with the propagation of the ITCZ, thunderstorm activity was concentrated within Northern Congo along with contrasting trends in $T_b$ between Northern and Southern Congo (Fig. 2.4) i.e., during AMJ, we observe a cooling (warming) Northern (Southern) Congo in the two $T_b$ data sets. The observed consistency among the four satellite datasets, together with our independent verification of results from another paper (i.e., Taylor et al. 2017), bolstered the confidence in the results (i.e., sections 3.1 and 3.2) using the GridSat-B1 $T_b$ dataset.
Figure 2.4: Spatial patterns of the mean (left columns) and trends (right columns) in $T_b$ (top two rows in K and Kyr$^{-1}$) and OLR (bottom two rows in Wm$^{-2}$ and Wm$^{-2}$yr$^{-1}$) from 1984–2009 during AMJ. Trends significant at p<0.05 are shown using the ‘+’ symbol.
Table 2.2: A list of satellite datasets used in this study with the corresponding reference, spatio-temporal resolution, and data availability.

<table>
<thead>
<tr>
<th>Dataset and Reference</th>
<th>Spatial Resolution</th>
<th>Temporal Resolution</th>
<th>Observation Platform</th>
<th>Time Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geostationary IR Channel Brightness Temperature - GridSat B1 (Knapp et al. 2011)</td>
<td>0.07°</td>
<td>3 hourly</td>
<td>Geostationary Satellite</td>
<td>+36 years (1982–present)</td>
</tr>
<tr>
<td>IR $T_b$ from CLoud Archive User Service (CLAUS) by Hodges et al. (2000)</td>
<td>0.33°</td>
<td>3 hourly</td>
<td>Geostationary Satellite</td>
<td>26 years (01 JUL 1983 to 30 JUN 2009)</td>
</tr>
<tr>
<td>NOAA OLR–Daily CDR PSD Interpolated Version (Lee et al. 2014)</td>
<td>1.00°</td>
<td>Daily mean</td>
<td>Polar Orbiting Satellites</td>
<td>+34 years (1979–2012)</td>
</tr>
</tbody>
</table>

The spatio-temporal resolution of thunderstorms that mostly operates in the mesoscale makes it nearly impossible to capture or reproduce thunderstorms in relatively lower resolution reanalysis datasets. However, given the significant long-term trends in thunderstorm activity over the Congo, we were curious in examining long-term trends in OLR, atmospheric dynamic (e.g., vertical motion and moisture fields). We hypothesize that the robust trends observed in thunderstorm activity at the mesoscale could potentially be projected onto the coarser resolution datasets. A decreasing trend in OLR can be attributed to an increasing trend in thunderstorm intensity (or the magnitude of very low cloud top $T_b$), and/or an increase in the spatial extent of thunderstorms. As expected, the OLR dataset revealed an overall decreasing (increasing) trend over Northern (Southern) Congo (Fig. 2.5a). Consistent with the findings from Fig. 2.4e where an increase in the mean areal extent of cold clouds top $T_b$ were observed over Northern Congo, the spatial mean for OLR decreased significantly (p<0.02) over Northern Congo. Analyzing trends in the number of pixels corresponding to tropical convection (i.e., pixels with value <200 Wm$^{-2}$) yielded a significant (p<0.02) increasing trend (Fig. 2.5b). Consistent with the findings from Fig.
2.4f where relatively weak and insignificant trends were documented in the net areal extent of thunderstorms over Southern Congo, the OLR trends over Southern Congo were weak and mostly insignificant (Fig. 2.5c).

**Figure 2.5**: a) Trends in AMJ OLR (shaded in Wm$^{-2}$yr$^{-1}$) calculated from 1982–2017 using interpolated and uninterpolated data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA (available at www.esrl.noaa.gov/psd/). Trends significant at p<0.05 are shown using the ‘+’ symbol. Interannual variations in the regional mean OLR (red curve; left axis) and the daily mean number of pixels (right axis) for OLR< 200 Wm$^{-2}$ are shown for b) Northern Congo, and c) Southern Congo. The linear trend ($\propto$) and its p-value (p) are shown in this panel. *Note: The
uninterpolated OLR data was interpolated following the techniques highlighted in Liebmann and Smith (1996) prior to being analyzed.

2.4.4 Changes in larger scale circulation and dynamics

A somewhat puzzling finding but consistent with previous research (e.g., Kawase et al. 2010; Hua et al. 2016, 2018) was a trend towards weaker ascent ($\partial \omega / \partial t > 0$, i.e., sinking tendency. Note that $\omega$ is the vertical pressure tendency in the atmosphere) observed both in the upper and lower troposphere diagnosed using the reanalysis datasets (Fig. 2.6a and 6c). The increase in subsidence over a broad area can likely be attributed to local mass conservation to offset the increase in the number of thunderstorm cells (convective towers) observed over the Congo. While a region characterized by weaker ascent is usually associated with a drying trend, we only found a drying trend in the lower troposphere (e.g., Fu 2015). Trends in specific humidity from the reanalysis dataset are in agreement with other studies that show moistening in the upper troposphere (Fig. 2.6b; e.g., Soden et al. 2005), and drying in the lower troposphere (Fig. 2.6d; e.g., Schroeder and McGuirk 1998). This would imply that the taller and wider thunderstorms, which have increased in number, are likely depositing moisture in the upper troposphere despite an increasing trend towards weaker upward vertical motion. This vertical transport of moisture, decreasing surface precipitation trend, and relatively high-water recycling ratio in the Congo (Dyer et al. 2017) are most likely resulting in a net drying trend in the tropical air mass over the Congo.
**Figure 2.6:** Trends in AMJ vertical velocity (shaded in $\times -1/4$ Pa s$^{-1}$yr$^{-1}$) for (a) 200–250 hPa and (c) 875–825 hPa, and trends in AMJ specific humidity for (b) 200–250 hPa ($\times 10^{-3}$ g kg$^{-1}$yr$^{-1}$) and (d) 875–825 hPa (g kg$^{-1}$yr$^{-1}$) calculated from ERA-Interim. Trends significant at $p<0.05$ are shown using the ‘+’ symbol.

### 2.5 Concluding Remarks

This study documented the changes in the number, size and intensity of thunderstorms activity over the Congo during AMJ using 35 years of high-resolution satellite $T_b$ data from GridSat-B1. To bolster the confidence in and validate our results, we also analyzed three other coarse resolution satellite datasets and found good agreement among the four datasets (Fig. 2.4).
Our results indicate an increasing trend in the number of thunderstorms, and an increasing (decreasing) trend in the mean thunderstorms area at lower (higher) $T_p$ thresholds over the Congo. We found opposite trends in the volume of thunderstorm activity i.e., increase (decrease) in Northern (Southern) Congo. Given the predominant location of the ITCZ during AMJ (i.e., northern tropical latitudes), over 55% of thunderstorm cells were documented in Northern Congo. While the overall trends in the number and total area of thunderstorms over the Congo show an increase for AMJ, the signal was stronger over Northern Congo (Fig. 2.3–5). At the same time, our work also suggests that thunderstorms have intensified resulting in taller and wider thunderstorm cells (Figs. 2.2b and 2.3c–d). The trends in OLR concurred that the trends in cold top clouds have increased from 1982–2017 (Fig. 2.5).

We would typically associate an increasing trend in thunderstorm activity to an increasing trend towards stronger vertical ascent (i.e., $\partial \omega / \partial t < 0$). However, in a likely response to offset the increase in thunderstorm activity and to conserve mass, large-scale trends favoring weaker ascent were ubiquitous across the vertical column of the atmosphere over the Congo (Fig. 2.6a and c). Consistent with taller thunderstorms and resulting increase in the spatial extent of cold cloud tops, it was found that the moisture content in the upper troposphere has increased (Fig. 2.6b; e.g., Soden et al. 2005). A decline in the moisture content in the lower troposphere was also documented (Fig. 2.6d; e.g., Schroeder and McGuirk 1998). Fig. 2.7 presents a schematic representation of the key findings in this study and other relevant research work, i.e., an increase in the number of thunderstorms, an increase in the mean areal extent of thunderstorm cold cloud tops, trends towards weaker ascent across all layers of the atmosphere, moistening (drying) trend in the upper (lower) troposphere, and decreasing trend in soil moisture (Jiang et al. 2019).
Figure 2.7: An illustration of changes observed over the Congo from 1982–2016. Trends include larger and more intense thunderstorms over Northern Congo, increase (decrease) in the mean size of thunderstorm at lower (higher) $T_b$, a drier (wetter) lower (upper) troposphere, and weaker ascent at both the lower and upper troposphere, and an overall reduction in soil moisture. These changes were found to be associated with a significant decrease in AMJ precipitation over the Congo during the same period.

The seasonality of the precipitation over the Congo is strongly linked to the poleward seasonal migration of the ITCZ (Washington et al. 2013), and studies such as Su et al. (2017), Byrne and Schneider (2016), and Fu (2015) have found the ITCZ to be narrower and strengthening in a warming climate, and explored variables governing the width of the ITCZ. While physical mechanisms responsible for the observed trends in thunderstorms over the Congo is beyond the scope of this chapter, fundamental knowledge pertaining to the trends in the number and areal extent of thunderstorms was presented. Our results show that the changes in the characteristics of

35
thunderstorms over the Congo have probably caused moisture being transported deeper into the upper troposphere resulting in lesser moisture available to rain down to the surface. It can also be argued that the increased drying trend noted in the lower troposphere (Fig. 2.6d; McCollum et al. 2000) may restrict raindrops from reaching the surface due to an increase in virga (Sassen and Krueger 1993). Furthermore, given the high recycling ratio of water over the Congo (e.g., Pokam et al. 2012; Dyer et al. 2017), even a slight decrease in surface precipitation attributed to the redistribution of moisture (for instance to the upper troposphere, or virga) can potentially have a significant impact on the water cycle and vegetation over the Congo.

One of the motivations for this work was linked to the long-term declining trend in rainfall over the Congo (e.g., Zhou et al. 2014; Hua et al. 2016) and subsequent browning of vegetation (Zhou et al. 2014). Since precipitation over tropical latitudes is strongly tied to convection, we found it worthwhile to study trends in thunderstorms with the hope of understanding surface precipitation trends over the Congo. The research work presented in this chapter along with other similar works (e.g., Taylor et al. 2017) have found increased thunderstorm activities over the Congo. The increase in thunderstorm intensity, number, and area can possibly be explained by a narrowing and strengthening of the ITCZ coupled with the expanding of the Hadley cell (Byrne and Schneider 2016). Since a strengthening ITCZ is characterized by stronger updrafts (i.e., strong upward vertical motion), a thunderstorm cell embedded in such an environment may reach higher heights (i.e., more intense thunderstorms) attributed to the vertical advection of a parcel by the environment. We illustrate the above hypothesis in Fig. 2.4 where we observed an increase in thunderstorm intensity along the AMJ climatological center of the ITCZ, and a decrease in thunderstorm intensity south of the ITCZ. The Congo has been experiencing an accelerated
drought whereas the Sahel has become greener due to the recent increase in surface precipitation (Taylor et al. 2017). This result suggests that an increase in thunderstorms activity may not result in a corresponding increase in surface precipitation.

As previously stated, the precipitation climatology and trend over the Congo poses fascinating questions involving many interconnected processes (e.g., ITCZ, SSTs, thunderstorms, and Walker circulation) across different spatiotemporal scales of motion, and we often find it difficult to decouple and isolate a single mechanism that may explain most of the observed rainfall trend. Therefore, future work is necessary to understanding physical mechanisms (e.g., water cycle and moisture budget, and cloud microphysics) responsible for the observed trends in thunderstorm activity presented in this chapter using both idealized and fully coupled numerical modeling experiments. Also, more work is needed to investigate trends in the lifecycle and duration of thunderstorms over the Congo, which will be of interest to better understand trends in precipitation frequency, intensity, and duration over the Congo.
Chapter 3: Trends in Tropical Wave Activity from the 1980s to 2016

Abstract

A frequency–wavenumber power ($P$) spectrum was constructed using satellite derived outgoing longwave radiation (OLR), and brightness temperature for the tropical latitudes. Since the two datasets overlap for over 34 years with non-intersecting sources in error and compare relatively well with each other, it is possible to diagnose trends in the tropical wave activity from the two datasets with confidence. The results suggest a weakening trend in $P$ characterized by high interannual variability for wave activity occurring in the low frequency part of the spectrum, and a steady increase in $P$ with relatively low interannual variability for wave activity occurring in the high frequency part of the spectrum. The results show the parts of the spectrum representing the Madden–Julian oscillation and equatorial Rossby wave losing $P$, and other parts of the spectrum representing Kelvin waves, mixed Rossby gravity waves, and tropical disturbance like wave activity gaining $P$. Similar results were obtained when trends in variance corresponding to the first principle component was produced using spectrally filtered OLR data representative of atmospheric equatorial waves. Spatial trends in the active phase of wave events, and the mean duration of events are shown for the different wave types. Linear trends in $P$ for the entire spectrum, and regional means in the spectrum corresponding to the abovementioned five wave types with confidence intervals are also presented in the chapter. Finally, we demonstrate that El Niño–Southern Oscillation variability does not appear to control the overall spatial patterns and trends observed in the $P$ spectrum.

3.1 Introduction
Holton and Hakim (2013) elegantly stated the necessity to study the tropics separately from the mid-latitudes given the complexity of dynamics making up the tropical circulation. Unlike the mid-latitudes that are mostly dominated by Rossby wave dynamics, the tropical latitudes house many different disturbances such as equatorial Rossby (ER) waves, Kelvin waves, mixed Rossby gravity (MRG) waves, Madden–Julian oscillation (MJO; Madden and Julian 1971, 1972), and tropical depression-type disturbances (TDs). Furthermore, the mid-latitude dynamics are relatively better understood and explained by using models such as the quasi geostrophic framework, but a similar parallel and concise dynamic–thermodynamic framework to understand tropical dynamics does not exist yet. Since these waves are strongly linked to the dynamics observed in the Earth’s atmosphere, understanding how these waves may have/continue to change will help us better understand atmospheric convection, precipitation characteristics, and energy redistribution. From the standpoint of climate change and variability, it is also critical to improve our understanding and prediction of the change of the Earth’s climate system. For instance, some studies have explored changes and long-term trends in the inter-tropical convergence zone (ITCZ) using observations and modeling experiments and have concluded that the ITCZ may be intensifying and narrowing in a warming climate (e.g., Byrne and Schneider 2016). If this is true, the ITCZ may more readily breakdown and result in an increased occurrence of tropical disturbances (e.g., Raghavendra and Guinn 2016). As an illustration, Fig. 3.1c shows the long-term changes in deseasonalized outgoing longwave radiation (OLR) anomalies from 1979–2016 where we observe an intensification and shift in convection over the northern tropical latitudes and vice-versa. There is also a slight preference for convection consistent with a La Niña-like state in Fig. 3.1b–c since we have experienced increased occurrence of La Niña in recent years (e.g., Cai et al. 2015).
**Figure 3.1:** Global tropical convection (15°N–15°S) from 1979–2016 using NOAA’s daily Interpolated OLR dataset (Liebmann and Smith 1996). a) Daily mean OLR, b) the difference in OLR between 1979–1987 and 2008–2016, and c) linear trends in OLR obtained after removing the seasonal cycle from the OLR dataset. The black dots indicate trends that are statistically significant (p-value<0.1).

While the behavior and anticipated changes of mid-latitude waves are well captured and documented with relatively high confidence using climate models (e.g., Francis and Vavrus 2012), a similar analysis is difficult and therefore lacking over the tropics. In fact, very few global climate models (GCMs) used in the Coupled Model Intercomparison Project (CMIP) phase 5 (CMIP5) were able to simulate what metrics such as the frequency(f)-wavenumber (k) power (P) spectrum (Wheeler and Kaladis 1999 hereafter WK99) suggest is a realistic MJO (Hung et al. 2013). Unfortunately, today’s weather and climate models (e.g., Hung et al. 2013; Schiraldi and Roundy 2017) struggle to accurately resolve these waves for many reasons. These limitations seen in models may be attributed to coarse resolution and poor parameterization of moist processes, and
the different and complex spatiotemporal structures of waves observed near the equator that are often ill-resolved by GCMs. Many studies have tried to understand changes in the tropical ocean (e.g., Rose et al. 2014), land surface (e.g., Zhou et al. 2014), and atmosphere (e.g., Hua et al. 2016; 2018) using observations, reanalyses, and regional/global models. These studies have proven imperative to improving our understanding of the role of the tropical latitudes in redistributing energy, momentum, and moisture across the globe, and regulating the Earth’s climate (e.g., Trenberth and Stepaniak 2004; Lewis 2006).

Since GCMs are generally unreliable to diagnose tropical waves in both the historic runs and possible future climate scenarios (Hung et al. 2013), long-term observations and reanalysis datasets are the best sources to capture possible effects of climate change and variability notwithstanding dataset uncertainties and caveats. Considering the paramount importance of the role of tropical waves and convection on global weather and climate (e.g., Lin et al. 2006), understanding long-term changes in tropical wave activity may provide valuable insight to better estimating the impacts of climate change over tropical latitudes, and global weather and climate patterns.

While numerous studies have investigated tropical waves across different timescales (e.g., Roundy and Frank 2004; Chen and Huang 2009; Huang and Huang 2011; Hung et al. 2013), this chapter is motivated by incomplete understanding of climate variability and change in tropical wave activity, and for the first-time sheds light on this glaring issue through the analysis of two long-term satellite based OLR and brightness temperature ($T_b$) gridded datasets. The datasets were used to document changes and trends in the $f$-$k$ $P$ spectrum over tropical latitudes (i.e., $15^\circ$N–
The chapter is organized as follows. Sections 2 and 3 provide a brief description of datasets and methods used. Results pertaining to the long-term trends in $P$ spectrum are presented in section 4. Major conclusions and possible physical mechanisms are discussed in section 5.

### 3.2 Satellite data

Two different (i.e., geostationary and polar orbiting) satellite datasets were used in this study. The gridded infrared (IR) channel brightness temperature $T_b$ dataset (GridSat-B1; Knapp, 2008; Knapp et al. 2011) was produced from geostationary satellite data for 1982–2016 (35 years) from the International Satellite Cloud Climatology Project (ISCCP; Schiffer and Rossow 1983) and was re-mapped on a 0.07-degree latitude equal-angle grid at a 3-hour temporal resolution. In order to meet the need for observational climate studies, much effort has been done to reduce intersatellite differences by rigorous intersatellite calibration and temporal normalization in the GridSat dataset (Knapp et al. 2011). A view zenith angle correction (Joyce et al. 2001) was also applied in producing this dataset. Out of the three channels available in the GridSat-B1 dataset (i.e., visible 0.7µm, IR 11.0µm, and water vapor 7.7µm), only the IR window channel data was used since the other channels did not satisfy the Climate Data Record (CDR) program quality (NRC, 2004). In order to speed-up the mathematical operations and statistical analysis, the 0.07-degree dataset was re-gridded and up scaled to 0.98-degree. The popular and relatively coarser resolution interpolated OLR dataset (Liebmann and Smith 1996) by the National Oceanic and Atmospheric Administration (NOAA) from 1979–2016 (38 years) was also used in this study. The OLR dataset has a temporal resolution of 1-day, a horizontal resolution of $2.5^\circ \times 2.5^\circ$, and was produced using data obtained from polar orbiting satellites. Missing data in both datasets were treated with the gap filling algorithm developed by Garcia (2010) and Wang et al. (2012) that
works particularly well for satellite derived datasets. In both datasets, the lower thresholds can be used to detect clouds and quantify cloud top temperatures (Schmetz et al. 1997). The negative OLR and $T_b$ anomalies are often used as a proxy to identify and detect tropical convection (e.g., Raghavendra et al. 2018a). While the OLR dataset has been used in numerous studies to understand convection and dynamics in the tropics (e.g., WK99; Roundy 2018), only few papers have performed similar analyses using $T_b$ data (e.g., Wang and Chen 2016; Wang and Li 2017).

Long-term satellite derived datasets have been widely used to detect and quantify climatic signals in many studies, particularly over the vast and inadequately observed tropical rainforests (e.g., Congo by Zhou et al. 2014; Raghavendra et al. 2018a; Jiang et al. 2019), landmasses such as the Sahara Desert (Wei et al. 2017) and Eurasia (Li et al. 2017), and the oceans (e.g., Barton 1995). However, despite large efforts made to minimize the intersatellite differences in the long-term satellite datasets as mentioned previously, trends established using these datasets are still prone to residual uncertainties and a tropic of considerable debate in the climate community. Often, the data record is relatively short and limited to the life span of a satellite or scientific mission, and long-term records such as the ones used in this chapter were created from multiple satellites and thus may contain non-climate biases and uncertainties (e.g., instrument calibration errors due to satellite drift/changover). In our case, the OLR dataset is constructed using NOAA operated polar orbiting satellites (Liebmann and Smith 1996), and the $T_b$ dataset relies on geostationary satellites deployed by multiple countries (Knapp et al. 2011). Since the two datasets use different types of satellites/sensors and are processed differently, they would be associated with non-intersecting sources of error and uncertainties between them. Here we include both datasets to study long-term changes and trends in tropical wave activity, which can enhance the confidence in our findings.
and may identify their differences (e.g., Raghavendra et al. 2018a). Although there are only two
datasets applied here, they are constructed from numerous satellites. While individual satellites
may be associated with systematic trends over short-term periods due to orbital decay and other
factors, these would affect the two datasets differently and would not likely produce monotonic
long-term trends over time.

3.3 Methods

After treating the OLR and $T_b$ for missing data and subsetting to include only the tropical
latitudes (i.e., $15^\circ$N–$15^\circ$S), the refined datasets were deseasonalized to prevent aliasing (WK99)
using five pairs of harmonics to the annual cycle ($X$; Roundy 2017). The regression coefficients
($C$) are given by Eq. 1

$$C = (X^T \times X)^{-1} \times X^T \times Y$$

(Eq. 1)

where $Y$ is the 3D (i.e., time, lat, and lon) matrix containing OLR or $T_b$ data. Using Eq. 1, the
seasonal cycle ($X \times C$) was calculated and later subtracted from $Y$ to obtain the anomalies with
respect to $Y$ (i.e., $Y_{anom}$). Using techniques similar to WK99, the symmetric ($Y_{symm}$) and
antisymmetric ($Y_{asym}$) components of the dataset were then computed (Eq 2–3).

$$Y_{symm} = \frac{Y_{anom}(15^\circ N–0^\circ) + Y_{anom}(15^\circ S–0^\circ)}{2}$$

(Eq. 2)

$$Y_{asym} = \frac{Y_{anom}(15^\circ N–0^\circ) - Y_{anom}(15^\circ S–0^\circ)}{2}$$

(Eq. 3)

The $Y_{symm}$ and $Y_{asym}$ were subjected to segmentation using 200-day time windows that were
detrended and tapered to zero along the ends of the time dimension using a cosine bell in order
to prevent spectral leakage (WK99). The 200-day windows were repeated along the data array
every 100 days. A 200-day window was chosen to increase the number of $f$ bins and resolve the
time scales of the motions of interest in this chapter. The discrete Fourier transform (DFT) using
a fast Fourier transform (FFT; Frigo and Johnson 1998, 2005) was then applied to each 200-day
time window, and an FFT shift was applied to rearrange the zero-\( f \) component to the middle of
the domain iteratively to obtain \( FFT(Y_{\text{symm}}) \) and \( FFT(Y_{\text{asym}}) \). Finally, the symmetric and
antisymmetric \( P \) was calculated by taking the complex conjugate (i.e., \( P_{\text{symm}} = FFT(Y_{\text{symm}}) \times \)
\( \text{conj}[FFT(Y_{\text{symm}})] \) and \( P_{\text{asym}} = FFT(Y_{\text{asym}}) \times \text{conj}[FFT(Y_{\text{asym}})] \)). Similar to WK99, the
mean time–latitude \( P \) spectrum for the symmetric and antisymmetric parts was obtained by divided
by the smoothened mean background spectrum (i.e., \( \frac{P_{\text{symm}} + P_{\text{asym}}}{2} \)); see Fig. 3.2 fornormalized \( P \)
spectrum). Note that normalization by the background is not necessary for this analysis and since
the background is constant it does not impact the trends.
Figure 3.2: The frequency-wavenumber power spectrum diagram normalized by the smoothed background spectrum similar to the technique developed by WK99. The individual panels represent the antisymmetric power spectrum using the a) OLR and c) $T_b$ datasets, and symmetric power spectrum using the b) OLR and d) $T_b$ datasets.

To demonstrate whether the trends in wave activity are consistent with trends in spectral variance corresponding to each wave band, an empirical orthogonal function (EOF) analysis (e.g., Kiladis et al. 2009) was applied to the filtered daily OLR anomaly data from 1979–2016 for the five different wave bands. Trends in signals projecting onto these patterns will correspond to trends
conforming to the target EOF modes themselves instead of the background “noise”. This analysis was performed by first spectrally filtering the daily long-term OLR dataset to retain only those frequencies and wavelengths representative of the target wave. The spectral filters applied are similar to the spectral bands illustrated in Fig. 3.2. A data matrix including the entire time series of filtered OLR data on the full tropical grid from 15°N to 15°S was created, and the eigenvectors of the covariance matrix were computed. Only the leading EOF (EOF-1), which explains the largest variance was retained. The filtered data were then projected onto EOF-1 to obtain the timeseries corresponding to the first principle component (PC-1). Variance was obtained by squaring the PC-1 timeseries.

Since $P$ depends on multiple factors such as frequency (how often an event occurs), period (how long an event lasts) and wavelength of the disturbance, and trends in $P$ alone do not necessarily reveal how a particular disturbance is changing over time. The filtered OLR data were also used to evaluate possible trends in anomaly characteristics in the given bands. The technique used here is similar to ones used in evaluating heatwave trends (e.g., Raghavendra et al. 2018b) where the frequency, intensity, and duration of heatwave events are calculated based on a threshold temperature. However, instead of using an arbitrary percentile threshold for filtered OLR representative of different equatorial waves, here we identify an event based on the spectrally filtered negative OLR anomaly present in the 38-year time series for each grid point between 15°N–15°S. This technique helps identify the frequency of occurrence, duration, and other measurements such as the mean OLR anomaly during the active phase of the disturbance (not shown since trends were mostly insignificant) for signals in the different wave filter bands.
The influence of El Niño–Southern Oscillation (ENSO) variability was accounted for by calculating the difference in the mean $\mathbf{P}$ for those time windows corresponding to a particular ENSO state based on the ERSSTv5 Niño 3.4 index (Huang et al. 2017) and the Niño 3.4 index data was obtained from NOAA’s Climate Prediction Center (CPC; http://www.cpc.ncep.noaa.gov/data/indices/). The threshold for an El–Niño time windows was a mean Niño 3.4 index greater than 0.75, La–Niña if the mean Niño 3.4 index was less than −0.75, and ENSO neutral conditions if the mean Niño 3.4 index was between ±0.25.

Here we use three approaches to quantify the changes in the spectral $\mathbf{P}$ obtained from the OLR and $T_b$ datasets. To quantify trends at the grid and regional mean levels, least squares regression was used to estimate the linear trend. The statistical significance ($p$-value) of the linear trend line was estimated by the two-tailed student’s t-test. A Mann-Kendall (MK) test was applied in some case in conjunction with a linear regression analysis to evaluate whether the trends are significant. Uncertainties in trends were captured by a Monte Carlo analysis. A two-sample t-test applied to the two pairs of populations to quantify if significant differences in $\mathbf{P}$ exist between the beginning and end of the datasets. In this study, $p$-value < 0.1 was adopted to be statistically significant.

3.4 Results

3.4.1 Changes in the mean spectrum

Using the techniques similar to WK99, Fig. 3.2 presents the mean normalized antisymmetric and symmetric parts of the $\mathbf{P}$ spectrum using both the OLR and $T_b$ datasets. Both datasets are remarkably similar to each other and capture the peak in $\mathbf{P}$ corresponding to different
types of wave activity observed in the tropical latitudes. These features are consistent with similar
works published in the literature (e.g., Roundy 2018; WK99). While the spectra obtained from the
OLR and $T_b$ datasets may be similar, they are not identical given the nature of the datasets. For
instance, around $k = 14$ the OLR dataset shows a local increase in $P$ (Fig. 3.2a–b) and WK99
attributes this inconsistency to the polar orbiting satellite making approximately 14 swaths around
the globe per day. By definition, the higher resolution geostationary satellites used to create the $T_b$
dataset does not move relative to a fixed geographical location on the Earth, and instead uses
multiple geostationary satellites to obtain a merged global picture (Knapp et al. 2011). In
comparison to the OLR dataset, $T_b$ dataset produces a smoother $P$ spectrum with fewer spurious
peaks (Fig. 3.2c–d).

In Fig. 3.3, we subtracted the mean of the first nine years from the mean of the most recent
nine years of the $P$ spectrum to identify any systematic shifts in the $P$ spectrum. The results suggest
a shift in $P$ where the magnitude of $P$ has increased in higher $f$ signals (0.2–0.5 cycles per day;
cpd, or 2 to 5-day period), and decreased in lower $f$ signals (0.0–0.2 cpd, or >5-day period). In
order to establish whether these trends are stable and significant in time, a latitude mean linear
regression analysis was applied to the $P$ spectrum (Fig. 3.4). Consistent with the results shown in
Fig. 3.3–4 shows relatively weak yet significant increases in $P$ between 0.2–0.5 cpd. While there
are some patches of blue in Fig. 3.4 between 0.2–0.5 cpd indicative of a decreasing trend in $P$,
these patches are characterized by an insignificant ($p$-value > 0.1) linear trend. Between 0–0.2 cpd,
we observed a mixture of both positive and negative trends in $P$ in Figs. 3.3–4. Overall, over 29%
of the trends in Fig. 3.4 were statistically significant.
**Figure 3.3:** Observed shift in the $\log_e$ spectral power calculated by taking the difference between the mean normalized power for 2008–2016 and 1979–1987 (for OLR dataset)/1982–1990 (for $T_b$ dataset). The individual panels represent the antisymmetric power spectrum using the a) OLR and c) $T_b$ datasets, and symmetric power spectrum using the b) OLR and d) $T_b$ datasets. A two-sample $t$-test applied to the two pairs of populations proved that the power for 2008–2016 is significantly different from the power for 1979–1987 at the 1% significance level.
3.4.2 Trends in spectral power

Since the $P$ spectrum captures many scales of motion observed in the tropical latitudes, by dividing the $f$ and wavenumber $P$ spectrum into different regions dominated by a particular phenomenon (WK99; Straub and Kiladis 2002; Roundy and Frank 2004, Kaladis et al. 2005, 2009), we may estimate how the characteristics of signals in bands of the wave number $f$ domain...
associated with a given wave may have changed. In this study, we analyzed trends in five different kinds of disturbances observed in the tropical latitudes i.e., MJO, ER waves, MRG waves, Kelvin waves, and TD-type disturbances from both the OLR and \( T_b \) datasets (Fig. 3.5). The trends in \( P \) for a given wave type closely follow the predominant trend for a given \( f \) since there is little variability across \( k \) for \( \sim 0.2 \) cpd or higher (Fig. 3.4). In general, lower \( f \) (0–0.2 cpd) is losing \( P \), and higher \( f \) (0.2–0.5 cpd) is gaining \( P \). The MJO and ER wave suggest decreasing trends in \( P \), but only the symmetric part of the \( P \) spectrum for the \( T_b \) dataset showed a statistically significant decrease. The other three wave types that are dominated by relatively higher \( f \) and are characterized by localized regions of significant \( P \) increases below 0.2 cpd mostly show statistically significant increasing trends in \( P \).
Figure 3.5: Interannual variations in the regional (see Fig. 3.2 for domain) mean log$_e$ power spectrum (red for antisymmetric part, and blue for symmetric part) corresponding to different wave types in the WK99 frequency-power spectrum diagram using the OLR (left column), and $T_b$ (right column).
column) datasets. The slope, and the p-value ($p$-val) of the linear trend lines are shown in the box embedded in each panel.

As the spatial structure and trends obtained from the OLR and $T_b$ datasets compare well with each other (Raghavendra et al. 2018a), we were not surprised to observe similar trends from the two datasets (Figs. 3.2–5). Figure 3.6 provides confidence thresholds for the slope of the curves in Fig. 3.5. Since the amplitude of the interannual variability is relatively high when compared to the net long-term change in $P$ (i.e., low signal to noise ratio), we observe a relatively large range of values making up the 5–95% confidence interval. Except for the symmetric part of the MJO and ER wave for the OLR dataset that coincidently have the highest p–value (least significant) linear trend in Fig. 5, the confidence intervals concur with the net change in sign for the observed trends in the $P$ spectrum (Fig. 3.5–6). As expected from the results illustrated in Figs. 3.3–4, the MJO and ER wave have lost $P$, and Kelvin waves, MRG, and TD–type waves have gained $P$. The linear trend analysis (Fig. 3.5) and confidence range (Fig. 3.6) also support the above conclusion.
Figure 3.6: A Monte Carlo analysis carried out by randomly rearranging the data points for each interannual variability curve 1,000 times in Fig. 3.5 without repetition in order to quantify uncertainties in the slope ($\text{units: } \times 10^{-2} \log_e(P) \text{ year}^{-1}$) of the linear trend line shown in Fig. 3.5. The upper (95th percentile) and lower (5th percentile) limits of the uncertainty is represented by the top and bottom whiskers respectively, and the slope values for the symmetric (S) and antisymmetric (A) components from Fig. 3.5 are represented using five symbols for each type of disturbance using both the OLR and $T_b$ datasets.

3.4.3 Trends in variance and trends in the leading modes of variability

We have thus far shown time trends in spectral power (Figs. 3.3–6). Furthermore, the spatial structure corresponding to the trends in OLR variance (Fig. 3.7) appears to be concentrated near regions characterized by a peak in annual mean variance presented in Kiladis et al. (2009). However, there is a possibility that trends in background noise may be strongly projecting onto the
trends in spectral power (Figs. 3.3–6), and thus making it unclear whether wave signals are changing in a similar manner. To address this concern, an EOF analysis was conducted to evaluate if patterns in the data conforming to the structures of convectively coupled waves change amplitude with time, via assessment of trends in variance of the PC-1 timeseries.

**Figure 3.7:** Trends in OLR variance calculated by squaring the spectrally filtered OLR anomaly for (a) the MJO, (b) ERW, (c) KWs, (d) MRG, and (e) TD from 1979 to 2016. The black dots indicate trends that are statistically significant ($p$ value < 0.1).

The spatial structure of the leading EOF (EOF-1) explains the maximum variance (Fig. 3.8) and the EOF-1 spatial pattern for MRG waves (Fig. 3.8d) closely resembles the MRG wave pattern in Kiladis et al. (2009). Since the amplitude of a leading EOF mode and preferred structure...
pattern can change over time, we compared the same analysis based on EOFs computed based on the first (1979–1993) and last (2002–2016) 15-year periods from the OLR dataset and found negligible differences in the spatial structure of the leading EOFs, and trends in variance corresponding to PC1 were not statistically distinguishable from the trends in PCs based on EOF patterns computed from the entire dataset (Figs. 3.8–9). The trends in variance corresponding to PC1 for five different wave types are shown in Fig. 3.9. In this figure, we observe a significant decrease in variance for the MJO band, and a significant increase in variance for KWs, MRG waves, and TD-type disturbances. An insignificant increasing trend is observed for ERWs. The trends from Fig. 3.9 compare favorably with Figs. 3.5–6, and Fig. 3.7, and we find mutually supporting evidence for four wave types (except ERW where the trend lines are not statistically significant). In summary, the analysis presented in Figs. 3.8–9 shows that signals that project onto the leading EOF mode trend similarly to variance in the filter bands themselves and proving that the waves themselves are part of the trend. So, regardless of whether background noise is trending, the wave signals are trending in the same direction as variance in the bands.
Figure 3.8: The spatial structure corresponding to the leading EOF for a) the MJO, b) ERW, c) KWs, d) MRG, and e) TD obtained by first filtering the daily OLR anomaly data from 1979–2016 for the five different wave bands, and then applying an EOF analysis. The percentage variance explained by the leading EOF are show in each panel.
**Figure 3.9:** Interannual variability of the variance corresponding to first PC of the band filtered daily OLR anomaly data from 1979–2016 (blue line) for a) the MJO, b) ERW, c) KWs, d) MRG, and e) TD. The slope, and the p-value ($p$-val) of the linear trend lines (red line), and the result and p-value from the Mann-Kendall trend test are shown in the box embedded in each panel. The spatial structure corresponding to the leading EOF for each wave is shown in Fig. 3.8.

### 3.4.4 Spatial trends in wave activity
This sub-section is motivated because we now understand changes in the \( P \) spectrum for over 35 years, and the trends in \( P \) associated with five tropical wave types, but we lack physical insight on how individual wave characteristics (i.e., trends in the number of events, and the duration of an event) corresponding to the five different spectral band many have changed. Furthermore, understanding spatial trends in wave activity, and the mean duration of the active period corresponding to a given wave may help us better understand mechanisms regulating tropical convection and precipitation. By identifying the convective phase for different wave types and calculating the occurrence and mean duration of an event (Fig. 3.10), we find those wave bands characterized by an increase in power at high \( f \) (e.g., KWs, MRG, and TD-type) show a significant upward trend in the mean number of events and accompanied by a decrease the mean duration of an event. There are fewer grid points showing significant trends for the MJO and ERW spectral bands, but the spatial distribution of trends in event occurrence and duration (Fig. 3.10 a–b and c–d) suggests a compensating effect between frequency and duration resulting in a tendency towards a homogeneous spatial field. To further elaborate, considering the MJO band, for instance, there is good agreement between observed trends (Fig 3.10a) and modeling efforts using GCMs (e.g., Jones and Carvalho 2006; Arnold et al. 2015; Song and Seo 2016; Adams et al. 2017) in the increased occurrence of MJO events attributed to global warming. While it is generally argued that MJO intensity will likely increase in a warmer climate, both observations and modeling studies discuss considerable uncertainties with regard to intensity and duration changes in the MJO. Furthermore, there are non-negligible biases in GCM realizations of the mean background state of the tropical atmosphere. Some of these issues include a cold bias for SSTs in atmosphere-ocean coupled runs, the double ITCZ problem (e.g., Lin 2007), and overestimated tropical OLR variability (e.g., Arnold et al. 2015). Therefore, while Fig. 3.5a–b suggests a negative trend in \( P \)
corresponding to the MJO, this does not imply a weakening MJO, or less frequently occurring MJO. However, the reduction in $P$ corresponding to the MJO does imply a reduced variance in the MJO (Fig. 3.7a), therefore either a reduction of amplitude, and/or a reduction of the longevity of active periods must be occurring (Fig. 3.10a–b). Fig. 3.3–4 suggests a shift in the MJO band towards higher frequencies, but additional analysis beyond the scope of this chapter on how changes in the combination of the amplitude and/or longevity of active periods of equatorial waves both on a regional and global scale may explain the observed trends in $P$. 
Figure 3.10: The mean number, and duration of events corresponding to (a–b) the MJO, (c–d) ERW, (e–f) KWs, (g–h) MRG, and (i–j) TD from 1979–2016 using daily OLR anomalies. The mean frequency and duration of events was calculated by applying a spectral filter for different wave types, and then using the negative OLR anomaly time series at each grid point to generate
the necessary statistics. A linear regression and t-test was applied to determine regions showing significant (p<0.1) increasing (black dot) and decreasing (white cross) trends.

### 3.4.5 ENSO’s impact on the power spectrum

Variability in ENSO is known to strongly influence tropical convection and a key player in climate variability (e.g., WK99; Neale et al. 2008). Not surprisingly, since tropical wave activity and convection are strongly coupled, variability in ENSO could strongly influence tropical waves and the trends in wave activity we observed in Figs. 3.3–6. In order to better understand the impact of ENSO on the $f$ and $k \mathbf{P}$ spectrum, we constructed difference plots (Fig. 3.11) between the mean spectrum for a given ENSO state and the total $\mathbf{P}$ spectrum (Fig. 3.2). Changes in $\mathbf{P}$ associated with El-Niño include enhanced KW, an increase in higher $f$, a decrease in lower $f$ for eastward propagating wave activity, and weaker TD-type disturbance activity. La-Niña shows the opposite effects. No coherent patterns in wave activity were observed for ENSO neutral state. While the six individual panels are significantly different from each other both in terms of structure and power, we are not convinced that the structure of the $\mathbf{P}$ spectrum corresponding to different phases of ENSO could possibly produce the trends in $\mathbf{P}$ shown in Figs. 3.3–6.
Figure 3.11: Difference in $P$ constructed using NOAA’s OLR dataset for each ENSO state for the antisymmetric and symmetric parts of the spectrum (a–f) relative to the mean power spectrum in Fig. 3.2. A two-sample $t$-tests shows significantly differences at the 1% level between panels a–f. g) The Niño 3.4 index derived from ERSSTv5. The blue and green lines represent the ±0.75 and ±0.25 thresholds used to segregate the time windows to obtain a composite spectrum for a particular ENSO state. The number of time windows in each ENSO state is shown in bold numbers.
3.5 Conclusions and remarks

In this study, the $f$ and $k_P$ spectrum for the tropical latitudes (i.e., $15^\circ$N–$15^\circ$S) was constructed using the method outlined by WK99 for OLR data obtained from polar orbiting satellites (Liebmann and Smith 1996), and $T_b$ data obtained from geostationary satellites (Knapp et al., 2011). Both datasets produced $P$ spectra that are similar to one another (Fig. 3.2). Since the fundamental goal of the chapter was to identify changes in the $f$ and $k_P$ spectrum, we subtracted the $P$ spectrum of the first nine years from that of the last nine years to investigate possible changes in the $P$ spectrum (Fig. 3.3). This exercise revealed a significant decrease in $P$ from $\sim 0$–$0.2$ cpd, and an increase in $P$ from $\sim 0.2$–$0.5$ cpd. The significance of the trend was also established via a linear regression (Fig. 3.4). Since different parts of the $f$ and $k_P$ spectrum are associated with different waves observed in the tropical latitudes (e.g., Kiladis et al. 2009), we averaged the $P$ corresponding to regions of the spectrum known to be occupied by signals from particular wave types and examined the trends.

Given the low signal to noise ratio observed with the $P$ trends in Fig. 3.5 and to quantify uncertainties in the results, a Monte Carlo analysis was carried out (Fig. 3.6). We found the bands of the MJO and the ER wave were characterized by a decreasing trend in $P$, and the bands of MRG waves, Kelvin waves, and TD-type disturbances were characterized by increasing trends in $P$ (Fig. 3.5–6). From Figs. 3.3–5, we infer an increase in variability at higher frequencies attributed to an increase in $P$ and vice-versa. To further evaluate the validity of the change in $P$ reported thus far and to ensure the changes in spectral power were linked to the waves and not the background “noise”, we evaluated trends in band filtered daily OLR anomaly data from 1979–2016 for
variance (Fig. 3.7), the structure of the leading EOF pattern (Fig. 3.8), and trends in the variance corresponding to PC-1. The PC analysis shows that signals that project onto the leading EOF mode trend similarly to variance in the filter bands themselves and demonstrate that the waves themselves are part of the trend. Therefore, concurrence between the time trends in the variance corresponding to the first principle component (PC1; Fig. 3.9) and spectral power (Figs. 3.5–6) should bolster our confidence in the results and help us draw to the conclusion that the trends in spectral power for each wave type is a consequence of changes in the wave characteristics, and not just background noise.

A possible relationship between changes in $P$ and changes in the frequency of occurrence and mean duration of wave events was also presented (Fig. 3.10). Results suggests the it may be possible to attribute that the increase in power at high $f$ (e.g., KWs, MRG, and TD-type) to a significant increase in the occurrence of high frequency disturbances, accompanied by a decrease the mean duration of an event. The results for a decrease in power at low $f$ (e.g., MJO and ERW) is difficult to explain given non-homogeneous trends in the mean duration of the events. Finally, we demonstrate the influence of ENSO on the $P$ spectrum (Fig. 3.11) and argue that the trends in $P$ documented in Figs. 3.3–5 are difficult to explain from the standpoint of variability in ENSO.

Our future research endeavors include diagnosing changes in the characteristics of tropical waves (e.g., $f$, amplitude, and persistence), and identifying mechanisms resulting in the observed change in the $P$ spectrum. The subset of our community that specialized in climate variability and change has published a considerable spectrum of works to better understand Earth’s atmosphere and ocean dynamics across different spatio-temporal scales. Therefore, there are many possible
future research avenues to understand mechanisms linked to changes in tropical waves and the
associated $f$-wavenumber $P$ spectrum presented in this chapter (Fig. 3.3–6). Some of these
research avenues and possible mechanisms that may explain changes and trends in tropical wave
activity include:

- The impacts of a narrowing ITCZ, changes in the breakdown of the ITCZ, and expanding
  Hadley cell (e.g., Byrne and Schneider 2016; Raghavendra and Guinn 2016).
- Changes in the profile of ocean heat transport and associated changes in the Hadley cell
  (Rencurrel and Rose 2018).
- An observed enhancement in the tropical Walker cell circulation associated with an increased
  temperature contrast between regions within the tropical latitudes (e.g., Kosaka and Xie 2013;
- Localized and non-localized convection/heating within the tropical latitudes (e.g., Neale and
  Hoskins 2000; Raghavendra and Guinn 2016; Raghavendra et al. 2018a) and associated Gill–
  Matsuno and tropical waves response to steady tropical heating (e.g., Cook and Vizy 2016).
- Extratropical influences, especially given recent studies highlighting arctic amplification and
  changes in the midlatitude Rossby wave train (e.g., Barnes and Polvani 2015) can alter the eddy
  momentum fluxes between the tropical and extratropical latitudes and consequently impact the
  monsoon and the large scale tropical circulation (e.g., Schneider and Bordoni 2008; Bordoni
  and Schneider 2010).
- Teleconnections such as Pacific decadal oscillation and North Atlantic oscillation may also
  prove to be useful endeavors to better understand convectively coupled equatorial waves.
Finally, current climate models are relatively poor in capturing observed tropical precipitation characteristics (e.g., Dai 2006) but may capture the dynamics of free and convectively coupled tropical waves to varying degrees of accuracy (e.g., Hung et al. 2013). Understanding the linkage between tropical waves and precipitation, and using projected changes in tropical wave activity to estimate precipitation change maybe a worthwhile exercise as well. A hierarchical modeling approach (e.g., Isca; Vallis et al. 2018) ranging from idealized to fully coupled GCMs may prove particularly useful in isolating mechanisms linked to the observed and possible future changes in the $f$-wavenumber $P$ spectrum. From a climate change and societal impact perspective, analyzing precipitation changes linked to the observed and projected changes in the dynamics of tropical wave activity over may offer insights on the water budget and availability over tropical latitudes.
Chapter 4: The MJO’s impact on rainfall trends over the Congo rainforest

Abstract

A significant declining trend in rainfall over the Congo basin has been observed over the past three decades. Since the Madden–Julian oscillation (MJO) is a major forcing mechanism for tropical convection and rainfall, the interannual variability and trend in rainfall over the Congo may be partly attributable to variability or changes in the MJO. This study explores the long-term (1979–2018) relationship between the active MJO diagnosed by the real-time multivariate (RMM) MJO phase index data and observed rainfall and cloud data over the Congo during October–March. Since the MJO may significantly enhance rainfall during the wet phases or suppress rainfall during the dry phases, the crux of this chapter includes how trends in MJO activity may impact the overall observed precipitation trend over the Congo. The relationship between MJO activity and rainfall over the Congo was documented using statistical techniques and composite analysis. A new, yet simple approach was developed to partition seasonal rainfall depending on the MJO phase (i.e., wet, dry, inactive, and other). Results show a significant correlation between the number of wet and dry MJO days, and rainfall enhancement and suppression over the Congo. While there exists considerable interannual variability in MJO activity and rainfall over the Congo, there is a significant increase in the number of dry MJO days (3.47 days decade⁻¹) which tends to intensify the large-scale drying trend over the Congo during October–March. The increasing trend in the number of dry MJO days is likely enhancing the net drying trend by 13.6% over the Congo.

4.1 Introduction
Possible mechanisms responsible for the drought over the Congo have been explored in the past several years. Hua et al. (2016) studied trends and patterns in tropical sea surface temperatures (SSTs) and reported the enhancement and westward shift of the descending branch of the tropical Walker circulation has increased subsidence over the Congo and subsequently resulted in a decline in rainfall. This finding was further substantiated in a follow-up study using climate models (Hua et al. 2018). A strong link was also found between the Indian Ocean Dipole (IOD), Walker circulation and convection over the maritime continents, and rainfall over the Congo using Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012) models (Creese and Washington 2018). Interestingly, satellite observations show an increase in thunderstorm activity and intensity (Raghavendra et al. 2018a). This unintuitive relationship between intensifying thunderstorm activity and decrease in rainfall over the Congo may be reconciled by applying the conclusions of other studies (e.g., Hamada et al. 2015) who found that the tallest and most intense thunderstorms do not produce the most rainfall in the tropical latitudes (especially over land). Needless to say, thunderstorms are essential for rainfall over the Congo (e.g., Jackson et al. 2009; Hamada et al. 2015; Taylor et al. 2017, 2018).

There exists agreement on some dynamic and thermodynamic responses to global warming in climate models (Held and Soden 2006). However, important sources of seasonal/sub-seasonal variability (e.g., the Madden–Julian Oscillation or MJO), tropical convection, rainfall characteristics, and associated large scale dynamics are poorly resolved by climate models (e.g., Dai 2006; Hung et al. 2013; Chen and Dai 2019). Therefore, climate models cannot explain the entirety of the rainfall trend over the Congo and thus resulting in uncertainties for future climate projections over the Congo. Even climate models forced with observed SSTs struggle to replicate
the strong drying trend over the Congo (e.g., Hua et al. 2018). Therefore, changes and variability in seasonal to sub-seasonal processes such as the MJO, Kelvin waves (Sinclaire et al. 2015), and other tropical waves (Raghavendra et al. 2019) which are important mechanisms that influence tropical convection and precipitation are poorly simulated by climate models, and an important source of uncertainty in climate models and future climate projections.

While climate models perform modestly in simulating tropical waves (Hung et al. 2013), long-term satellite observations have suggested an increase in high-frequency variability and a decrease in low-frequency variability in Convectively Coupled Atmospheric Equatorial Waves (CCAEWs; Raghavendra et al. 2019). While the variability between CCAEWs and precipitation has been previously studied (e.g., Sinclaire et al. 2015), trends in the relationship between CCAEWs and precipitation has received little attention. Furthermore, while the role of the MJO and other tropical waves on rainfall over Africa has been previously investigated, these studies have usually limited their domain of interest to Southern Africa (e.g., Pohl et al. 2018), Western Africa/Sahel (Schlueter et al. 2019a, b), or Eastern Africa (e.g., Pohl and Camberlin 2006a, b; Berhane and Zaitchik 2014). This has resulted in a lack of understanding of the MJO’s impact over CEA (especially the Congo rainforest).

Since the MJO (Madden and Julian 1971, 1972) is an important dynamic–thermodynamic mechanism connected to the variability in the large-scale circulation of the tropics and extratropics, and modulates rainfall, we need to study changes in MJO activity and associated rainfall impacts as a possible contributor to the overall rainfall drying trend over the Congo rainforest. Understanding the mechanisms for the phasing between the MJO and the tropical rainbelt over
Africa is also motivated by a declining trend in spectral power (variance) corresponding to the MJO frequency–wavenumber band (Raghavendra et al. 2019). Given the importance of the Congo rainforest and the potential impact MJOs have in modulating tropical rainfall, this chapter studies the long-term (1979–2018) relationship between the MJO and precipitation over the Congo rainforest using observations and reanalysis data. The impact of trends in MJO activity on rainfall over the Congo are also investigated in this study.

4.2 Data

In this study, four datasets detailed below which are available at daily or higher temporal resolution from 1979–2018 (40-year period) and 1983–2018 (36 years) were used:

1. The daily MJO RMM phase index data (Wheeler and Hendon 2004) were obtained from the Bureau of Meteorology (Australia) website (www.bom.gov.au/climate/mjo/). The RMM index is better suited to evaluate rainfall over the Congo when compared to other MJO indices (e.g., outgoing longwave radiation-based MJO Index–OMI) because it incorporates the lower- and upper-tropospheric zonal wind, which influence vertical motion over Africa through interaction with topography or through confluence of flow. Also, outgoing longwave radiation (OLR) has a smaller impact compared to the upper and lower tropospheric zonal windfield on the MJO RMM index (Wheeler and Hendon 2004), and OLR is poorly correlated with rainfall over the Congo and other parts of Africa (e.g., Schlueter et al. 2019a). Furthermore, the RMM index is widely used and hence makes it easier to relate the research presented in this chapter with previous works. As suggested by previous studies (e.g., LaFleur et al. 2015), days with an MJO amplitude ≥ 1 were regarded as active MJO days, and days with an MJO amplitude < 1 were regarded as inactive MJO days. RMM phase 2 was regarded as the wet phase (enhanced
rainfall), and phases 5 and 6 were regarded as the dry phases (suppressed rainfall) for Equatorial Africa (Gottschalck et al. 2010; Raghavendra et al. 2017; Zaitchik 2016). These RMM phase combinations to define the wet and dry MJO regimes yielded the most significant distinction between wet and dry conditions (Fig. 4.1). Furthermore, sensitivity tests for other practical choices and combinations for wet or dry RMM phases (e.g., phases 1 and 2 for wet MJO days, or phases 4 and 5 for dry MJO days) did not qualitatively impact the arguments and conclusions presented in this chapter.

Figure 4.1: a) Seasonal cycle of rainfall over the Congo using daily CPC rainfall data (see plot legend for details). b) Boxplot showing the average seasonal rainfall by MJO category. c) Mean and d) anomalous rainfall (shaded in mm day$^{-1}$) for each month and RMM phase. In b), non-overlapping notches indicate that the true medians differ at the 95% confidence level, and the top
and bottom whiskers indicate the maximum and minimum values. Days with an RMM amplitude < 1 are omitted in b–d.

2. The NOAA Climate Prediction Center (CPC) global unified gauge-based daily precipitation data (in mm day\(^{-1}\)) was obtained from NOAA/OAR/ESRL/PSD website (www.esrl.noaa.gov/psd/) at 0.5\(^\circ\) horizontal resolution. The daily mean precipitation over the Congo was calculated by spatially averaging the precipitation between 7.75\(^\circ\) N–7.75\(^\circ\) S and 12.25\(^\circ\) E–32.75\(^\circ\) E (study region depicted by a dashed green line in Fig. 4.2b). The rainfall estimates from this dataset compared well to other datasets such as the Global Precipitation Climatology Centre (GPCC) and a new observational precipitation dataset (NIC131) developed by Nicholson et al. (2018) over the Congo region. However, unlike GPCC and NIC131 where the long-term record is only available at monthly resolution, the CPC global unified gauge-based analysis is available at a daily temporal and relatively higher spatial resolution.
3. Rainfall variability over the Congo Basin is closely linked to the large-scale atmospheric circulation in the lower- and middle-troposphere (Hua et al., 2019). The 850 hPa zonal (u) and meridional (v) wind data every 6-h at 0.7° horizontal grid resolution were obtained from the
European Centre for Medium-Range Weather Forecast (ECMWF) interim reanalysis (ERA-I; Dee et al. 2011). This 6-h data was converted to daily (24-h) temporal resolution since the RMM phase and precipitation datasets are only available at daily resolution. The horizontal resolution was reduced by interpolating the data onto a 2.5° grid to focus on large-scale circulation. The wind divergence anomaly field i.e., $\left(-\frac{\partial u'}{\partial x} + \frac{\partial v'}{\partial y}\right)$ (where $x$ and $y$ are the latitudinal and longitudinal directions, and $'$ indicates anomaly from the seasonal mean) was calculated to assess different circulation patterns associated with RMM phases using composite analysis. Since the composite analysis is centered around the RMM phases from different MJO events with large variability in the background meteorological conditions, statistical significance testing for the seasonal composites was performed by using a bootstrap random re-sampling tests with 1000 iterations (e.g., Ventrice et al. 2012; Sinclair et al. 2015). Other reanalysis products could be used in this study but it is difficult to identify the “best” reanalysis dataset over the Congo Basin given the lack of surface observations and radiosonde network (Washington et al. 2013; Hua et al. 2019). Nevertheless, the bias and root-mean-square error associated with the ERA-I windfield is comparable with other datasets (Hua et al. 2019) and hence the ERA-I is suitable for this study.

4. Rainfall over the Congo relies on thunderstorm activity (e.g., Jackson et al. 2009; Hamada et al. 2015; Taylor et al. 2017, 2018). Given limited rainfall observations available over the Congo (e.g., Alsdorf et al. 2016; Nicholson et al. 2018), here we use the areal extent of satellite measured cloudiness as an independent proxy for rainfall activity to confirm our results from the CPC dataset. Cold cloud top cover indicative of thunderstorm activity was evaluated using infrared (IR) brightness temperature ($T_b$) $<-40$ °C from the gridded satellite (GridSat-B1)
dataset (Knapp 2008; Knapp et al. 2011) from 1986–2018. Daily mean cloud cover was obtained by calculating the number of pixels with \( T_b < -40 \) °C between 5° N–5° S and 12° E–30° E during 18:00 and 21:00 UTC. A slightly smaller domain was chosen for the cloud analysis since heatmaps for thunderstorms and lightning activity show significantly higher activity over the Congo basin (e.g., Zipser et al. 2006). Rainfall on the other hand was evaluated over a larger domain since precipitation occurring near the edges of the Congo basin at higher elevations are orographically forced into the Congo basin. We choose the GridSat-B1 IR channel \( T_b \) as it satisfies Climate Data Record (CDR) program quality (NRC 2004) and is suitable for climate research and application (Knapp 2008; Knapp et al. 2011; Raghavendra et al. 2018), particularly over northern and central Africa (Knapp et al. 2011; Raghavendra et al. 2018). Note that the GridSat-B1 \( T_b \) is available from 1982–present, but the period 1982–1985 is excluded from this analysis due to the relatively higher frequency of missing data when compared to other years, and the abnormal low \( T_b \) values associated with the 1982 eruption of El Chichón volcano. Similarities in the assessment of MJO characteristic from the CPC and GridSat-B1 datasets should improve the confidence in the results presented in this study.

### 4.3 Methods

The methods used to analyze the abovementioned datasets are purely statistical. The temporal trends in precipitation and cloud cover were established using multiple linear regression and their statistical significance (\( p \)-value) were assessed using a two-tailed Student’s t test. As the linear trend is sensitive to the start/end points of the data series, when applicable, the non-parametric (distribution-free) Mann–Kendall (MK) test (Hirsch et al. 1982), which overcomes the abovementioned limitation, was also applied to check the significance of the trend. The analysis
presented in this study is limited to the months ranging from October–March since the MJO signal and RMM amplitude are significantly stronger during this period (e.g., Adames et al. 2017; Zhang and Dong 2004). These months contain the rainiest month of October, the December–February (DJF) dry season, and the start of the wet season around March as the tropical rainbelt over the Congo migrates southward during October to January, and northward back towards the basin during February to April (e.g., Washington et al. 2013; Nicholson 2018).

In this chapter, the interannual variability of the seasonal rainfall and number of days in each MJO category is broken down using the MJO RMM phase and RMM amplitude. The total number of days in each season may be decomposed as the sum of the number of wet (RMM phase 2), dry (RMM phases 5 and 6), inactive (RMM amplitude < 1), and other (RMM phases 1, 3, 4, 7 and 8) MJO days i.e., $\text{All days} = \text{MJO}_{\text{wet days}} + \text{MJO}_{\text{dry days}} + \text{MJO}_{\text{inactive days}} + \text{MJO}_{\text{other days}}$. A similar approach was applied to decompose the total seasonal rainfall for each year i.e., $\text{PR} \text{total} = \text{PR}_{\text{wet days}} + \text{PR}_{\text{dry days}} + \text{PR}_{\text{inactive days}} + \text{PR}_{\text{other days}}$ (Note: precipitation is abbreviated as “PR”). The rainfall during these four types of MJO days contributes to the overall seasonal rainfall which is outlined below. First, Oct–Mar daily average seasonal rainfall ($\overline{\text{PR}}$) for each year is decomposed as the fractional sum of the daily average rainfalls observed during the wet, dry, inactive, and remainder (other) MJO days i.e.,

$$\begin{align*}
\overline{\text{PR}}_{\text{total}} &= \left(\text{MJO}_{\text{wet days}} \times \overline{\text{PR}}_{\text{wet days}}\right) + \left(\text{MJO}_{\text{dry days}} \times \overline{\text{PR}}_{\text{dry days}}\right) + \left(\text{MJO}_{\text{inactive days}} \times \overline{\text{PR}}_{\text{inactive days}}\right) + \left(\text{MJO}_{\text{other days}} \times \overline{\text{PR}}_{\text{other days}}\right) \\
&= \text{All days} \quad \text{(Eq. 1)}
\end{align*}$$

Applying Eq. 1 for all 40 years of data yields a timeseries that breakdowns the daily average seasonal rainfall as the sum of four parts defined by the RMM phase and amplitude.
Next, we may categorically extract the association of the MJO signature to the overall rainfall trend by excluding one term at a time in the right-hand side (R.H.S.) of Eq. 1. For instance, the contribution of $MJO_{dry\ days}$ may be assessed by omitting the second term in the R.H.S. of Eq. 1 and subtracting $MJO_{dry\ days}$ from All days in Eq. 1 i.e., $\overline{PR}_{total-dry} = \left( (MJO_{wet\ days} \times \overline{PR}_{wet}) + (MJO_{inactive\ days} \times \overline{PR}_{inactive}) + (MJO_{other\ days} \times \overline{PR}_{other}) \right) \div (All\ days - MJO_{dry\ days})$. An estimate of a lower bound of the MJO categories’ contribution is quantified by calculating the percentage difference in the slopes of the linear trend for a given category and compared to the All days trend. A similar approach was also applied for fractional cloud cover derived from the GridSat-B1 dataset.

4.4 Results

4.4.1 Interactions between the MJO and the seasonal cycle of rainfall

Since the Congo is situated along the Equator, the region is characterized by a bimodal precipitation distribution (i.e., two dry and two wet seasons per year) modulated by the migration of the tropical rainbelt (Fig. 4.1a; Washington et al. 2013; Nicholson 2018; Jiang et al. 2019). The wet seasons include the months of March, April, and May (MAM) and September, October, and November (SON), while the dry season is composed of December, January, and February (DJF), and June, July, and August (JJA). Figure 4.1a shows the seasonal cycle over the Congo characterized by high interannual variability with deviations frequently exceeding $\sim 25\%$ when compared to the climatological mean. The long-term drying signal is also evident in the rainfall record i.e., the monthly mean rainfall from the period 2009–2018 is considerably below the 1979–1988 mean (e.g., Zhou et al. 2014; Hua et al. 2016; Nicholson et al. 2018; Jiang et al. 2019).
The relationships between the MJO categories as defined in this chapter and daily mean seasonal average rainfall over the Congo are presented in the form of a boxplot in Fig. 4.1b. A combination of the sample sizes and inter-quartile ranges of the distribution are used to assess statistical significance (McGill et al. 1978). Figure 4.1b shows significantly higher rainfall amounts during the wet phase, and the lowest median rainfall amounts for MJO dry days when compared to all other MJO categories. Rainfall during inactive and other MJO days are very similar and appears to have a neutral impact on rainfall over the Congo. The combined influences between the seasonal cycle and MJO RMM phases is shown in Fig. 4.1c. In other words, Fig. 4.1c illustrates the precipitation impact associated with the phasing of the MJO coinciding with the seasonal migration of the tropical rainbelt over Central Africa.

To better assess the impact of the RMM phases on rainfall, precipitation anomalies were generated by first calculating the seasonal cycle using five harmonic components to the annual cycle and then subtracting the seasonal cycle from the raw precipitation (methods outlined in Roundy 2017 and Raghavendra et al. 2019). While the daily mean rainfall is generally higher during the months of MAM and SON, and lower during the months of DJF and JJA (Fig. 4.1a), there are strong rainfall anomalies across different MJO RMM phases during different seasons (Fig. 4.1d). While the migration of the tropical rainbelt strongly dictates seasonal rainfall amounts and thunderstorm activity (e.g., Nicholson 2018; Taylor et al. 2018) across all RMM phases, there is a significant distinction between rainfall amounts observed during the wet and dry RMM phases across different months of the year. Rainfall is typically enhanced during the wet RMM phases and reduced during the dry RMM phases.
Since the tropical rainbelt (Nicholson 2018) and the MJO serve as important dynamic–
thermodynamic forcing mechanisms regulating tropical rainfall (e.g., Madden and Julian 1972;
Zhang and Dong 2004; Barnes et al. 2015; Adames et al. 2016), it is not surprising to observe the
synchronized seasonality and differences in rainfall across different RMM phases over the Congo
(Fig. 4.1c–d; e.g., Pohl and Camberlin 2006a, b; Berhane and Zaitchik 2014; Pohl et al. 2018).
However, some of the strongest modulations of rainfall may be attributable to the MJO RMM
phases from Oct–Mar. This relationship is weak during other months and likely results from other
forcing mechanisms such as the onset of the West African monsoon, which dominates the
circulation between May–Aug (Sultan and Janicot 2003). For the Oct–Mar period, rainfall during
MJO RMM phase 2 as the wet phase with positive rainfall anomalies, and RMM phase 5 and 6 as
the dry phases with negative rainfall anomalies show statistically significant differences (Fig.
4.1b). While the results are sensitive to choices in three parameters i.e., season, cut-off RMM
amplitude applied to define an active or inactive MJO days, and practical choices for RMM phases
used to define the wet and dry MJO spell, these choices do not impact the overall conclusions
presented in this chapter.

4.4.2 Spatial composite analysis of wet and dry MJO days

The wet and dry MJO days over the Congo are associated with significantly different
circulation patterns (Fig. 4.2). During wet MJO days, westerly wind anomalies dominate the lower
troposphere (850 hPa) and were associated with the injection of moisture from the Atlantic Ocean
into the Congo basin. Recent studies such as Dyer et al. (2017) have also found a strong association
between westerly wind anomalies from the Atlantic Ocean and positive rainfall anomalies over the
Congo. There is also a strong convergence-divergence dipole located near Lake Victoria and East-
African Highlands during wet MJO days (Fig. 4.2a). Since thunderstorms usually form over the East-African Highlands during the late-afternoon (e.g., Hill and Lin 2003) and are steered westward by the prevailing lower tropospheric easterly flow (e.g., Corfidi et al. 1996), the invigorated circulation may likely promote thunderstorm development by increasing the windshear (e.g., Taylor et al. 2018). At the same time, westerly wind anomalies may act to reduce the strength of the background easterly flow which slows down the propagation speed of thunderstorm cells over the Congo. These intense and relatively slow propagating thunderstorms cell likely increase the rainfall amount over the Congo. The lower tropospheric circulation anomaly reverses during dry MJO days. This reversal in circulation likely advects drier continental airmass from northern and eastern Africa which in turn suppresses thunderstorm activity over the Congo during dry phases. Figure 4.2 also compliments the findings of Fig. 4.1 b–d by showing wet RMM phases are associated with positive rainfall anomalies and vice versa.

From the standpoint of seasonal to sub-seasonal variability, since the number of days during Oct–Mar (i.e., ~182 days) may allow for multiple MJO episodes with time windows ranging from 30 to 60 days (Madden and Julian 1971, 1972; Wheeler and Kiladis 1999), there exists potentially 3–6 time windows during which the MJO may substantially enhance or suppress precipitation amounts over Africa. An important argument to be considered is whether random variability in MJO activity intersecting with the migration of the tropical rainbelt would produce a long-term low frequency trend in rainfall. The crux of this chapter includes how trends in MJO activity may contribute to the overall observed precipitation trend over the Congo during the months of Oct–Mar. These arguments are explored in more detail in Sections 4.4.3–4.
4.4.3 A brief overview of the MJO categories and corresponding rainfall

An overview of the interannual variability of the MJO days and rainfall by category are presented in Fig. 4.3. During the period of study, the overall occurrence of MJO wet days was 7.82%, dry days was 17.6%, inactive days (i.e., RMM amplitude < 1) was 35.7%, and other days was 39.2%. Dry days are more frequent when compared to wet days since two RMM phases (i.e., phases 5 and 6) were regarded as dry phases, but only one RMM phase (i.e., phase 2) was regarded as dry phase. The definitions for the different MJO categories used in this study result in a large number of inactive and other days and are consistent with the findings of similar studies using the RMM index (e.g., LaFleur et al. 2015). In Fig. 4.3a, number of days in a season vary between 182 (regular year) and 183 (leap year), therefore the total number days ($\text{All\ days}$) is constant in time. This however is not the case for rainfall, which shows considerable year-to-year variability and a strong drying trend (Fig. 4.3b). The percentage-based breakdown of MJO days is presented in Fig. 4.3c. Since there is practically no variability in the total number of days per season, Fig. 4.3a and 4.3c appear identical. Similar to Fig. 4.3b, a percentage-based breakdown for rainfall by MJO category is presented in Fig. 4.3d. The substantial year-to-year variability and trend in rainfall however results in some differences between Fig. 4.3b–d. The percentage-based breakdown of rainfall by MJO category is as follows: 9.29% for wet days, 15.7% for dry days, 35.6% for inactive days, and 39.2% for other days. In other words, rainfall amount by MJO category closely follows the number of MJO days in each category. However, on average 7.82% of MJO wet days bring 9.29% of the total rainfall while 17.6% of MJO dry days bring 15.7% of the total rainfall. The fraction of rainfall from inactive and other days align almost perfectly with the fractional breakdown of the number of inactive and other days (Figs. 4.1b, 3c–d).
Figure 4.3: Stacked area plot showing the Oct–Mar raw and percentage based interannual variability decomposed by MJO category for a, c MJO days, and b, d rainfall. The solid line represents the categorically integrated climatological mean. The trend in total seasonal rainfall amount is depicted using a dotted red line in b.

As shown in Figs. 4.1–2, rainfall is significantly enhanced during wet MJO days, and suppressed during dry MJO days. This relationship is also extractable from Fig. 4.3 by comparing the fractional contribution of rainfall from the corresponding MJO category. Therefore, a reasonable hypothesis to consider includes: do seasons characterized by larger number of wet or dry MJO days result in significantly different seasonal rainfall anomalies? To answer this question, the correlation between the number of wet and dry MJO days, and the seasonal rainfall anomaly are presented in Fig. 4.4. Results suggest an increase in the number of wet MJO days is
characterized by a positive rainfall anomaly (R = + 0.26 and p value = 0.10), while an increase in
the number of dry MJO days is characterized by a negative rainfall anomaly (R = − 0.30 and p
value = 0.06). In sum, the effect of wet MJO and dry MJO days may be evaluated by calculating
the difference in the number of wet and dry MJO days for each year normalized by the number of
RMM phases used. The difference in the number of wet and dry MJO days and rainfall anomaly
shows a stronger relationship (R = + 0.35 and p value = 0.03) when compared to the individual
parts. Overall, Fig. 4.4 demonstrates a significant correlation between the number of wet and dry
MJO days and observed rainfall over the Congo.
**Figure 4.4:** Scatter plot showing the relationship between the Oct–Mar mean rainfall anomaly and a number of wet MJO days, b number of dry MJO days, and c difference between the number of wet and dry MJO days normalized by the number of RMM phases chosen for wet and dry RMM phases from 1979–2018. The linear regression line (red line), correlation coefficient (R) with significance level (p value in parentheses), and ±25% of the regression prediction interval (gray shading) are displayed in each panel.

### 4.4.4 Categorical evaluation of trends in MJO days and rainfall

Attributing rainfall to a single mechanism (e.g., the MJO) is likely an impossible task given the complex, coupled and sometimes competing interactions observed among different controlling factors in the tropical atmosphere (e.g., Roundy 2012; Holton and Hakim 2013). However, by calculating the daily average seasonal rainfall by omitting iteratively one of four types of MJO days (i.e., wet, dry, inactive, and other days) and comparing it to the overall mean rainfall trend (see Eq. 1 and Section 3), a useful starting point is developed in this chapter to quantify the impact of the trends in MJO activity on rainfall over the Congo. The rainfall variability captured by the individual parts in Eq. 1 was able to reproduce 100% of the total observed rainfall.

The interannual variability across seasons in the number of active MJO wet (W) and dry (D) days, W–D days, rainfall anomaly, and rainfall anomaly during an active MJO are presented in Fig. 4.5a. From 1979–2018, Oct–Mar shows a significant increase in the number of dry MJO days. Similar to the results presented in Fig. 4.4, the trend of the difference in the number of wet and dry MJO days is stronger when compared to the trends in the number of dry MJO days. The trends in the number of MJO days for each category is explicitly presented in Fig. 4.5b. Only dry
MJO days show a significant increase of 0.34 days year\(^{-1}\) from 1979–2018. While rainfall over the Congo has decreased during all seasons (e.g., Hua et al. 2016; Jiang et al. 2019), these results suggest that the declining rainfall trend is likely enhanced by the MJO. Notwithstanding a strong role by large-scale mechanisms outside MJO dynamics (e.g., SSTs, IOD, and the Walker circulation; Hua et al. 2016, 2018) in modulating rainfall over the Congo, the increasing trend in the number of dry MJO days is acting to strengthen the overall drying trend over the Congo (Figs. 4.1b, 2, and 4).

**Figure 4.5:** a) Interannual variability in the number of MJO wet (blue), dry (red), and wet–dry days (grey bar) normalized by the number of RMM phases used. Precipitation anomaly (PR; mm day\(^{-1}\); blue circles) from 1979–2018 is displayed against the right vertical axis. The slope of
the trend line and p value (in parentheses) are displayed in the legend. \textbf{b}) Interannual variability and trend of MJO days by category. The slope (bold indicates significant trend as per the MK-test) and p value for trend lines are displayed next to \textbf{b}.

In Fig. 4.6, the mean Oct–Mar rainfall shows a significant decreasing trend consistent with the enhanced subsidence observed over the Congo (Hua et al. 2016; Raghavendra et al. 2018). This trend persists even if the variability attributable to the MJO is categorically removed. When compared to the overall mean rainfall trend ($-0.21 \text{ mm day}^{-1} \text{ decade}^{-1}$), the slope of the rainfall trend is practically unchanged with the removal of wet MJO days, 13% weaker with the removal of dry MJO days ($-0.18 \text{ mm day}^{-1} \text{ decade}^{-1}$), 21% stronger with the removal of inactive MJO days ($-0.26 \text{ mm day}^{-1} \text{ decade}^{-1}$), and 3.8% weaker with the removal of other MJO days ($-0.21 \text{ mm day}^{-1} \text{ decade}^{-1}$). The strong contribution from dry and inactive MJO days was expected considering the significantly increasing trend in dry MJO days ($+3.47 \text{ days decade}^{-1}$) and decreasing (albeit statistically insignificant) trend in inactive MJO days ($-2.83 \text{ days decade}^{-1}$; Fig. 4.5b).
Figure 4.6: Interannual variability and linear trend in the Oct–Mar mean rainfall (black line) with a) wet day, b) dry days, c) inactive days, and d) other MJO days categorically removed from the overall timeseries (blue line). The slope for trend lines are displayed within each panel. The title in a–d also shows the % contribution (ct) to the overall rainfall trend for each MJO category removed from the reconstruction.

There are very few reliable and long-term rainfall datasets over the Congo at daily or higher resolution. Furthermore, there is considerable spread amongst model (reanalysis) derived rainfall estimates over the Congo (e.g., Washington et al. 2013; Lee and Biasutti 2014; Alsdorf et al. 2016; Nicholson et al. 2018; Hua et al. 2019). Therefore, cloud cover is used as a proxy for thunderstorm and rainfall from a high-quality satellite dataset. Results obtained by applying Eq. 1 to the areal extent of cold cloud tops derived from the GridSat-B1 dataset concur with the findings using rainfall data (Fig. 4.7). As in Fig. 4.6, when compared to the overall cloud cover trend (−0.47%
decade$^{-1}$) from 1986–2018, the slope of the rainfall trend is practically unchanged with the removal of wet MJO days, 14% weaker with the removal of dry MJO days ($-0.40\%$ decade$^{-1}$), 8.4% stronger with the removal of inactive MJO days ($-0.51\%$ decade$^{-1}$), and 3.8% weaker with the removal of other MJO days ($-0.53\%$ decade$^{-1}$; Fig. 4.7).

**Figure 4.7:** Interannual variability and linear trend in the Oct–Mar areal extent of cold cloud cover (black line) with a wet day, b dry days, c inactive days, and d other MJO days categorically removed from the overall timeseries (blue line). The slope for trend lines are displayed within each panel. The title in a–d also shows the % contribution (ct) to the total cold cloud cover trend for each MJO category removed from the reconstruction.

4.5 Concluding Remarks
Since the MJO is an important dynamic-thermodynamic forcing operating on the seasonal/sub-seasonal timescale (e.g., Barnes et al. 2015; Madden and Julian 1972), this chapter aimed to study precipitation variability and trends from a seasonal/sub-seasonal prospective over the Congo by analyzing the role of the MJO. First, the overall climatological impact of the MJO on rainfall over the Congo using four MJO categories (i.e., wet, dry, inactive, and other) from Oct–Mar from 1979–2018 are explored in Figs. 4.1–3. The phasing of the tropical rainbelt over Africa with the different RMM phases of the MJO was also analyzed in Fig. 4.1c–d. The relationship between rainfall and the number of wet and dry MJO days (Fig. 4.4), and the interannual variability and trends in the MJO days (Figs. 4.5–7) suggests a non-trivial impact from the increase in the number of dry MJO days on the seasonal rainfall observed over the Congo. While changes in the large-scale circulation of the atmosphere and other teleconnections are important in determining rainfall trends over the Congo across decadal and multi-decadal timescales (e.g., Hua et al. 2016, 2018), this study demonstrates that trends and changes in seasonal/sub-seasonal variability (e.g., the MJO and other CCAEW; Raghavendra et al. 2019) in both the present and future climate are also equally important for the rainfall totals and overall wellbeing of the Congo rainforest.

The impact of the MJO on rainfall is quantified by evaluating the contribution from each of the four MJO categories to the overall seasonal rainfall trend. Though the Wheeler and Hendon (2004) MJO RMM index is not a direct measure of Congo rainfall, the algorithm used here uses Congo rainfall data to distinguish between the favored local moist or dry phases of the RMM index. While multiple rainfall and vegetation datasets shows a significant trend towards drier conditions (e.g., Zhou et al. 2014; Jiang et al. 2019), RMM index data suggest an increasing trend in the number of days in dry phases for equatorial Africa over time. Trends in the RMM data
compliment the large-scale drying over the Congo (e.g., Hua et al. 2016) even though the RMM index data implies little explicitly about Congo rainfall. In other words, changes in the MJO over time may explain some of the change in rainfall since the declining trend in rainfall is smaller if the dry MJO days were removed (Figs. 4.5–7).

Results suggest that the trends in the number of dry MJO days may contribute 13.6% to amplify the overall Oct–Mar declining rainfall trend over the Congo (Figs. 4.5–6). Since there are few products and large uncertainties for rainfall estimates over the Congo, cloud cover from the GridSat-B1 Tb dataset was used as a proxy for rainfall. The analysis of cloud cover suggests that the trends in the number of dry MJO days may contribute approximately 14.2% to the Oct–Mar fractional cloud cover trend over the Congo. While attributing precipitation to the MJO or other tropical waves is difficult since it is not possible to completely associate tropical rainfall with singular physical mechanisms, the long-term trends in the relationship between rainfall over the Congo and the impact of the MJO appear robust. Given the significant relationship between the MJO and rainfall over the Congo (Figs. 4.1–3), one may conclude that the rainfall trends observed over the Congo are at least partially enhanced by a significant increase in the number of dry MJO days.
Chapter 5: Dynamic Aspects of Orographic Enhancement of Rainfall Over the Congo Basin

Abstract

The Congo rainforest located in central equatorial Africa is surrounded by complex orographic features such as the East African highlands. A primitive understanding of precipitation processes such as mesoscale convective dynamics magnifies uncertainties in the future climate projections of the hydrological cycle over the Congo. Furthermore, the effects of orography is an important forcing for convection and precipitation are poorly resolved by climate models, and ill-conceptualized over the Congo. To address this knowledge gap, perturbed orographic forcing experiments are conducted using a high-resolution convection permitting mesoscale numerical model. Results show that the direct dynamical impact of the East African highlands includes blocking of the tropical easterlies, increasing the mid/lower tropospheric windshear, and intensifying the meridional channeled flow around the mountain. When compared to the experiment with reduced orography, the control run is characterized by a weaker zonal wind, enhanced meridional wind convergence over the Congo basin, and slower propagating and intense mesoscale convective systems with enhanced rainfall.

5.1. Introduction

Tropical rainforests are usually associated with copious amounts of rainfall (~2500 mm yr\(^{-1}\) over the Amazon rainforest; Adler et al. 2003). Fascinatingly, the second largest and one of the most understudied regions of the world i.e., the Congo located in equatorial Africa is also the driest (rainfall totaling ~1500 mm yr\(^{-1}\)) when compared to other major rainforests (Alsdorf et al. 2016; Zhou et al. 2014). The Congo rainforest exists despite the significantly lower rainfall amount, is
an important influence in the global carbon cycle, and the most vulnerable to climate change (Haensler et al. 2013; Malhi et al. 2013). In fact, even the general circulation models (GCMs) used in the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al. 2012) produce a large spread in the historic and future climate projections of precipitation over the Congo basin (e.g., Haensler et al. 2013; Washington et al. 2013). Some of these uncertainties may be attributable to the coarse representation of orography (Fig. 5.1) and mesoscale convective dynamics (e.g., Chen and Dai 2019; Dai 2006) in low-resolution datasets.

**Figure 5.1:** Topographical input data used in the a) WRF CTL run presented in this study, b) a typical GCM (e.g., CMIP5 models), and c) a higher-resolution GCM.
One of the biggest research puzzles includes the orographic modification of rainfall by the highlands surrounding the Congo basin. Orography plays a profound role as an atmospheric forcing. For instance, atmospheric flow over a mountain may result in atmospheric wave activity, flow blocking, cyclogenesis (lee cyclogenesis; e.g., Pontopiddan et al. 2019), and precipitation enhancement/suppression (e.g., Sotillo et al. 2003). Other factors that encourage the study of orography include micrometeorological constraints such as sunlight availability for photosynthesis for plants growing over mountainous regions (e.g., Motzer 2005). Over the Congo, there is still considerable debate on what role topographical features such as the Ethiopian highlands, Turkana channel, and East African Highlands play in channeling moisture from the Indian ocean into the Congo (e.g., Dyer et al. 2017; Sori et al. 2017), or whether these orographic features surrounding the Congo work to enhance or suppress thunderstorm activity and rainfall.

The Congo basin is often regarded as a “convective engine” of the global atmospheric circulation, and is the world’s lightning hotspot (Malhi et al. 2013). Furthermore, MCSs are the primarily source for rainfall across tropical Africa (Jackson et al. 2009; Taylor et al. 2018). While large scale influences of Africa’s orography have been investigated to understand the south east Asian Monsoon (Wie and Bordoni 2016), and the influence of the east African highlands on the atmospheric circulation, temperature and rainfall over Africa have been evaluated using numerical models (e.g., Slingo et al. 2005; Sommerfeld et al. 2016), many unanswered questions pertaining to mechanisms for MCS activity and rainfall over the Congo persist. Jackson et al. (2009) inferred that the combination of local topography in the surrounding highlands and wind anomalies play an important role in deriving interannual variability in convection and MCS activity over the
Congo basin. But, the association between rainfall and topography was based on empirical analyses of satellite observations and reanalysis data, which cannot directly clarify causality. This chapter seeks to narrow the knowledge gap by establishing a clearer understanding of the role that African orography plays in modulating MCS activity and rainfall over the Congo. In this study, a high-resolution convection permitting mesoscale numerical modeling framework is invoked. Since orography is the only perturbed field in such an experiment, changes in the atmosphere, convection, and rainfall characteristics may be predominantly attributable to orographic changes (e.g., Rasmussen and Houze 2016).

5.2. Model Setup

The NCAR Advanced Research Weather Research and Forecasting (ARW-WRF) model version 3.6.1 (Skamarock et al. 2008) was used to simulate a large mesoscale convective event that are frequently observed over the Congo. The EUMETSAT/ESA’s Meteosat-10 geostationary satellite observed MCSs characterized by a large spatial extent over the Congo basin on 05-Nov-2014 (see Fig. 5.2) and contained both large and small convective cells. A study of Meteosat-10 satellite images from the Global ISCCP B1 Browse System (GIBBS; Knapp 2008) infrared channel (~11μm) showed that a few isolated and relatively weak thunderstorm cells at 00:00 UTC on 05-Nov over the East African Highlands propagated westward and entered the lowlands of the Congo basin. Once over the Congo basin, these thunderstorm cells organized to form a large, quasi-linear shaped MCS between 12:00–18:00 UTC. On 06-Nov between the hours of 03:00–12:00 UTC, the MCS dissipated.
The model configuration for the simulations utilized the ARW-WRF version 3.6.1 run as a compressible, nonhydrostatic, and three-dimensional mesoscale model. The model was initialized with the European Centre for Medium-Range Weather Forecast (ECMWF) interim reanalysis (ERA-I; Dee et al. 2011) data at 00:00 UTC 02-Nov-2014 and ran continuously without spectral nudging for 120 hrs. (i.e., simulation ends on 00:00 UTC 07-Nov-2014) using a large domain [1300 (latitude) × 700 (longitude) grid points] at 4 km horizontal resolution centered around the Congo basin (Fig. 5.1a). The first 48 hours were reserved for model stabilization and spin-up, and a detailed evaluation of the simulations is presented from 12:00 UTC 05-Nov to 12:00 UTC 06-Nov. The simulation used 38 vertical levels with the finest resolution in the planetary boundary layer (PBL) and incorporated the following parameterization schemes which closely follows Rasmussen and Houze (2016): Longwave Radiation: Rapid Radiative Transfer Model (Mlawer et al. 1997), Shortwave Radiation: Dudhia (Dudhia 1989), Surface Layer: Revised MMR surface layer Scheme (Jimenez et al. 2012), Microphysics: Thompson 6-class scheme with graupel, double moment for cloud ice, (Thompson et al. 2008), Land Surface: Noah Land Surface (Chen and Dudhia 2001), and PBL: Yonsei University PBL (Hong et al. 2006). Given the relatively high horizontal resolution, convection was explicitly resolved, and a cumulus parameterization scheme was not invoked.

Three simulations including the control run (CTL) were conducted using the ARW-WRF model. The CTL run followed the model setup previously described in this section and utilized the USGS (U.S. Geological Survey) topography and land classification. Two perturbation runs were setup in a manner identical to the CTL run with the exception of the input orography file. The model run with a 50% lower orography (TOPO_{50%}) compared to the CTL was supplied with a
modified topography file where the African orography was multiplied by 0.5 and smoothened once using 10 grid points in each direction. The result closely resembles the input orography file for a typical GCM (Fig. 5.1b). On the other hand, the model run with a 50% higher orography (TOPO_{150%}) compared to the CTL was supplied with a modified topography file where the African orography was multiplied by 1.5. The differences in the topographical input for the three model runs may be visualized in Fig. 5.2.

5.3. Model Validation

Geostationary satellite derived gridded infrared (IR) channel brightness temperature (Tb) from the GridSat-B1 dataset (Knapp et al. 2011) available at a 0.07-degree horizontal grid at 3-hr temporal resolution was used to validate the spatial extent and timing of the MCS simulated by the WRF model. The WRF model derived outgoing longwave radiation (OLR) data was converted to radiative temperature to simplify the comparison between the satellite and model data. Studying the spatial patterns and temporal evolution of the MCSs observed by the GridSat-B1 data, and MCSs and rainfall simulated by the WRF model provides snapshots to validate the CTL run. Figure 5.2 shows the spatial extent and intensity of convective activity from the observations and three model runs for five timesteps. A qualitative analysis of the OBS and CTL images shows that the CTL run is able to reasonably reproduce the major features including the location, development, and propagation of thunderstorms from OBS. The NNW-SSE oriented quasi-linear squall line over the Congo at 12:00 UTC on 05-Nov in the OBS is simulated with a WNW-ESE orientation in the CTL run. At 18:00 UTC on 05-Nov however, the MCSs are reasonably well captured in the CTL run. A single organized thunderstorm cluster located near the eastern edges of the Congo at 00:00 UTC on 06-Nov in the OBS is simulated as multiple scattered thunderstorm
cells across the Congo. A significant reduction in thunderstorm activity during the morning hours of 06:00 to 12:00 UTC on 06-Nov are well-captured in both the OBS and CTL run. Some deviations from observations are expected in the CTL run since it is unrealistic to expect a model initialized and forced with a coarser resolution reanalysis data to reproduce observations without some degradation. Furthermore, the WRF model is sensitivity for the choice of parameterization schemes invoked, and spectral nudging which forces the WRF model output closer to the input data was not incorporated (e.g., Stratton et al. 2018).
Figure 5.2: The evolution of MCSs diagnosed using cold cloud top $T_b$ over equatorial Africa shown every 6-h from 12:00 UTC on 05-Nov to 12:00 UTC on 06-Nov 2014 from GridSat-B1, and CTL, $TOPO_{50\%}$ and $TOPO_{150\%}$ runs. Zonal and meridional wind vectors from ERA-I.
(800 to 500 hPa layer mean for OBS) and the WRF model (2 to 5 km layer mean) are also displayed. Color bars for orography (in meters) and brightness temperature (in °C) are displayed below the figure.

A Hovmöller diagram (Fig. 5.3a–e) was also constructed to evaluate the CTL run against the satellite observations. Unlike the spatial comparison of thunderstorms in Fig. 5.2, the Hovmöller diagram allows for the comparison of timing and propagation characteristics of thunderstorms between the OBS and CTL run. The primary MCS analyzed in this study is well-represented in the OBS and CTL run starting at 12:00 UTC on 05-Nov near 22°E. The thunderstorm cells propagate westward and linearly in time starting from about 22°E to 12°E over a 24-hour period. The propagation characteristics of thunderstorms are analogous between the OBS and CTL run. Furthermore, there is a significant correlation ($R = 0.86$) in the time evolution of cold cloud over the Congo (Fig. 5.3h). As in the OBS, the CTL run also reproduces the tropical diurnal cycle of thunderstorm activity over land. Due to the sparse surface observation network over the Congo (Washington et al. 2013), calibrated precipitation estimates from the Integrated Multi-satellitE Retrievals for GPM (IMERG; Huffman et al. 2019a) available at 0.1-degree horizontal grid at 30-min temporal resolution (Huffman et al. 2019b) was also used for additional model validation (Fig. 5.3c–e). The time evolution of rainfall between the OBS and CTL run was also significantly correlated ($R = 0.73$). Given the strong relationship between convective activity and rainfall, the differences in rainfall between the OBS and CTL run closely follow the differences in the spatial extent of convective activity (Fig. 5.3a–b). In summary, Figs 5.2–3 demonstrates that the WRF model performs reasonably well in capturing the MCSs which occurred between 05-Nov to 06-Nov-2014. Additional methods to validate the model output with observations is challenging.
over the Congo due to the lack of high-frequency surface or air/space-borne observations (Washington et al. 2013; Alsdorf et al. 2016), and the inability to properly resolve mesoscale events and precipitation characteristics even in the latest high-resolution reanalysis products such as ERA-5.
**Figure 5.3**: Hovmöller diagrams showing the longitude-time evolution of $T_b$ from a) GridSat-B1 and b) OLR from the $CTL$ run, rainfall from c) IMERG, d) $CTL$ run, e) $CTL$ run − IMERG, f) $TOPO_{50\%} − CTL$ run, and g) $TOPO_{150\%} − CTL$ run. h) Spatial extent of cold clouds. All data was spatially averaged between $5°N/S$ and $12°$ to $28°$.

### 5.4. Results

The orographic impacts on the circulation and precipitation characteristics between the CTL, $TOPO_{50\%}$, and $TOPO_{150\%}$ runs are presented in this section in three sub-parts. In section 4.1, the horizontal structure of lower tropospheric winds, thunderstorms, and thunderstorm propagation characteristics are analyzed using OLR and rainfall. Differences in the vertical (height–longitude) cross sectional view of winds, specific humidity, and precipitation are analyzed in section 4.2. Finally, the dynamic impact attributable to horizontal and vertical windshear is presented in section 4.3.

#### 5.4.1 Horizontal extent of MCS activity

Differences in the horizontal extent of thunderstorms and their intensity between the three WRF model runs are illustrated in Fig. 5.2. At all timesteps, the $TOPO_{50\%}$ run produces fewer and weaker thunderstorms, while the $TOPO_{150\%}$ run is characterized by stronger and more intense thunderstorms. Thunderstorms in the $TOPO_{50\%}$ run generally propagate the fastest, while thunderstorms in the $TOPO_{150\%}$ run are slower moving. The differences in the propagation speed of thunderstorms between the three model runs may be explained by studying the lower tropospheric winds. In Fig. 5.2, the $TOPO_{50\%}$ run is characterized by faster lower tropospheric zonal winds, and weaker meridional winds when compared to the $TOPO_{150\%}$ run. This difference
may be attributable to a reduction in the blocking of the tropical easterlies by the east African highlands in the TOPO$_{50\%}$ run. The faster zonal winds in the TOPO$_{50\%}$ run helps steer the thunderstorms cells relatively quickly across the Congo basin. The differences in the propagation characteristics are also visible in the Hovmöller diagrams (Fig. 5.3e–g) which show rainfall leading in time for the TOPO$_{50\%}$ run and lagging in time for the TOPO$_{150\%}$ run. The weaker thunderstorm cells in the TOPO$_{50\%}$ run also produce less rainfall, and the TOPO$_{150\%}$ run appears to produce higher rainfall when compared to the CTL run (e.g., Slingo et al. 2005; Rasmussen and Houze 2016; Sommerfeld et al. 2016). A 50% reduction and smoothening of orography appears to play a stronger role when compared to a 50% increase in orography.

A secondary effect caused by blocking the lower tropospheric easterly flow is the enhanced meridional wind convergence over the Congo basin in the TOPO$_{150\%}$ run when compared to the TOPO$_{50\%}$ run. The increase in the meridional flow may be attributable to mountain blocking and circumventing flow around the east African highlands. The increase in lower level mass convergence in an already moist tropical environment will enhance the low-level moisture flux convergence, which is an important ingredient for thunderstorm activity (e.g., Cloutier-Bisbee et al. 2019). This is explored in more detail in section 4.3.

5.4.2 Vertical cross-sectional analysis and rainfall

The longitudinal-height cross section of precipitation (rain+ice) particle number concentration, zonal and vertical winds, and specific humidity are presented in Fig. 5.4. The cross-section was evaluated by averaging 10 latitude points across the equator. The most pronounced differences between the CTL, TOPO$_{50\%}$, and TOPO$_{150\%}$ runs are the intensity and diameter of the
precipitation shaft which is proportional to the orographic forcing, and the strength and propagation of the convective updrafts and downdrafts. The \( \text{TOPO}_{150\%} \) run is characterized by a stronger and wider precipitation shaft, and consequently produces the largest rainfall when compared to the \( \text{TOPO}_{50\%} \) run. Reinforcing the larger rainfall amounts in the \( \text{TOPO}_{150\%} \) run is the slower propagation speed of the rain shaft when compared to the \( \text{TOPO}_{50\%} \) run. When compared to the CTL run, the lower rainfall in the \( \text{TOPO}_{50\%} \) run leads in time whereas the higher rainfall in the \( \text{TOPO}_{150\%} \) run lags in time. This difference in the propagation speed of the thunderstorm cells are also visible in the Hovmöller diagrams (Fig. 5.3f–g). The rainfall at each time step and integrated over time are presented in Fig. 5.5a–b. As shown in Figs. 5.2–4, larger MCSs between 15:00 UTC on 05-Nov and 12:00 UTC on 06-Nov produce rainfall at the surface, and higher rainfall amounts are produced in the \( \text{TOPO}_{150\%} \) run when compared to the \( \text{TOPO}_{50\%} \) run (Fig. 5.5a–b). The slower propagating, and larger and more intense rain shaft in the \( \text{TOPO}_{150\%} \) run results in an enhancement of rainfall accumulation over the Congo basin when compared to the \( \text{TOPO}_{50\%} \) run.
Figure 5.4: Longitude-height cross section along the equator showing the rain/ice particle number concentration (shaded), specific humidity \((g \, kg^{-1})\), grey contour), zonal and vertical wind \((\times 10)\).
vector, the freezing level (dotted blue line), and rainfall (mm; blue bars along the x-axis) for the 
\(CTL, TOPO_{50\%}\), and \(TOPO_{150\%}\) runs.

5.4.3 An analysis of vertical windshear

Vertical windshear is an important ingredient for the maintenance and longevity of an MCS 
(e.g., Coniglio et al. 2010; Chen et al. 2015; Taylor et al. 2018). The time evolution of the \(~5\) km 
and \(~2\) km tropospheric horizontal winds are presented in Fig. 5.5c–h. Here, a quantitative analysis 
is provided to support the qualitative descriptions of the atmospheric circulation in sections 4.1–
4.2. For the period 12:00 UTC 05-Nov to 12:00 UTC 06 Nov: The magnitudes of the time mean 
zonal windshear for the \(TOPO_{50\%}\) run is 1.0 ms\(^{-1}\), and \(TOPO_{150\%}\) run is 4.9 ms\(^{-1}\). This result points 
to a mean increase of 3.9 ms\(^{-1}\) in the zonal windshear between the low and high orography runs 
(Fig. 5.5g–h). On the other hand, the magnitudes of the time mean meridional windshear for the 
\(TOPO_{50\%}\) run is 2.2 ms\(^{-1}\), and \(TOPO_{150\%}\) run is 3.1 ms\(^{-1}\). This results in a small increase in the 
mean meridional windshear by 0.9 ms\(^{-1}\) with higher orography (Fig. 5.5c–h). Changes in the zonal 
wind is stronger and likely more important than the smaller changes in the meridional winds in the 
three model runs. At the upper levels, there is a narrow spread in the mean wind speed between 
the three runs and ranges between 7.7 to 8.0 ms\(^{-1}\). However, the mean wind speed for the lower 
level for the three runs shows a larger spread and ranges between 3.1 to 8.8 ms\(^{-1}\) (Fig. 5.5g). Not 
surprisingly, the \(TOPO_{50\%}\) run is characterized by the largest lower level winds due to the absence 
of mountain blocking. Consequently, the \(TOPO_{50\%}\) produces the weakest mean vertical windshear 
of -1.0 ms\(^{-1}\), while the \(TOPO_{150\%}\) run produces the strongest mean vertical windshear of 4.2 ms\(^{-1}\) 
(Fig. 5.5h). The enhanced MCS and rainfall in the \(TOPO_{150\%}\) run is at least partially attributable 
to the increase in vertical windshear which de-couples the thunderstorm updraft downdraft pair
and disallows the weakening of the updraft by the downdraft. This decoupling of the thunderstorm updraft downdraft pair during the mature phases of the thunderstorm’s lifecycle prolongs the duration of the thunderstorm and allows the thunderstorm to potentially evolve into a complex and well organized MCS (e.g., Marion and Trapp 2019).
**Figure 5.5:** a) Hourly and b) accumulated rainfall, c–d) Zonal and e–f) meridional wind at ~5 km and 2 km, g) wind magnitude at 5 km (solid line) and 2 km (dashed line), and h) windshear. Data was spatially averaged between 5°N/S and 12 to 28°E and shown from 00:00 UTC on 05-Nov to 00:00 UTC on 07-Nov-2014.

**5.5 Discussion and Conclusions**

In this study, a large MCS event over equatorial Africa is simulated using WRF at a convection-allowing resolution to investigate the dynamic aspects of perturbing orography. Only a single case study was presented due to the computational expenses associated with convective permitting high-resolution simulations, and the variability in the quality of the simulation when compared to satellite observations. But the sensitivity of rainfall and other dynamic changes over the Congo basin to orographic changes from five other extreme MCS case studies, which were forced using different initial and boundary conditions produced similar results (Fig. 5.6). Therefore, the reduction in rainfall in the TOPO50% run when compared to the CTL run is most likely a systematic change driven primarily by orographic forcing and not some random chaotic development in the WRF model with sensitive dependence on initial conditions (Lorenz 1963).
Figure 5.6: Hourly rainfall from five extreme MCS events over the Congo basin from the CTL and \( \text{TOPO}_{50}\% \) runs. The data was spatially averaged between 5\(^\circ\)N/S and 12 to 28\(^\circ\)E. The WRF model simulation were initialized three days prior to the day of the event in a manner identical to the primary case study analyzed in this article (see section 2).

Given the poor representation of orography in GCMs (Fig. 5.1), the purpose of this study is to fill an important knowledge gap by highlighting the important relationship between African orography and rainfall over the Congo basin. While the complex orographic features surrounding
the Congo basin have been suggested to play some role in modulating thunderstorms and rainfall (Jackson et al. 2009), the physical mechanisms have not been previously investigated. This work provides a detailed dynamic assessment of orography, and the overall results complement previous studies such as Slingo et al. (2005) and Sommerfeld et al. (2016). In summary, decreasing the orography reduces the convective intensity and rainfall amount. The direct dynamical impact of the African orography which includes blocking of the tropical easterlies, increasing the vertical windshear, and intensifying the channeled flow (meridional wind) around the mountain. The weaker zonal wind and increased meridional wind convergence act to increase windshear (Fig. 5.2), likely increases the lower level moisture flux convergence (e.g., Cloutier-Bisbee et al. 2019), and producing slower propagating well-sheared (e.g., Marion and Trapp 2019) intense MCSs (Figs. 5.3–4) that enhances rainfall (Fig. 5.5) over the Congo basin.
Chapter 6: Concluding remarks

In this dissertation, insights from the limited scientific literature and research over the Congo basin were used to broaden our understanding of rainfall variability and trends over the Congo. This study is primarily motivated by recent findings that show a long-term and large-scale drying trend over the Congo basin (e.g., Zhou et al. 2014; Hua et al. 2016; Jiang et al. 2019). The final chapter of this dissertation restates the hypotheses from Chapter 1, summarizes the results reported in Chapters 2–5, provides some clarifications pertaining to the major results, and includes a future work section containing some on-going efforts which may be partially attributable to this dissertation work within the Liming Zhou Research Group at the University at Albany.

In this dissertation, numerous seasons were studied and include April–June in Chapter 2, all 12 months in Chapter 3, October–March in Chapter 4, and case studies during the month of November in Chapter 5. The seasons were chosen for specific reasons which are summarized here. Thunderstorms were evaluated during the April–June to investigate the drying trend presented for the same season in Zhou et al. (2014). An investigation with possible mechanisms for all seasons in a year are presented in a recent study by Alber et al. (2020). All 12-months were analyzed in Chapter 3 given the large-scale study region lying between the tropical latitudes. The MJO was studied during the northern hemispheric winter months of October–March in Chapter 4 since the MJO signal is relatively weak and difficult to study during the summer months. In Chapter 5, November was chosen to select the case studies since the lower tropospheric zonal wind speed over the African highlands is strongest during this month.
**Revisiting Chapter 2:** Central Africa is one of the most convective regions of the world and characterized by intense thunderstorm activity (Zipser et al. 2006). Since thunderstorms are convective systems accompanied by the occurrence of lightning, the Congo is known as the thunderstorm and lightning capital of the world (Cecil et al. 2015). Because most of the accumulated rainfall in tropical latitudes originates from convective type precipitation (Dai 2006), large changes in atmospheric convection activities are expected to have significant impacts on rainfall patterns over this region. Understanding such changes could provide insights into observed variations in rainfall characteristics and future rainfall trends in a warming climate over Africa, one of the most vulnerable continents to climate change and climate variability (Maidment et al. 2015).

On a related note, there are important distinctions between thunderstorms and MCSs. All MCSs are thunderstorms, but the reverse is not true. MCSs are generally larger (>25,000 km²) convective systems which last over 6-hrs. While thunderstorm activity has increased over the Congo, preliminary work by the author of this dissertation suggests the rain bearing MCS activity has decreased over the Congo basin. Also, there appears to be a weak relationship between the strength of the convection and surface rainfall. More work is therefore necessary to improve our understanding of rainfall, convective systems, and related physical mechanisms over the Congo basin (Alber et al. 2020).

**Hypothesis #1:** The long-term significant decrease in rainfall observed during AMJ and associated decline in vegetation may be attributable to a decrease in thunderstorm activity. This decrease in thunderstorms results in lesser surface rainfall.
**Findings:** Thunderstorm activity has increased over the Congo basin from 1982–2016. In fact, thunderstorms have become more intense, frequent, and larger in size (Raghavendra et al. 2018). However, studies from spaceborne observational datasets i.e., TRMM suggest that the tallest and most intense thunderstorms do not produce the largest rainfall, and there exists a weak linkage between the tallest thunderstorms and heaviest rainfall (Hamada et al. 2015).

**Future Work:** By applying a thermodynamic index, i.e., the Gálvez-Davison index, which can more accurately measure thunderstorm potential over the tropical latitudes, mechanisms responsible for the long-term intensification of thunderstorms and reduction of rainfall over the Congo are presently being investigated (Alber et al. 2020). Parallely, TRMM data in conjunction with the rainfall and storm classification data from the University of Washington TRMM Database (UWD; trmm.atmos.washington.edu) are being analyzed to better our understanding of thunderstorm, rainfall, and lightning activity over the Congo.

**Revisiting Chapters 3 and 4:** One of the most intriguing phenomena observed over the tropical latitudes includes the presence of a wide spectrum of tropical waves. Given the complexity of dynamics composing the tropical circulation, it is necessary to study the tropics separately from the mid-latitudes (Holton and Hakim 2013). Unlike the mid-latitudes that are mostly dominated by Rossby wave dynamics, the tropical latitudes contain many different disturbances such as equatorial Rossby (ER) waves, Kelvin waves, mixed Rossby gravity (MRG) waves, Madden–Julian oscillation (MJO; Madden and Julian 1971, 1972), and tropical depression-type disturbances (TDs). Furthermore, mid-latitude dynamics are relatively better understood and explained using
models such as the quasi-geostrophic framework, but a similar parallel and concise dynamic–thermodynamic framework to understand tropical dynamics does not exist yet. Since these waves are strongly linked to the dynamics observed in the Earth’s atmosphere, understanding how these waves may have/continue to change will help better understand atmospheric convection, precipitation characteristics, and energy redistribution.

A conscious effort was made to study the MJO in more detail over other atmospheric tropical waves due to the lack of a consensus of the MJO over central equatorial Africa. While recent works such as Schlueter et al. (2019a, b) suggest that the MJO plays a smaller role compared to other CCAEW, other works such as Pohl and Camberlin (2006a) and Pohl et al. (2018) show that the MJO is a relatively important forcing for rainfall variability over East Africa. These diverging opinions may be attributable to different methods used to characterize the MJO. In Chapter 3, the Wheeler and Kiladis (1999) frequency-wavenumber power spectrum method was used to study all CCAEW. The inter-annual variability shows a decrease in spectral power, which points to a decrease in MJO variance, and likely indicates reduced MJO associated convective activity globally. Over the Congo basin however, the trends in variance are mostly non-significant. Therefore, in Chapter 4, the Wheeler and Hendon (2004) principle component analysis technique was used to describe the intensity and propagation characteristic of the MJO, and a significant relationship between MJO activity and rainfall was found over the Congo basin.

**Hypothesis #2a:** Interannual variability and trends in the frequency, intensity, and duration of CCEW and the MJO plays an important role in determining the enhancement and suppression of thunderstorm activity over the Congo.
**Findings:** The results suggest a weakening trend in spectral power characterized by high interannual variability for wave activity occurring in the low-frequency part of the spectrum and a steady increase in power with relatively low interannual variability for wave activity occurring in the high-frequency part of the spectrum. The results show the parts of the spectrum representing the MJO and equatorial Rossby wave losing power and other parts of the spectrum representing Kelvin waves, mixed Rossby–gravity waves, and tropical disturbance–like wave activity gaining power.

**Future Work:** The interannual variability of Kelvin waves and rainfall over the Congo was presented in Sinclair et al. (2015). Schlueter et al. (2019a, b) studies the relationship between CCAEW and rainfall over northern Africa. However, the relationship between trends in rainfall and CCAEW activity is still ripe for research. For instance, the Gálvez-Davison index contains a mid-tropospheric warming index, which represents destabilization of the atmosphere by ridges and troughs. Therefore, long-term trends in CCAEW (especially symmetric waves such as Kelvin waves and equatorial Rossby waves) likely plays a non-trivial impact on convective activity over the Congo basin.

**Hypothesis #2b:** A decreased occurrence of MJO wet phases and an increased occurrence of MJO dry phases over the Congo is partially responsible for the enhancement of the drying trend over the Congo.
**Findings:** Results show a significant correlation between the number of wet and dry MJO days, and rainfall enhancement and suppression over the Congo. While there exists considerable interannual variability in MJO activity and rainfall over the Congo, there is a significant increase in the number of dry MJO days ($3.47 \text{ days decade}^{-1}$) which tends to intensify the large-scale drying trend over the Congo during October–March. The increasing trend in the number of dry MJO days is likely enhancing the net drying trend by 13.6% over the Congo.

**Future Work:** The approach described in Raghavendra et al. (2020) which establishes the relationship between the MJO and Congo basin rainfall should be used to assess the importance of other CCAEW. Also, the findings reported in Chapter 5 are consistent with previous works (e.g., Pohl and Camberlin 2006b), and the MJO may significantly enhance or suppress rainfall over the Congo. Therefore, studying such interactions from a present and future climate prospective is crucial to improving our understanding of future climate projections of rainfall and ecology over the Congo rainforest. It is however difficult using existing climate models (e.g., the models used in CMIP5) which are unable to properly simulate large-scale disturbances such as the MJO (Hung et al. 2013). This will remain as a big challenge to predict the future climate over the Congo until climate models are significantly improved to simulate tropical rainfall and its interaction with the rainbelt, and able to simulate modes of tropical variability such as the MJO and other CCAEW.

**Revisiting Chapter 5:** African orography is complex, and few studies have alluded to the role of African orography on atmospheric flow and precipitation over Equatorial Africa (e.g., Slingo et al. 2005). However, the large spatial scale of the East African highlands which stretches over 1500 km, and the strong diurnal temperature and associated regional wind response (e.g., upslope and
downslope flow across a mountain) over the Congo basin may potentially have a direct impact on MCS initiation and development. Besides sparse yet motivating evidence from reanalysis and climate models (e.g., Jackson et al. 2009; Munday and Washington 2018), no study to the author’s knowledge has established the dynamics and thermodynamics alteration attributable to the orography surrounding the Congo basin. As shown over other regions such as South America (e.g., Rasmussen and Houze 2016), orography may act to increase the convective available potential energy (CAPE) and thus produce an environment favorable for MCS initiation and development.

Studies such as Dyer et al. (2017) and Sori et al. (2017) have demonstrated the relatively high-water recycling ratio of ~30% over the Congo basin, and a large seasonally dependent moisture contribution for different parts of the Indian ocean using climate models and reanalysis datasets. But there exists a lack of clarity regarding the degree to which the direct injection of moisture advected from different Ocean basins into the Congo rainforest may enhance rainfall over the Congo. Following some of the conclusions regarding the direct relationship with orographic height and CAPE from Rasmussen and Houze (2016), there is a possibility that the Congo rainforest may not be as sensitive to moisture transport from the Indian ocean as suggested by Dyer et al. (2017) and Sori et al. (2017), and large amounts of preexisting moisture over the tropical latitudes (including over the Congo basin) may precipitate from the atmosphere via rainfall generated by MCSs. An environment that will likely produce more MCSs and rainfall include anomalously strong westward winds which helps generate greater windshear over equatorial Africa (especially over the Congo), and thus promotes the transformation of ordinary thunderstorms into MCSs. A mesoscale, high-resolution, convection allowing numerical modeling
framework with perturbed orography was used to investigate the orographic modification on rainfall over the Congo.

The large amounts of pre-existing tropical moisture and the high-water recycling ratio over the Congo (Dyer et al. 2017) may be the cause for significant differences between the leeward precipitation characteristics for a tropical mountain compared to a mid-latitude mountain. A typical mid-latitude mountain such as the Rockies or Andes blocks moisture over the windward side resulting in a rain shadow across the leeward side of the mountain (Houze 2012). This is however not true over the tropical Congo rainforest. From a dynamic standpoint, the Coriolis parameter may also play a role in the mid-latitudes but is negligible over the tropical latitudes ($f = 0$). Therefore, while an increase in rainfall may be expected with a decrease in orography over the Congo, the results from Chapter 5 indicate otherwise and illustrate some differences between a tropical and mid-latitude mountain.

**Hypothesis #3**: The Congo rainforest is surrounded by complex orographic features. The orographic modification of the atmospheric flow plays a critical role in producing an environment conducive for MCS development over the Congo.

**Findings**: Perturbed orographic forcing experiments conducted using a high-resolution convection permitting mesoscale numerical model show that the direct dynamical impact of the East African highlands includes blocking of the tropical easterlies, increasing the mid/lower tropospheric windshear, and intensifying the meridional channeled flow around the mountain. The weaker zonal
wind and enhanced meridional wind convergence over the Congo basin produces slower propagating and intense mesoscale convective systems with enhanced rainfall.

**Future Work:** The Congo basin acts as a catchment zone, and the complex orography and vegetation distribution making up the Congo basin (Runge 2007; Zhou et al. 2014; Alsdorf et al. 2016; Jiang et al. 2020) results in substantial difference between the Congo river basin (watershed) and the Congo rainforest. The watershed is larger and includes nine riparian countries, including the relatively arid southern Congo basin. The rainforest on the other hand refers to the region that encompasses the humid tropical region with relatively higher rainfall amount (Runge 2007; Alsdorf et al. 2016). Therefore, the spatial distribution of rainfall plays an important role in determining the hydrology (e.g., water table, soil moisture, and runoff) and ecology of the Congo basin. Therefore, investigating this complex relationship between the spatial distribution of thunderstorm activity, rainfall, and vegetation could potentially lead to a better understanding of observed long-term drying trend and future of the Congo rainforest. These hydrological properties of the Congo basin could be further investigated by using models such as WRF-Hydro® (Gochis et al. 2020).

Finally, improving the horizontal resolution and the representation of orography in GCMs (e.g., Chen and Dai 2019; Dai 2006), or incorporating high-resolution regional climate models (e.g., Future Climate for Africa FCFA, Improving Model Processes for African Climate - IMPALA project; Stratton et al. 2018) will significantly improve our understanding of the hydrological cycle and reduce uncertainties of future climate projections over the Congo. Future work includes the statistical and composite analysis using the IMPALA data to identify mechanisms (e.g., low-level
jet, thermodynamic stability, and windshear) responsible for high and low convective events for each season for both the present and future climates. Finally, the dynamical changes linked to perturbing orography also results in microphysical changes such as the orographic seeder–feeder mechanism (e.g., Wilson and Barros 2014) which act to enhance rainfall and should be analyzed in future studies. In conclusion, it is likely that the Congo rainforest may not have existed without the orography (especially the East African highlands; E.g., Slingo et al. 2005; Sommerfeld et al. 2016) surrounding the Congo basin.

Rainforests such as the Congo play in important role in the Earth’s climate system. The destruction and decline of world’s rainforests have many negative ramifications. Therefore, the browning of vegetation and long-term/large-scale drying trend over the Congo is of global concern. Furthermore, the lack of reliable and long-term surface observations and research initiatives over the Congo basin has resulted in a significant knowledge gap and considerable research opportunities (Alsdorf et al. 2016; Washington et al. 2013). This dissertation work answers some factors that partially explain rainfall variability and trends over the Congo. At long-term (>30-years) analysis of both mesoscale and large-scale synoptic/dynamic atmospheric features helped address the broader knowledge gap over the Congo basin. Finally, this dissertation work also outlines a few on-going and future research opportunities to further our knowledge over the Congo basin.
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135


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