REGIONAL HYDRO-CLIMATIC IMPACTS OF CONTEMPORARY AMAZONIAN DEFORESTATION

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A DISSERTATION
PRESENTED TO THE FACULTY
OF PRINCETON UNIVERSITY
IN CANDIDACY FOR THE DEGREE
OF DOCTOR OF PHILOSOPHY

RECOMMENDED FOR ACCEPTANCE
BY THE PROGRAM IN
ATMOSPHERIC AND OCEANIC SCIENCES
ADVISER: DAVID MEDVIGY

NOVEMBER 2016
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Abstract

More than 17% of the Amazon rainforest has been cleared in the past three decades triggering important climatological and societal impacts. This thesis is devoted to identifying and explaining the regional hydroclimatic impacts of this change employing multidecadal satellite observations and numerical simulations providing an integrated perspective on this topic.

The climatological nature of this study motivated the implementation and application of a cloud detection technique to a new geostationary satellite dataset. The resulting sub daily, high spatial resolution, multidecadal time series facilitated the detection of trends and variability in deforestation triggered cloud cover changes. The analysis was complimented by satellite precipitation, reanalysis and ground based datasets and attribution with the variable resolution Ocean-Land-Atmosphere-Model.

Contemporary Amazonian deforestation affects spatial scales of hundreds of kilometers. But, unlike the well-studied impacts of a few kilometers scale deforestation, the climatic response to contemporary, large scale deforestation is neither well observed nor well understood. Employing satellite datasets, this thesis shows a transition in the regional hydroclimate accompanying increasing scales of deforestation, with downwind deforested regions receiving 25% more and upwind deforested regions receiving 25% less precipitation from the deforested area mean. Simulations robustly reproduce these shifts when forced with increasing deforestation alone, suggesting a negligible role of large-scale decadal climate variability in causing the shifts. Furthermore, deforestation-induced surface roughness variations are found necessary to reproduce the observed spatial patterns in recent times illustrating the strong scalesensitivity of the climatic response to Amazonian deforestation. This phenomenon, inconsequential during the wet season, is found to substantially affect the regional hydroclimate in the local dry and parts of transition seasons, hence occurring in atmospheric conditions otherwise less conducive to thermal convection. Evidence of
this phenomenon is found at two large scale deforested areas considered in this thesis. Hence, the ‘dynamical’ mechanism, which affects the seasons most important for regional ecology, emerges as an impactful convective triggering mechanism. The phenomenon studied in this thesis provides context for thinking about the climate of a future, more patchily forested Amazonia, by articulating relationships between climate and spatial scales of deforestation.
Acknowledgements

My decision to pursue atmospheric science research was greatly influenced by a chance interaction with drought displaced farmers of central India. Because I have never been able to formally acknowledge their contribution towards my PhD elsewhere, I’d like to do it now, first and foremost. I can never forget how they stirred me up with their plightful yet unbroken spirit to overcome all odds - reminds me of ‘The seventh horse of the Sun’ by Hindi writer Dharamvir Bharti, narrating the story of the downtrodden class which rises above its circumstances and drives the society forward. Climate change refugees, drought had bereaved these people of their homeland. I can’t forget their contempt for the injustice they received from the developing world, which was looting them of their natural resources and homes, carefully preserved by their forefathers. One can not but feel guilty about such a situation, so did I. It is my sincere wish that I can make my life geared towards safeguarding their voice and interests.

Thanks to David, my thesis advisor, who has made this tough journey possible for me. I was his first student, and we learnt many a lessons together, but he still handled a novice me with utmost perseverance. I have learnt from him more than I have from any of my other teachers or mentors. Thanks to him for helping me evolve from a student in to a scientist. I am also thankful to him for giving me this chance to experience learning at a great institution like Princeton University which was certainly the best academic experience I ever got.

On the same note, I sincerly thank Prof Robert Sica who was my Master’s advisor at University of Western Ontario, Canada. I thank him for giving me the golden opportunity to enter and experience the western World, for giving me the first flavor of atmospheric science research and for enthusiastically supporting me to explore new academic opportunities in North America. The inception of this journey would not be possible without him.
My committee members Kirsten Findell, Stephan Fueglistaler and Elie Bou Zeid have been a great support throughout!! I can’t thank them enough for the scientific, academic and moral support they so earnestly provided. They brought in diversity of thought and helped me address several nuanced details in my PhD projects. There off course were several times of distress in the past five years but they always provided me comfort and motivation to move forward in such times.

Stephan proved to be a great mentor to me. I can’t emphasize enough his instrumental contributions to my overall PhD experience. He brought me back on track whenever I veered. His scientific contribution to my research projects is invaluable. My heartfelt thanks to him. I hope many more students will benefit from his farsightedness and compassion for them.

Thanks also to Prof Eric Wood, who served as a committee member for the first two years of my PhD. His role was instrumental in making me realize the science direction I ultimately chose to pursue. I thank him for his stern scrutiny of my pre-generals work which helped me better evaluate my scientific goals.

Thanks to Dr Walko who provided a key technical support in my pursuit of understanding the World of numerical modeling. His inputs proved to be crucial in understanding certain aspects of my numerical simulations which I had previously overlooked. Needless to say, I benefited quite a bit from his experience in the field.

I thank the National Science Foundation for funding me throughout the course of my PhD. Thanks also to the computational resources supported by the PICSciE OIT High Performance Computing Center and Visualization Laboratory at Princeton University who provided the technical support in performing mammoth numerical tasks.

I thank all the administrative staff, in the Program in Atmospheric and Oceanic Sciences and the department of Geosciences - Anna Valerio, Laura Rossi, Joanne Curcio, Sheryl Robas, Dawn Reading, Georgette Chalker, Eva Groves, David Luet,
Doreen Sullivan, Mary Rose - whose contribution in making our office lives easier cannot be overemphasized. I thank all my friends I made at Princeton - Arnab da, Shaoni, Jahnavi, Tejal, Rakeshji, Ashu, Atri da, Lipi boudi, Sucharit da, Urmi - words really fall short in describing your contributions. My extraordinary group members Anna Trugman, Xiangtao, Youmi, Annette and Jennifer - thanks for being such great friends and thanks for making our lab the most envied lab in the program!! Geeta, Hannah, Todd, Jeff, Junyi and Spencer - although I did not get to spend a lot of time with you guys but I will always feel proud of being a part of this fun group. I have never had a better cohort than I did at Princeton.

Pathikrit (Path), my partner, is credited for breaking and making me and I will forever be indebted to him for that. I can’t explain what I mean by this phrase in three pages, so I wont even dare try. I just hope he will never give up on me.

Mueed bhai needs a special mention amongst all the friends Path and I made at Princeton. Calling him friend will be understating his importance in our lives - he is family. Thanks Mueed bhai!!

Thanks to Path’s parents who spared Pathikrit to be a part of my life and supported us in our academic pursuits.

My immediate family - my ma, papa and Rishi bhaia - thanks for giving me a beautiful childhood and keeping faith in me when I left the nest. Thanks for trusting mine and Path’s decisions over the past eleven years and sharing our dreams of a better future with us. Most of all, thanks for never giving up on us in all the harsh circumstances we have faced over the past several years.
To all Aboriginal people of the World
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3.14 Comparison of the in situ observed and simulated diurnal cycles of (a) surface sensible and (b) latent heat fluxes around the LBA pasture site Fazenda Nossa Senhora and forest site Reserve Jaru averaged over the month of August. Simulated data is obtained from the experiment DEF06SS00 and observed data is obtained from the in situ measurements from the LBA-ECO CD-32 dataset (Saleska et al., 2013).
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3.16 Effect of mesoscale circulations on simulated precipitation in the early and contemporary time periods. (a) DEF86SST80, (b) DEF06SST00, (c) DEF86SSTcl and (d) DEF06SSTcl precipitation totaled between 1600 LT and 2000 LT. All results are averaged over all days in August and over all ensemble members. Figures show percentage difference of the field from deforested area average. Stippling show differences significant at the 1% level.

3.17 Simulated mesoscale circulations in the early and contemporary time periods. Horizontal cross sections of vertical and horizontal wind averaged between 1500 LT and 1600 LT at (a), (b) 967 m, (c), (d) 1207 m and (e), (f) 1457 m for (a), (c), (e) DEF86SSTcl - FORprSSTcl and (b), (d), (f) DEF06SSTcl - FORprSSTcl. The data is averaged for all days in August and over all ensemble members. The horizontal wind vectors are not to scale.
3.18 Effects of sensible heat variations, surface roughness variations and topographical variations in the 'late' period. 1717 m altitude relative humidity averaged between 1300 LT and 1800 LT in (a) DEF06SSTcl-dyn, (b) DEF06SSTcl-sh (c) mean(DEF06SSTcl-dyn,DEF06SSTcl-sh), (d) DEF06SSTcl-topo, (e) DEF06SSTcl-dyn - FORprSSTcl (f) DEF06SSTcl-sh - FORprSSTcl, (g) mean(DEF06SSTcl-dyn,DEF06SSTcl-sh) - FORprSSTcl and (h) DEF06SSTcl-topo - FORprSSTcl-topo. All results are averaged over all days in August and over all ensemble members. (a), (b), (c) and (d) show percentage difference of the field from deforested area average. Stippling shows differences significant at the 1% level.

3.19 Effects of surface sensible heat fluxes on simulated dipole strength. 1717 m altitude relative humidity averaged between 1300 LT and 1800 LT in the experiments shown in the legend. All results are averaged over all days in August and over all ensemble members.
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3.21 Transition in the dominant convective regime with increasing scales of deforestation. In the early period (top), convection over the deforested region is enhanced by thermal triggering alone. In the contemporary period (bottom), horizontal variations in surface roughness result in a suppression of convection in the upwind sector and enhancement of convection in the downwind sector.

4.1 Area ‘AREA-1’ (red box) in Rondônia used for the analysis of temporal variability. This is the area over which the atmospheric variables are averaged to quantify the regional atmospheric state for studying the relationships between the dipole and the atmospheric conditions.
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4.3 Annual cycles of daily scale 1700 LT (a) TRMM-DS (b) TRMM 3B43 monthly average daily precipitation, 1400 LT (c) wind magnitude just below boundary layer top (BLW) (d) Lifting condensation level (LCL) and (e) CAPE. The variables BLW, LCL and CAPE are obtained using the ERA-interim reanalysis data averaged over AREA-1 (Figure 4.1). DS is obtained using TRMM 3B42 data over the deforested area in Rondônia and Precipitation seasonal cycle is obtained using TRMM 3B43 monthly averaged data in the 5° by 5° area around Rondônia. The variables, except panel (b), are daily resolution smoothed with a 5 day moving window. The variability is inter-annual variability of the smoothed daily data between 2001 and 2014. Shading represents one standard deviation of this inter-annual variability.

4.4 Seasonal variation of the dynamical mechanism as captured by the GridSat cloud clover data in Rondônia. Average of 1400 LT and 1700 LT percentage cloud occurrence between 2001 and 2008 in (a) April, (b) May (c) June, (d) July and August average (e) September and (f) October. Note that panel (d) is average over two months which have a very strong dipole signal hence combined. The data is presented as percentage deviations from the deforested area mean (shown at the top of each panel). Arrows show the average horizontal winds at the boundary layer top in the corresponding months.
4.5 Seasonal variation of the dynamical mechanism as captured by the TRMM 3B42 precipitation data in Rondônia. 1700 LT hourly precipitation averaged between 2001 and 2014 in (a) April, (b) May (c) June, (d) July and August average (e) September and (f) October. Note that panel (d) is average over two months which have a very strong dipole signal hence combined. Data is presented as percentage deviations from the deforested area mean (shown at the top of each panel). Arrows show the average horizontal winds at the boundary layer top in the corresponding months.

4.6 Relationships between seasonally (DJF, MAM, JJA and SON) averaged model variables - the response variable TRMM Precipitation DS and predictor variables CAPE, Lifting Condensation Level (LCL) and wind magnitude just below the boundary layer top (BLW). The predictor variables are calculated using ERA-interim data averaged over AREA-1 (Figure 4.1). The variables are averaged each year between 2001 and 2014. 1400 LT average wind magnitude at the boundary layer top, Lifting condensation level and CAPE are used as predictor variables and 1700 LT TRMM precipitation DS (color coded) is used as the response. The seasons are represented by different symbols (legend). The correlation coefficients between each pair of predictor variables is reported at the bottom left of each panel.
4.7 Whisker plots showing that the ‘high’ and ‘low’ dipole days occupy different spaces on the predictor phase space. Columns represent different bi-monthly periods: (a,d,g) - AM, (b,e,hl) - JJ, (c,f,i) - AS. Blue and red colors represent the top 120 high and low DS days respectively. The yellow color represents days when less than 5% of the total deforested area is covered with clouds. The error bars represent median, 25th and 75th percentiles. The range of the DS on high and low dipole days is also shown at the top of the panels in the bottom row.

4.8 Sensitivity of the daily scale multiple regression model (Equation 4.1) to the percentage of data used to define ‘high’ and ‘low’ dipole days. The x-axis represents the percentage of the full daily scale data set used for the regression. Per% on the x-axis implies that the ‘high’ and ‘low’ dipole days each comprise Per/2% of the full data. (a, b, c) Regression coefficients, (d ,e , f) corresponding p-values and (g, h, i) corresponding R^2 for multiple regression models in the bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September.

4.9 Maps of 1700 LT average TRMM precipitation occurrence for ‘high’ DS days and ‘low’ DS days with corresponding average wind vectors. Rows represent average (a, b, c), ‘high’ dipole (d, e, f) and ‘low’ dipole (g, h, i) days. Columns represent individual bi-monthly periods AM (a, d, g), JJ (b, e, h) and AS (c, f, i). Data is averaged between 2001 and 2014. The average precipitation occurrence in the period within the deforested area is also reported at the top of each panel. Note the different color scales in the different panels.
4.10 Relationships between the simulated DS, LCL and BLW. The DS is calculated with 1600 LT relative humidity at 1700 m altitude and LCL and BLW are calculated at 1600 LT in the month of August. The values are calculated with daily data. Error bars represent median, 25th and 75th percentiles of the predictors during ‘high’ and ‘low’ dipole days.

4.11 Average maps of simulated 1700 m altitude relative humidity for (a) ‘high’ and (b) ‘low’ dipole days. Data is averaged over the month of August over all ensemble simulation. The average 1700 m altitude relative humidity within the deforested area is also reported at the top of each panel.

4.12 Co-evolution of DS, LCL and LCL-BLH from radiosonde data from the pasture site at Fazenda Nossa Senhora collected between 18 and 29 September 2002. (a) Time series of TRMM-DS at 1700 LT between 18 and 29 September 2002. (b) LCL and (c) LCL-BLH at the pasture site at 1400 LT between 18 and 29 September 2002.

4.13 Applicability of daily scale physical processes (correlations) on the inter-annual time scale. Correlations between DS, LCL, BLW and CAPE in each bi-monthly period AM, JJ and AS. The values represent monthly averages for each year between 2001 and 2014. Hence each period of each year, for example JJ 2004, contributes two monthly averages. Each period has $2 \times 14$ values. The figures show the predictors during ‘high’ and ‘low’ dipole months in the 14 year period. The low and high dipole months are respectively the top 15% and lowest 15% dipole months of the 14 year data.
4.14 Increase in downwind cloudiness with increase in deforestation in southern Pará. 1400 LT average percentage cloud occurrence in JJA between (a) 1983 and 1990, (b) 1991 and 1999 and (c) 2001 and 2008 calculated using GridSat data (Knapp et al., 2011). Data is presented as the anomaly from the 5° by 5° area mean. The 1400 LT, 800 mb, JJA average horizontal wind vectors calculated using the NCEP reanalysis 2 (Kanamitsu et al., 2002) is also shown with the red arrow for the corresponding periods. Dashed line represents deforested boundary in the corresponding period and solid line represents deforested boundary in 2008.

4.15 Correlations between patterns of cloudiness and scale of deforestation in the contemporary period in Pará. (a) Bivariate probability distribution function (PDF) of 1400 LT JJA percentage occurrence of cloudiness and fraction of deforested area under the corresponding grid cell in 2001 to 2008. (b) Corresponding univariate PDF of % deviations of cloudiness from area mean.

A.1 Flowchart of the cloud detection algorithm described in (Rossow and Garder, 1993).

A.2 Flowchart to generate brightness temperature and albedo clear sky composites. Infrared values are in Kelvins and visible in percentage scaled radiance. The definitions of the different symbols are provided in Table A.1. T_{CLR} and R_{CLR} are the final 5 day clear IR and VIS radiances assigned to a pixel.

B.1 DEF-FOR surface sensible heat fluxes at different times of day averaged over all days in August and over all ensemble members. For definitions of the experiments see Table 3.2.
B.2 DEF-FOR Vertical winds at 1700 m altitude at different times of day averaged over all days in August and over all ensemble members. For definitions of the experiments see Table 3.2.

B.3 Abundant soil types around Rondônia. Data obtained from USDA Global Soil Regions.

B.4 August averaged soil moisture in the top 20 cm depth of soil in (a) DEF-FOR and (b) DEF06SScl-FORprSSTcl. For definitions of the experiments see Tables 3.2 and 3.3 respectively.

B.5 DEF06SSTcl-FORprSSTcl surface sensible heat fluxes at different times of day averaged over all days in August and over all ensemble members. For definitions of the experiments see Table 3.3.

C.1 Scatter plots between daily scale TRMM-DS and (a, b, c) BLW, (d, e, f) LCL and (g, h, i) CAPE. Columns represent different bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September.

C.2 Whisker plots showing that the 'high' and 'low' PERSIANN dipole days occupy different spaces on the predictor phase space. Columns represent different bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September. Blue colors represent the top 120 high DS days and red colors represent the top 120 low DS days. The yellow color represents days when less than 5% of the total deforested area is covered with clouds.

C.3 Same as Figure C.2 but for GridSat data between 2001 and 2008.
C.4 Quantile regression for the model presented in Equation 4.1 between TRMM-DS and predictors BLW, LCL and CAPE. X-axis represents the percentile at which regression is performed. (a, b, c) Standardized coefficients and (d, e, f) corresponding $p$-values for the three predictors as functions of the quantile. Columns represent different bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September.

C.5 Maps of daily average PERSIANN precipitation occurrence for ‘high’ DS days and ‘low’ DS days with corresponding average wind vectors. Rows represent average (a, b, c), ‘high’ dipole (d, e, f) and ‘low’ dipole (g, h, i) days. Columns represent individual bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September. Data is averaged between 2001 and 2014. The average precipitation occurrence in the period within the deforested area is also reported at the top of each panel. Note the different color scales in the different panels.

C.6 Same as Figure C.5 but for GridSat data between 2001 and 2008.
Chapter 1

Introduction

1.1 Amazonian Deforestation - Known and Unknown Impacts

The Amazon river basin supports the world’s largest rainforest (original extent of \(~6 \text{ million km}^2\); Soares-Filho et al. (2006); Fearnside (2005)). At almost the size of the 48 contiguous states of the United States of America (\(~8 \text{ million km}^2\)), this unique river basin accounts for \(~20\%\) of the world’s total fresh water discharge (Salati and Vose 1984; Dai and Trenberth 2002) while nurturing a forest that hosts a quarter of the world’s terrestrial species (Dirzo and Raven 2003). Awe-inspiringly, this rainforest sustains itself and its unique ecosystems through a recycling of nearly 30\% of its annual rainfall (Brubaker et al. 1993; Eltahir and Bras 1994; Dominguez et al. 2006) regulating tropical and global atmospheric dynamics in the process (Eltahir 1996; Findell et al. 2006; McGuffie et al. 1995; Medvigy et al. 2013; Werth 2002).

The intact and regrowing portions of the forest also account for nearly 25\% of annual carbon sequestered by land, which is 2.5 petagrams of carbon per year (Pg C year\(^{-1}\)), hence offsetting \(~10\%\) of global fossil fuel emissions (Pan et al. 2011). The remarkable adaptation of the forest for seasonal drought stress, through its deep rooted tress,
Figure 1.1: Historical and current state of deforestation in the Amazon rainforest. (a) Dominant vegetation cover in northern South America in 2012. Data obtained from Brazilian National Institute for Space Research (INPE) TerraClass Project (Coutinho et al., 2013). The deforested regions in the state of Rondônia are shown enclosed in the red box. (b) Time series of annual rate of deforestation in the whole forest (line), total deforestation (bars) and percentage deforestation (numbers on top of bars). Data aggregated from Soares-Filho et al. (2006) and INPE-PRODES (2015).

Results in continued photosynthetic activity even during the dry season (Myneni et al., 2007; Saleska et al., 2003, 2007). This forest plays a significant role in maintaining and regulating the Earth’s climate making it indispensable to protect this unique natural heritage.

But, several decades of large-scale exploitation for human settlement, agricultural expansion, cattle grazing, timber etc. has resulted in the removal of more than 17% of the original forest cover (INPE-PRODES, 2015; Davidson et al., 2012; Soares-Filho et al., 2006; Fearnside, 2005), which has already been correlated with several ecological, social and environmental consequences (Davidson et al., 2012; Malhi et al., 2008; Gash et al., 1996a). This deforestation is concentrated along the southern through eastern boarder of the rainforest and is referred to as the ‘Arc of deforestation’ (Figure 1.1) which is also the driest part of Amazonia. Approximately 70% of this deforestation is devoted to un-irrigated pasture lands for commercial cattle grazing (Nepstad...
et al., 2006; Kaimowitz et al., 2004), which have substantial effects on the surface energy balance as they are sub-par, compared to evergreen trees, at maintaining normal levels of transpiration due to shallow rooting depths (von Randow et al., 2004). The adverse impacts of conversion to pasture on local hydroclimate may result in a delay in the wet season arrival which has been shown to be positively correlated with evapotranspirative fluxes by the forest during the Spring season (Li and Fu, 2004; Fu and Li, 2004). Forest degradation may also result in changes in ecosystem adaptation due to the transition of the regional climate to dry precipitation regimes characteristic of seasonal forests (Malhi et al., 2009, 2008; Nobre and Borma, 2009). But, despite being the driving force of these effects, the impacts of evolving scales of deforestation on regional precipitation are still neither well-observed nor well-understood (Lawrence and Vandecar, 2014; D’Almeida et al., 2007). Hence, this thesis has been devoted to understanding the impacts of current and evolving scales of deforestation on the regional cloudiness and precipitation (hydroclimate from now on) in Amazonia.

Over the past few decades multiple observational and numerical studies have been performed to understand the impacts of deforestation on regional hydroclimate in Amazonia. Results from two major Amazonian field campaigns, conducted at multiple forested-deforested paired sites during the early phase of deforestation (in early and late 1990s), show that deforestation on an average leads to local warmer and drier conditions, despite the increase in albedo due to the replacement of the dark forests with brighter pasture/cropland (Gash et al., 1996b,a; Gash and Nobre, 1997; Hodnett et al., 1996; Wright et al., 1996a). This is due to the increase in Bowen ratio (ratio of sensible and latent heat fluxes) induced by shallow rooted (∼1 m) pastures that replace deep rooted (∼5 m) and heavily transpiring trees (Hodnett et al., 1996; von Randow et al., 2004). Site measurements show that this difference in sensible heat fluxes can be as large as ∼100 W/m² during the midday hours creating a spatial, thermal heterogeneity between deforested and forested areas. Interestingly, a num-
Figure 1.2: Schematic of thermally triggered mesoscale circulation induced by deforestation of the scale of a few kilometers as suggested by numerical studies (Avissar and Schmidt, 1998; Roy and Avissar, 2000, 2002; Roy, 2009; Wang et al., 2000) and evidence shown by observational studies (Cutrim et al., 1995; Chagnon et al., 2004; Chagnon and Bras, 2005; Negri et al., 2004; Wang et al., 2009). See reviews by D’Almeida et al. (2007); Lawrence and Vandecar (2014); Seneviratne et al. (2010).

A number of high resolution numerical (Wang et al., 1996; Avissar and Schmidt, 1998) and observational (Cutrim et al., 1995; Negri et al., 2004; Wang et al., 2009) studies have shown that such spatial thermal heterogeneities induced by small scale deforestation (of the order of a few kilometers) can result in organized thermal circulations with their upward branch placed preferably over the deforested patch (Figure 1.2). These circulations result from the decrease in the atmospheric stability induced by and over deforested patches. These ‘deforestation breezes’ result in an increase in mostly non-precipitating shallow cloudiness over deforested areas (Cutrim et al., 1995; Negri et al., 2004; Wang et al., 2009), although there is some evidence of an increase in dry season precipitation frequency as well (Chagnon et al., 2004).

On the other hand, a number of coarse resolution General Circulation Model (GCM) studies have investigated the hydroclimatic effects of hypothetical, large, basin-wide scales of deforestation. Most of these studies found that at basin-wide scales of deforestation the increase in albedo results in an area wide sinking anomaly over Amazonia, hence offsetting the increase in thermally induced upwelling caused
by increase in sensible heat fluxes. This results in a reduction in evapotranspiration
and precipitation over most of the forest (see D’Almeida et al. (2007) for a review).

But with the recent increase in the availability of high computational power, global
or large spatial scale mesoresolution (of the order of a few kilometers to a few tens of
kilometers) models have been used to investigate the impacts of realistic intermediate
scales (a few tens to hundreds of kilometers) of deforestation. In this respect, a few
studies have investigated the hydroclimatic effects of either idealized (Saad et al.,
2010; Nobre et al., 2009) or realistic future patchy deforestation (Walker et al., 2009)
in Amazonia. These studies indicate that the precipitation response is dependent
on the scale of deforestation, which slightly increases at small scales of deforestation
before rapidly decreasing at larger basin wide scales of deforestation. However, none of
these studies investigate the driving physical processes nor are there any observational
studies that investigate the climatological effects of increasing scales of deforestation.

Overall, all the above studies corroborate that the net atmospheric response to
land cover change depends on the spatial scale of the clearings. In particular, some
high resolution idealized modeling studies (Wang et al., 1996; Avissar and Schmidt,
1998; Gopalakrishnan et al., 2000; Patton et al., 2005) show that deforestation-
induced thermally triggered mesoscale circulations are active only upto a hetero-
genity scale of the order of a few kilometers, above which scale these circulations
are replaced by random thermal turbulence. It should be noted that most of the
observational and numerical studies which report the existence of thermally triggered
mesoscale circulations were performed for deforestation occurring at scales of a few
kilometers only. For example, almost all of the above studies investigate the hydrocli-
matic impacts of the deforested areas in the Brazilian state of Rondônia in southern
Amazonia which lies between 65°W, 60°W, 13°S and 8°S (Figures 1.1 and 2.1). The
deforested landscape in Rondônia has historically consisted of forest clearings along
a complex network of parallel roads creating adjacent patches of forest and pasture
with a characteristic length scale of about 1 km (Gash and Nobre 1997; Gash et al. 1996a,b). In particular, conversion to pasture in the 1980s in this region, with characteristic length scale of a few kilometers, has been correlated with increased regional cloudiness and precipitation frequency.

However, the deforested patches in Rondônia and elsewhere along the ‘Arc of deforestation’ have expanded with time (Rodriguez et al. 2010; D’Almeida et al. 2007), and are expected to continue expanding in the coming decades (Soares-Filho et al. 2006). The coupled effect of this expansion with the impending climate change has the potential to tip the conversion of evergreen forest vegetation to seasonal forests or savanna (Malhi et al. 2009; Nobre et al. 2009) making it indispensable to evaluate the hydroclimatic impacts of these changes. But, the atmospheric response, and the driving mechanisms, to even the current day scales of deforestation, which are well past the few-kilometers threshold for thermal mesoscale circulations, are not yet well observed or understood.

Additionally global scale climate variability has been known to impact Amazon rainforest’s hydroclimate at least on a decadal time scale. Specially, the Pacific sea surface temperatures (SSTs), tropical North Atlantic SSTs and South Atlantic SSTs have been correlated with hydroclimatic extremes in the Amazon rain forest (Yoon and Zeng 2010; Lorenz and Kunstmann 2012; Zeng et al. 2008). As such, it is important to separate the effects of global climate change over the past several decades and the simultaneous increase in deforestation in Amazonia.

1.2 Goals and Scope of This Thesis

The aim of this thesis is to identify and attribute trends in the Amazonian regional hydroclimatic impacts of these changes. But, the atmospheric response, and the driving mechanisms, to even the current day scales of deforestation, which are well past the few-kilometers threshold for thermal mesoscale circulations, are not yet well observed or understood.

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separating the influence of large-scale climate variability. This aim is achieved by addressing the following research questions in the thesis:

1. What does the hydroclimatic response to current, intermediate scales of deforestation (several tens to a few hundreds of kilometers) look like in observations? Is it different from the hydroclimatic response to small scale (a few kilometers) deforestation which characterized the landscape in the 1970s and 1980s? Does this atmospheric response have a significant impact on regional precipitation unlike the atmospheric response to early small scale deforestation which induced mostly non-precipitating shallow cloudiness?

2. What is the deforestation-induced physical mechanism which produces this hydroclimatic response to contemporary deforestation? How does it compare with the systematic mechanism of ‘thermal’ circulations which were induced due to early period deforestation?

3. How generalizable and hence influential is this physical process both in time and in space at various deforested regions in the Amazon rain forest? What is the inter-annual variability of the detected atmospheric response?

The above questions are addressed sequentially in the chapters that follow. Chapter 2 focuses on the observational detection of the regional hydroclimatic impacts of Amazonian deforestation. The focus of the investigation is on the deforested regions in Rondônia, Brazil and the local dry season (months of June, July, August and September). Rondônia, as will be discussed in Chapter 2, is ideal for a climatological study of increasing deforestation because this region has been incrementally deforested for more than three decades hence providing a suitable ground for studying different scale dependent physical mechanisms. Simultaneously, it has been the subject of several deforestation studies, so valuable datasets are available for this region. As mentioned previously, the relative control of large scale atmospheric conditions
on boundary layer processes is stronger during the regional dry season making land-
atmosphere coupling stronger during this period of the year than the other seasons. Moreover, dry season precipitation variability is also important for vegetation adaptation (Malhi et al., 2008; Nobre and Borma, 2009) and wet season arrival (Fu and Li, 2004; Li and Fu, 2004). The full analysis of the seasonal cycle of the regional hydroclimatic effects of contemporary deforestation in Amazonia will be addressed in Chapter 4 in the thesis. But to constrain our understanding of the dominant hydroclimatic impacts of deforestation, the prominent signals produced during the local dry season in Rondônia will be analyzed first.

A major task accomplished in this work and discussed in Chapter 2 is the development of a high resolution, long time period cloud cover dataset which made the climatological study possible. This dataset was developed by applying a customized version of a standard cloud detection algorithm to a newly available climate quality geostationary satellite dataset. This contribution can possibly facilitate similar climatological studies in other parts of the deforested Amazon rainforest and elsewhere.

Chapter 3 focuses on understanding the physical processes responsible for the hydroclimatic changes observed in the satellite data in Chapter 2. First, the influence of global scale SSTs on the observed hydroclimatic changes is analyzed and then attribution to local scale deforestation-induced physical process is performed by capturing observations of the hydroclimate with a numerical model. A major advancement in this thesis is the use of a variable resolution Global Circulation Model for performing the numerical experiments. The advantage of such an approach is the simulation of a desired region of the globe at a meso-resolution (a few kilometers to a few tens of kilometers) without the need for lateral boundary conditions. The model used in this thesis does a remarkable job at capturing the average signal and variability present in observations, facilitating a thorough understanding of the driving mechanisms. The combined results of Chapter 2 and Chapter 3 show the existence of a common phys-
ical phenomenon in both observational and numerical datasets, providing context to re-evaluate our understanding of the hydroclimatic impacts of increasing scales of deforestation in the Amazon rain forest.

Chapter 4 presents the temporal and spatial variability of the detected signal within the deforested regions of the Amazon rainforest utilizing both satellite observations and numerical simulations. The variability is assessed with respect to regional atmospheric and boundary layer conditions and sea surface temperature indices using data spanning over more than a decade. The key finding, from this analysis, using both observational and numerically simulated data, is that the newly found physical mechanism is a stronger convective triggering mechanism than the regular thermal triggering as it occurs during periods characterized by more stable conditions than normal. This physical phenomenon affects the cloud formation and precipitation in the dry as well as some parts of the transition seasons, precipitation variability during which, as discussed earlier, can be consequential for regional ecosystem dynamics and dry season length. This phenomenon is found to be relevant in two large scale deforested areas that are considered in this study with one of the regions showing a stronger signal than the other. Overall, the results presented in this chapter will show that the newly found deforestation induced physical mechanism is relevant for a substantial time during the year in the current stage of deforestation in the Amazon rainforest.

The analysis presented in this thesis is likely the first such integrated study of a multidecadal variation in the regional hydroclimate associated with tropical deforestation. The conclusions from this thesis and its potential impacts on future research are discussed in Chapter 5. The limitations of the methodology used for analysis in this thesis and related future work will also be presented.
1.3 Publication and Coauthorship

The projects presented in this thesis are a result of the work done by me under the supervision of my thesis advisor David Medvigy. The conception of the projects, experimental design and data analysis have been done with mutual collaboration between us. Some of the work is also performed in collaboration with Stephan Fueglistaler at the Program in Atmospheric and Oceanic Sciences, Princeton University and Robert Walko at the Rosenstiel School of Marine and Atmospheric Science, University of Miami. In each case the research tasks and writing of results were performed by me. Coauthors also contributed with their inputs in improving the manuscripts.

Research presented in the first part of Chapter 3 done in collaboration with David Medvigy, has been published in the Journal of Geophysical Research - Atmospheres (Khanna and Medvigy, 2014a). Results presented in Chapter 2 and second part of Chapter 3 done in collaboration with David Medvigy, Stephan Fueglistaler and Robert Walko, have been compiled into a manuscript (Khanna et al., submitted) at the time of submission of this thesis. Results presented in Chapter 4 done in collaboration with David Medvigy, are being prepared as a manuscript to be submitted to a peer reviewed journal. Some of the results reported in this thesis have also been presented in the Fall Meetings of the American Geophysical Union (Khanna and Medvigy, 2013, 2014b, Khanna et al., 2015a) and the Annual General Assembly of the European Geosciences Union (Khanna et al., 2015b).
Chapter 2

Identification of Regional Hydroclimatic Changes Due to Three Decades of Amazonian Deforestation

2.1 Motivation

Regional hydroclimatic (clouds and/or precipitation) changes triggered by small scale, spatial, thermal heterogeneities induced by land cover change (Figure 1.2) have been detected at several places in the World. For example, small scale deforestation in the Amazon rainforest (Cutrim et al., 1995; Chagnon et al., 2004; Chagnon and Bras, 2005; Negri et al., 2004; Wang et al., 2009), in the Congo rainforest (Taylor and Ellis, 2006; Taylor et al., 2007) and in central USA (Rabin and Martin, 1996; Weaver and Avissar, 2001) have impacts on regional cloud cover. Drier and warmer conditions over deforested/urbanized areas result in an increase in the local atmospheric instability and upward motion, in the planetary boundary layer preferably over the disturbed
land, resulting in systematic circulations addressed as ‘vegetation breezes’ (Figure 1.2; see Seneviratne et al. (2010) for a review of such studies). The ‘observable’ signal generated by such systematic circulations is apparently seen in the spatial patterns of regional shallow cloud cover and/or rain. As such, satellite imagery of clouds and precipitation has proven particularly useful in monitoring and understanding these phenomena (Cutrim et al. 1995; Negri et al. 2004; Chagnon et al. 2004; Wang et al. 2009).

In the Amazon, most observational studies have relied on time slices from the NOAA Geostationary Operational Environmental Satellite (GOES) (Minnis et al. 1995; Weinreb et al. 1997) data for case studies of preferential occurrence of clouds over deforested regions as compared to nearby forested areas. But, as GOES were launched primarily as weather satellites, inter-satellite normalization is a prerequisite for any climatological application of the GOES data. This is possibly one reason why no climatological study of the impacts of increasing scales of deforestation on regional cloudiness has been performed. Due to this limitation the Amazonian studies have focused only on spatial preference of cloud occurrence, on deforested versus forested areas, only for early period small scale deforestation. But, as discussed in Chapter 1 a long time period climatological analysis is desirable because 1) scales of deforestation have been increasing in the Amazon rain forest and are expected to increase even further in the next century, requiring a thorough analysis of scale dependent atmospheric responses to deforestation and 2) the thermal vegetation breezes are expected to die down when the deforestation scales increase beyond a few kilometers in size, requiring an identification of the atmospheric response to current large scale deforestation in Amazonia.

Not many high resolution, multidecadal cloud observation datasets exist. Roughly three decades of cloud observation data is available from the International Satellite Cloud Climatology Project (ISCCP) but at a resolution much coarser (~250 km) than
is required for the detection of mesoscale spatial patterns in cloud cover. In this respect, a new dataset, the Gridded Satellite (GridSat) dataset, which has recently been produced under the NOAA Climate Data Record program, is quite promising (Knapp et al. 2011). GridSat combines ∼3 decades of GOES (and other international Geostationary satellites) data taking care of inter-satellite and temporal normalization, mapping, calibration etc. to produce a continuous time series of Earth’s outgoing shortwave and longwave observations (see section 2.2.2). The GridSat data, however, needs to be post processed to derive cloud cover information from it. After some correspondence with Dr Kenneth Knapp at NOAA, Asheville, NC, a customized version of the ISCCP cloud detection algorithm was implemented to generate cloud cover maps for this study, which makes the climatological analysis possible.

This chapter is devoted to the identification of climatological changes in regional clouds and precipitation and their co-evolution with increasing Amazonian deforestation over the past three decades using observational datasets. The following questions are addressed:

1. What is the hydroclimatic response to contemporary intermediate scale (a few hundreds of kilometers) deforestation?

2. Can this hydroclimatic response be explained by the regular deforestation-induced thermal mesoscale circulations?

3. What and how much effect does this atmospheric response have on regional precipitation?

To answer these questions a representative deforested region is chosen - a region for which long time period land cover, cloud and precipitation data is available (subsection 2.2.1). Multitude of satellite based datasets of changing land cover and changing hydroclimate are utilized to capture the changes and their co-evolution (subsection 2.2.2). The cloud detection algorithm and its evaluation is presented in subsection
2.2 Methods

2.2.1 Region and Period of Investigation

The study is performed over the deforested regions of the Brazilian state of Rondônia which lies in the southern parts of the rainforest between 65°W, 60°W, 13°S and 8°S (Figure 2.1). In the analysis that follows the Large-Scale Biosphere-Atmosphere-ECOlogy experiment (LBA-ECO) ND-01 land cover time series (1984 to 2010) (Roberts et al., 2013) and the Brazilian National Institute for Space Research Amazon Deforestation Monitoring Project (INPE-PRODES) estimates of annual deforestation (since 1988) (INPE-PRODES, 2015) are used to quantify vegetation cover change over Rondônia. As seen in Figure 2.1, spatial scales of forest clearing in this region have spanned a large range over the past 30 years making it a favorable test-bed for studying different scale-dependent mechanisms of convective triggering. The length scale of deforestation has increased from a few kilometers in the 1980s to a few hundred in the 2000s. Among the notable features in the 1980s are the highly deforested regions along the highway BR-364, previously shown to be conducive to thermally triggered mesoscale circulations due to their favorable length-scale in that period (Avissar and Schmidt, 1998; Roy and Avissar, 2002; Patton et al., 2005). The region is relatively flat with some high hills towards the south and southwestern periphery of the contemporary deforested area (Figure 2.2). Most observational studies (D'Almeida et al., 2007; Wang et al., 2000; Negri et al., 2004; Chagnon et al., 2004; Chagnon and Bras, 2005) have focused on the hydroclimatic impacts of early period deforestation in this region and have attributed these impacts to the small-scale patchy deforestation pattern characteristic of this region in the 1980s and
Figure 2.1: Increasing scales of deforestation in Rondônia over the last three decades. Deforested regions of Rondônia in (a) 1984, (b) 1990, (c) 1996, (g) 2002, (h) 2008 and (i) 2010. (d), (e), (f), (j), (k) and (l) are the corresponding zoomed in images over the red box. Highway BR 364 running from southeast to northwest of the deforested domain is represented by the black-dashed line. Land cover data is obtained from the 28 m resolution LBA ECO ND 01 land cover maps (Roberts et al., 2013) derived from LANDSAT images.
early 1990s. This also makes Rondônia an apt test region for the analysis presented in this thesis as this is the most studied deforested region of Amazonia and hence a relatively large number of good, long time period datasets are available for analysis for this region.

The analysis focuses on the local dry season months of June, July, August and September (JJAS henceforth). The dry season is chosen for the analysis because 1) land atmosphere coupling is more pronounced during the dry season when the region is less affected by synoptic scale fronts and weather (Wang et al., 1996), 2) dry season precipitation variability and land surface induced convective processes are important for vegetation adaptation to dry season hydroclimate (Nobre and Borma, 2009; Malhi et al., 2008, 2009) and 3) the dry season is also important in regulating the timing of the transition seasons and hence may affect wet season arrival (Fu and Li, 2004; Li and Fu, 2004) which in turn may feedback to vegetation adaptation.
2.2.2 Datasets Used for Signal Detection

Cloud Cover Data

The Gridded Satellite (GridSat) dataset [Knapp et al., 2011], produced under the NOAA Climate Data Record (CDR) program by the International Satellite Cloud Climatology Project (ISCCP), has been utilized to carry out the multidecadal analysis in this study. This dataset combines several decades of geostationary data from all over the globe, cross-calibrating between different instruments in time and space (in time between different GOES satellites, and in space between GOES and other geostationary satellites that are a part of the ISCCP project).

ISCCP GridSat visible (VIS, 0.6 µm) and infrared (IR, 11 µm) channel data were used to infer cloud cover over Rondônia. This 3-hourly dataset is available from 1980 to present at a spatial resolution of 8 km. The analysis was performed using instantaneous data at 1400 LT and 1700 LT for the months of June, July, August and September (JJAS) between 1983 and 2008 (visible data being severely incomplete in other years). The JJAS 1400 LT average visible channel and brightness temperature
over Rondônia for the decades of 1980s and 2000s are shown in Figure 2.3 just as an example of the data (all the analysis in the study is performed with averages of 1400 LT and 1700 LT data). There is observed a trend in the data set due to which the area averaged albedo decreases and brightness temperature increases with time. This trend may be due to climate change over these three decades. The cloud detection algorithm (subsection 2.2.3) helps remove the effect of this temporal trend on our analysis because the algorithm is sensitive only to spatial variability of albedo and brightness temperature at each time point.

Precipitation Data

The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Climate Data Record (PERSIANN-CDR) global precipitation dataset (Ashouri et al., 2015) is primarily used for the trend analysis over the study period of three decades. This dataset is available as daily total precipitation at 25 km spatial resolution. The period used in this study is 1983 to 2015. PERSIANN-CDR employs the PERSIANN algorithm on GridSat infrared satellite data, and employs the training of the artificial neural network using the National Centers for Environmental Prediction (NCEP) stage IV hourly precipitation data and is then adjusted using the Global Precipitation Climatology Project (GPCP) monthly product. Hence it is not independent of the GridSat data. The Tropical Rainfall Measuring Mission (TRMM) 3B43 global monthly averaged and TRMM 3B42 3-hourly precipitation products (Huffman and Bolvin, 2014) are also utilized to identify spatial patterns in the contemporary time period. The analysis showed (figures not shown) that there is no precipitation observed preferentially over deforested areas at 1400 LT in the TRMM 3B42 data. Hence the results from TRMM 3B42 data are reported at 1700 LT, when such a signal was observed. Also the TRMM 3B42 data represent a nominal ±90-minute span around the nominal hour. Both datasets are available at
25 km spatial resolution since November 1997. The period of TRMM data used in this study is 2002 to 2014.

2.2.3 Cloud Detection Algorithm and Its Evaluation

A standard cloud detection algorithm (Rossow and Garder, 1993) is used to generate GridSat cloud cover maps in this study. The main test in this algorithm is to determine cloudy pixels by applying 1) a lapse rate threshold on the surface temperature and 2) a threshold on the surface albedo of the corresponding pixel:

\[
\begin{align*}
IR_{\text{clear}} - IR_{\text{pixel}} & > IR_{\text{threshold}}, \\
VIS_{\text{pixel}} - VIS_{\text{clear}} & > VIS_{\text{threshold}}.
\end{align*}
\]

Here, \( IR_{\text{clear}} \) and \( VIS_{\text{clear}} \) are the brightness temperature and albedo, respectively, of the pixel under clear conditions, \( IR_{\text{pixel}} \) and \( VIS_{\text{pixel}} \) are the brightness temperature and albedo of the pixel at the time of observation, and \( IR_{\text{threshold}} \) and \( VIS_{\text{threshold}} \) are thresholds based on the atmospheric lapse rate and observed statistical differences between clear and cloudy pixels. The value of \( IR_{\text{threshold}} \) and \( VIS_{\text{threshold}} \) is 6 K and 6% respectively. All the threshold values used in this implementation have been taken from (Rossow and Garder, 1993).

The cloud detection algorithm is designed to generate the cloud cover field by making the best possible estimates of \( IR_{\text{clear}} \) and \( VIS_{\text{clear}} \). In the ISCCP cloud detection algorithm (Rossow and Garder, 1993), the surface temperature and albedo for each group of pixels is determined based on the statistical characteristics of cloud occurrence in that region, both over space and time, and then applying several spatial and temporal tests to find pixels which have a high chance of being clear in every 5-day period. A 5-day period is chosen because that is the observed time scale of synoptic scale events in this region (Kousky, 1988). The algorithm then assigns a
Figure 2.4: Sample of a cloud occurrence map obtained using the cloud detection algorithm. (a) Albedo, (b) brightness temperature at 1400 LT on 1st August 2008 and (c) corresponding binary cloud cover image.

5-day spatio-temporal averaged surface temperature and surface albedo to these pixels, which are then used, along with equation 2.1 to distinguish between cloudy and clear pixels. For optimal performance, IR statistics are collected over spatial regions that are sufficiently small to minimize the probability of false clear detection due to large spatial variability in land properties, but sufficiently large so that the contrast due to cloud and clear pixels is well-captured. For this study this area is chosen to be 28 km by 28 km in size. Sensitivity tests done with somewhat different sizes produced similar results. The output of the algorithm is a binary image of cloudy pixels at each time snap (Figure 2.4). A detailed description of the algorithm and the simplifications made to it for this study are presented in Appendix A.

The algorithm is applied to GridSat VIS and IR images of the type shown in Figure 2.3. Figure 2.4 shows a sample of the binary cloud image produced given a VIS and IR scene. The algorithm identifies cloudy and clear pixels in a scene and hence divides the VIS and IR histograms into cloudy and clear parts, the former occupying high albedo and low brightness temperature regions (Figure 2.5). The algorithm is also evaluated through its ability to reproduce persistent regional natural features like orographic convective triggering over the hills (63.7°W, 10.9°S and 62.2°W, 11.1°S).
and thermal convective triggering over the natural savanna (61.8°W, 8.75°S) shown in Figure 2.1. These features are robustly reproduced throughout the 26 year analysis period as seen in Figure 2.6 and discussed in section 2.3.1.

A second, simpler cloud detection algorithm, a variant of algorithms used by previous studies (Negri et al., 2004; Wang et al., 2009) was also used for comparison. This algorithm assumes that at a given time 20% of the pixels in a given scene can be cloudy. The scene in this study is defined as the area between 65°W to 60°W and 13°S to 8°S. Of these top 20% brightest pixels, the ones that are more than 5 K cooler than the monthly average surface temperature of the scene are defined to be cloudy. The monthly average surface temperature is defined to be the average of the top 5% warmest pixels in the whole month. This brightness temperature cutoff ensures that non-cloudy bright pixels, like bare land, are not flagged cloudy. A binary image at each time snap is generated with the algorithm, which is then combined to generate the maps of percentage occurrence of cloudiness. Due to the design of this algorithm it will underestimate cloud cover in situations of widespread overcast; however, widespread cloud cover is uncommon in the dry season.
2.2.4 Quantifying Spatial Patterns in the Hydroclimate with Dipole Moment Vector

It would be shown in Section 2.3 that the contemporary scale deforestation results in a redistribution of clouds and precipitation over the downwind and upwind deforested sector. To quantify this dipole like spatial pattern of cloud cover or precipitation present over the deforested area in each year, a dipole moment vector of cloudiness and precipitation occurrence is calculated according to the formula:

\[
D_x = \sum_{i=1}^{N} d_i \times x_i,
\]

\[
D_y = \sum_{i=1}^{N} d_i \times y_i,
\]

\[
D = \sqrt{D_x^2 + D_y^2} \tag{2.2}
\]

Where, D is the magnitude of the dipole moment vector whose X and Y components are \(D_x\) and \(D_y\). \(d_i\) is the percentage deviation of the variable in the \(i^{th}\) pixel from the deforested area mean value. \(x_i\) and \(y_i\) are the coordinates of the \(i^{th}\) pixel. Only the pixels within the deforested boundary (neglecting areas above 9.5°S as they form a separate deforested patch) of the corresponding year are used in the calculation; thus, the area used to define the dipoles is different in each year. The dipole moment is calculated for different hydroclimatic variables like observed cloud occurrence, precipitation occurrence, numerically simulated relative humidity and precipitation (in Chapter 3). The dipole is calculated using the percentage deviations from the deforested area mean because we are interested in spatial patterns rather than larger-scale trends possibly associated with (multi) decadal modes of climate variability or deforestation.
2.2.5 Effects of Temporal Trends and Spatial Biases in Satellite Data

As observed in Figure 2.3, the JJAS averaged albedo and brightness temperature from GridSat have negative and positive trends respectively. Although the performance of precipitation datasets has been evaluated in different parts of South America (Hsu and Sorooshian, 2008; Demaria et al., 2011), similar temporal trends or biases in precipitation data as compared to station datasets may also exist. For example, it is shown that in eastern South America both TRMM and PERSIANN have biases in estimating precipitation features of mesoscale convective storms using station data as benchmark. But TRMM precipitation estimates have less bias than PERSIANN estimates when compared to rain gauge data (Demaria et al., 2011). It is also shown that PERSIANN precipitation estimates may have more spatial biases in representing the location of mesoscale convective storms as compared to TRMM estimates (Demaria et al., 2011). For the above reasons, all the observational analysis metrics in this study were designed based on percentage deviations from the deforested area mean to minimize the effect of the above mentioned temporal trends and spatial biases in the satellite data. Also the cross validation of the results of spatial redistribution of clouds and precipitation between three satellite based products - GridSat, TRMM and PERSIANN, provides greater confidence in the changes in the spatial patterns detected over the study region. It should be noted that this study serves to detect trends in the spatial organization of clouds and precipitation with increasing deforestation and not trends in absolute values of clouds and precipitation.

2.2.6 Statistical Significance

The linear regression, wherever used, is an ordinary least square fit calculated with the MATLAB in-built function fitlm. The significance of the trend line is tested using
the p-value derived from the t statistics under the assumption of normal errors. The trend line for the cloud occurrence dipole (Figure 2.13) is calculated neglecting the years that have at least 50% data missing. The same years are also removed from the trend calculation of the precipitation occurrence dipole (Table 2.2). Correlation analysis is done using the MATLAB in-built function corrcoef.

Statistical significance of differences, wherever used, has been calculated with a two tailed t-test at the 1% significance level (Figures 2.6, 2.8, 2.9 and 2.10). The null hypothesis being tested in each case is that the mean cloudiness or precipitation in each pixel is equal to the deforested area mean cloudiness or precipitation. A pixel-wise 5 day running average is applied to the GridSat cloud occurrence and PERSIANN and TRMM 3B42 precipitation time series before the t-test is performed. Additionally, to access the robustness of the test results, a Z-test was also performed on the sampling distribution of the sample means obtained from 200 bootstrapped samples for each pixel in Figures 2.6, 2.8, 2.9 and 2.10. The bootstrapped sampling distributions were verified to be normal on a quantile-quantile plot. All the results of hypothesis tests reported in these figures were further verified to be robust under resampling.

2.3 Results and Discussion

2.3.1 Changing Decadal Average Spatial Patterns in Cloud and Precipitation - The Emerging ‘Dipole’ Pattern

The multidecadal evolution of the average of 1400 LT and 1700 LT JJAS mean cloud occurrence fields are plotted in Figure 2.6 aggregated into three periods to increase the signal-to-noise ratio: 1983 to 1990 (early), 1990 to 1999 (mid), and 2001 to 2008 (late). As known from previous studies, during the 1980s, the percentage cloud cover is uniformly high around BR-364 (Figure 2.6a, d, g) slightly shifted towards the
west of the road possibly because of advection of the clouds with easterly winds at the boundary layer top. But as the scales of deforestation increase, this feature is replaced by a dipole-like structure in cloud cover over the deforested area (Figure 2.6 b, c, e, f, h and i) aligned with the near-surface southeasterly winds (Figure 2.7). Use of the second cloud detection algorithm also produces similar spatial patterns (Figure 2.8).

Additional support for a changing hydroclimate is obtained from precipitation datasets. Daily precipitation from PERSIANN-CDR (Ashouri et al., 2015), available between 1983-2008, show a gradual emergence of an east-west dipole (Figure 2.9 a-c). Note however that PERSIANN-CDR is derived in part from GridSat and so is not completely independent of it. An east-west precipitation dipole is also evident in TRMM 3B43 monthly and TRMM 3B42 3-hourly precipitation data (Huffman and Bolvin, 2014) at 1700 LT (Figure 2.9 d, e). The TRMM datasets are independent of GridSat but start only in late 1997 and hence are too short for trend detection.

While some persistent cloud cover features are associated with hills at 63.7°W, 10.9°S and 62.2°W, 11.1°S (Figure 2.2), within the deforested area the spatial patterns in cloud cover in JJAS 2001-2008 are not correlated ($p>0.1$) with local topography. 1400 LT boundary layer winds obtained from NCEP/NCAR reanalysis 1 (Figure 2.7) do not show any significant trends between 1983 and 2008 (trends in wind magnitude and direction at 1000 mb, 925 mb and 850 mb all have $p>0.1$) suggesting that the observed transition in hydroclimate is not a result of large-scale wind changes.

### 2.3.2 Intra-seasonal Variations of the Dipole

The multidecadal transition from a spatially uniform to a ‘dipole’ structure in cloud cover observed in the JJAS averaged hydroclimate is also apparent in the individual months of June, July, August and September (Figure 2.10). But, the signals in the individual months and the overall multidecadal transition is most pronounced in the
Figure 2.6: Emergence of the southeast-northwest cloud ‘dipole’ with increasing deforestation in Rondônia. 1400 LT and 1700 LT average percentage cloud occurrence in JJAS between (a) 1983 and 1990, (b) 1991 and 1999 and (c) 2001 and 2008 calculated using GridSat data (Knapp et al. 2011). (d), (e) and (f) corresponding maps at 1400 LT and (g), (h) and (i) at 1700 LT. Data is the percentage difference from the deforested area average in the corresponding period (reported on top of each panel).

months of July and August. This is clearly indicated by the high spatial correlation of the July and August cloud cover with the JJAS cloud cover in all the three decades (Table 2.1) and the similarity of the 26 year trend in the cloud ‘dipole’ strength particularly in the month of August with that in JJAS (Table 2.2; subsection 2.3.5).
Figure 2.7: Boundary layer horizontal winds around Rondônia showing clockwise veer near the surface. 1400 LT JJAS ambient winds at 1000 mb, 925 mb and 850 mb averaged over -65°W, -60°W, -13°S and -8°S between 1983 and 2010. Wind data is from NCEP/NCAR reanalysis 1 (Kalnay et al. 1996).

Figure 2.8: Same as Figure 2.6 (d, e and f) but calculated using the second cloud detection algorithm.

2.3.3 Statistical Robustness of the Dipole Pattern in Cloud Cover

In this section we test the statistical robustness of the ‘dipole’ atmospheric response observed in the contemporary period and show that it is different from the atmospheric response in the early period. The robustness is tested by showing that the spatial pattern in the late or contemporary period is not a random pattern. This
Figure 2.9: Emergence of the southeast-northwest precipitation dipole with increasing deforestation in Rondônia. Daily averaged precipitation in JJAS between (a) 1983 and 1990, (b) 1991 and 1999 and (c) 2001 and 2008 calculated using PERSIANN precipitation (Ashouri et al., 2015). (d) JJAS daily precipitation from TRMM 3B43, (e) JJAS 1700 LT precipitation from TRMM 3B42 and (f) JJAS daily precipitation from PERSIANN averaged between 2002 and 2014. Data is presented as the percentage difference from the deforested area average in the corresponding period (reported on top of each panel). Stippling represents differences significant at the 1% level. Solid lines represent deforested boundaries in the corresponding decades (see Figure 2.1). Dashed lines represent deforested boundary in 2005 and is provided for reference. The high cloudiness signal along the southwestern flank of the 2005 deforested boundary, present in all panels, is due to a hill range (see Figure 2.2).

is tested by showing that the pattern emerges even in the difference cloud field between the late and the early periods. For this analysis three types of JJAS average cloud cover maps averaged over 1400 LT and 1700 LT are generated: 1) mean cloud occurrence map between 1983 to 1994, 2) mean cloud occurrence map between 1997 and 2008 and 3) a cloud occurrence map which is a difference between the above two periods. A joint probability distribution function (PDF) is obtained between the
Figure 2.10: Time evolution of spatial patterns of clouds over the deforested area in June, July, August and September. 1400 LT and 1700 LT averaged percentage occurrence of clouds in June (a, e and i), July (b, f, and j), August (c, g and k) and September (d, h and l) in 1983 to 1990 (a-d), 1991 to 1999 (e-h) and 2001 to 2008 (i-l). Data is derived from GridSat measurements and is presented as percentage difference from the deforested area average (reported in the bottom of each panel).

Latitude and cloud occurrence from each of these three average maps. The joint PDFs for the periods 1983 to 1992 and 1997 to 2008 are obtained using 2000 bootstrapped samples from each period. Using these same samples the joint PDF for the difference cloud occurrence field is generated. The joint probability distributions are estimated using the percentage deviations of cloud occurrence from the deforested area mean of the corresponding decade. Results are presented in Figure 2.11.
Table 2.1: Spatial correlations between monthly average and JJAS average GridSat cloud occurrence fields (calculated within the deforested boundary). All the coefficients are significant with \( p<10^{-10} \).

<table>
<thead>
<tr>
<th></th>
<th>Spatial corr. with JJAS average</th>
</tr>
</thead>
<tbody>
<tr>
<td>June</td>
<td>0.51</td>
</tr>
<tr>
<td>July</td>
<td>0.69</td>
</tr>
<tr>
<td>August</td>
<td>0.71</td>
</tr>
<tr>
<td>September</td>
<td>0.59</td>
</tr>
</tbody>
</table>

The analysis presented in Figure 2.11 shows that there exists a statistically significant systematic spatial ‘redistribution’ of clouds between the early (1980s) and contemporary time periods (2000s). The early time period PDF (Figure 2.11a) shows that the cloud cover deviation field (deviations from deforested area mean) is slightly negative in the south of the deforested area, becomes slightly positive towards its center and then roughly zero in the north. Whereas, in the contemporary time period (Figure 2.11b) there is a distinct region of negative cloud occurrence deviations in the southern half and positive cloud occurrence deviations in the northern half of the deforested area. This systematic spatial redistribution is also apparent in the difference field (Figure 2.11c) which resembles the southeast northwest dipole of cloud occurrence observed in the contemporary period (Figure 2.11b). This analysis corroborates our claim that there is a statistically significant and systematic (as shown by the bootstrapped sample) dipole signal present in the contemporary times which is different from the uniform cloudiness observed over highly deforested areas in the early time period.

2.3.4  A ‘Non-thermal’ Origin of the Dipole Pattern

In this section we will investigate if the ‘dipole’ signal, observed in the contemporary or late period, is generated by thermally triggered mesoscale circulations. This anal-
Figure 2.11: Robustness of the ‘dipole’ spatial pattern of cloudiness in the contemporary decade. Figure shows bivariate PDFs between latitude (10.87°S set as origin) and % deviations of cloudiness from area mean for average of 1400 LT and 1700 LT JJAS cloud cover maps in different periods. The marginal PDFs of cloud occurrence are obtained by binning deforested pixels into latitudinal bins. (a) and (b) show bivariate PDFs using cloud occurrence maps averaged between 1983 to 1994 and 1997 to 2008 respectively. The pixels falling within the deforested boundaries of 1986 and 2005 were used to generate the PDFs in the two periods respectively. (c) shows the bivariate PDF using the difference of cloud cover maps averaged between the two periods 1983 to 1994 and 1997 to 2008. The pixels falling within the deforested boundary of 2005 was used to generate the PDF from the difference cloud field. The data is obtained using 2000 bootstrapped samples from each period.

Analysis will be performed by comparing the correlations of pixel level cloud occurrence with the amount of deforestation in the early and late periods. The signature characteristic of a thermally triggered mesoscale circulation is - preferential updrafts over warmer deforested patches and preferential downdrafts over nearby cooler forested areas (Figure 1.2 [Avissar and Schmidt (1998)]. However, it is argued that the late time period is characterized by high cloud occurrence over downwind deforested areas and suppressed cloud occurrence in the upwind deforested areas, despite deforestation scales being similar in both regions. This response is markedly different from the uniform-cloudiness-over-deforested-areas response observed in the early time period. This is clearly seen in the probability distribution functions plotted in Figure 2.12. These probability distribution functions are generated using 1400 LT JJAS percent-
age cloud cover averaged over 1983 to 1990 and 2001 to 2008 and the corresponding
land cover maps in 1985 and 2005 obtained from LBA-ECO ND-01 Landsat 28.5-m
Land Cover Time Series (Roberts et al., 2013). Both datasets are re-gridded to a
2.4 km by 2.4 km grid using 2-d interpolation for cloud cover and by calculating the
fractional deforested area under each coarse grid cell.

Two inferences are made from the analysis presented in Figure 2.12: 1) that a
change in scale of deforestation between 1980s to 2000s results in a change in the
distribution of clouds over the deforested area - change from a unimodal to a bimodal
distribution. In the early period the clouds preferentially occur over moderately de-
forested grids (with deforested fraction larger than 0 but smaller than $\sim 0.3$), and a
majority of the sparsely deforested grids ($\sim 0$ fraction of deforestation) are charac-
terized by negative anomalies in cloud occurrence suggesting a relative suppression
of clouds as compared to moderately deforested grid cells. But, in the contemporary
period roughly an equal number of grids are populated by high as well as low cloud
cover as depicted by the bimodal distribution. 2) In the contemporary period the
regions of high and low cloud cover occur at similar levels of deforestation (grids
with $\sim 85\%$ of deforestation) i.e. despite the amount of deforestation being the same,
there is a preference of high cloudiness in some regions and low cloudiness in others
- signifying a secondary role of thermal triggering.

This result conforms with standardized modeling studies (Avissar and Schmidt,
1998; Gopalakrishnan et al., 2000; Wang et al., 1996; Patton et al., 2005) that pre-
dict a die down of thermal mesoscale circulations as the scale of surface thermal
heterogeneities grows beyond a scale of a few kilometers. In the contemporary times
when almost all of the grid boxes are nearly completely deforested (Figure 2.12c) the
thermal circulations were expected to be inconsequential.
Figure 2.12: Correlation between patterns of cloudiness and scale of deforestation in the early and contemporary periods. Bivariate probability distribution functions (PDF) (a, c) of 1400 LT JJAS percentage occurrence of cloudiness and fraction of deforested area under the corresponding grid cell in (a) 1983 to 1990 and (b) 2001 to 2008. Percentage difference from the deforested area average in the corresponding period is used to generate the PDFs. Corresponding univariate PDFs of % deviations of cloudiness from area mean (b and d).
To quantify the time evolution of the east-west dipole pattern in cloud occurrence and precipitation occurrence, the dipole moment vectors of the yearly JJAS cloud and precipitation occurrence fields are calculated. The dipole vector time series show a statistically significant positive trend with $p<10^{-4}$ which co-evolves with deforestation in Rondônia (Figure 2.13, Table 2.2). The temporal evolution of the direction
of the dipole (Figure 2.13 inset) indicates a transition from spatially uniform to a
southeasterly dipole in cloud occurrence. This temporal trend is also observed in the
individual months of June, July, August and September. The JJAS precipitation
occurrence dipole is highly correlated with the cloud occurrence dipole (correlation
coefficient=0.7, \( p<10^{-4} \)), and also shows larger values in the 2000s than in the 1980s
(Figure 2.13; Table 2.2).

It should be noted that the dipole moment strength presented in Figures 2.13 and
Table 2.2 have been calculated using grid points falling within the annually evolving
deforested boundaries. To remove the bias introduced by the time evolving region
over which the dipole is calculated, another calculation was performed in which the
dipole strength is estimated with a fixed deforestation boundary of 2005. The trend
in the resulting dipole series is found to be 267 \% km year\(^{-1}\) \( (p=0.0016) \).

Interestingly, no significant trends were observed in the precipitation amounts
over the deforested region calculated using the 33 year PERSIANN daily precipita-
tion time series for JJAS 1983 to 2015 (figures not shown). The precipitation trends
were calculated using data averaged over three regions: 1) the deforested area within
the deforested boundary of the corresponding year, 2) the northwestern region be-
tween 64\(^\circ\)W, 63\(^\circ\)W, 10.75\(^\circ\)S and 9.75\(^\circ\)S and 3) the southeastern region between 62\(^\circ\)W,
61\(^\circ\)W, 12.3\(^\circ\)S and 11.3\(^\circ\)S. The corresponding \( p \)-values for the least squares fit to the
time series are 0.2, 0.7 and 0.08 respectively. These results show that there is no
detectable trend in precipitation either over the whole deforested area or the down-
wind and upwind regions suggesting that the inter-annual variability in the regional
precipitation is stronger as compared to the changes due to the dipole signal.
Table 2.2: Cloud and Precipitation observations showing statistically significant increase in ‘polarity’ in individual months calculated from 26 years of data. Table listing linear trends (p-value) in cloud and precipitation dipole strength in J, J, A, S and JJAS.

<table>
<thead>
<tr>
<th></th>
<th>GridSat Cloud Occurrence</th>
<th>PERSIANN Precip. Occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>JJAS</td>
<td>345 (e-05)</td>
<td>25 (2.9e-05)</td>
</tr>
<tr>
<td>June</td>
<td>690 (0.0032)</td>
<td>66 (0.11)</td>
</tr>
<tr>
<td>July</td>
<td>578 (0.0085)</td>
<td>61 (0.036)</td>
</tr>
<tr>
<td>August</td>
<td>357 (0.0045)</td>
<td>52 (0.0018)</td>
</tr>
<tr>
<td>September</td>
<td>246 (0.00062)</td>
<td>21 (2.7e-05)</td>
</tr>
</tbody>
</table>

2.4 Conclusions

An analysis of the past three decades of regional hydroclimatic change over the deforested areas of Rondónia, Brazil were performed. The deforestation scales in this region have evolved from a few kilometers to a few hundreds of kilometers over this time period. Climate data records of satellite data of sub-daily albedo and brightness temperature (GridSat between 1983 and 2002) and daily precipitation (PERSIANN between 1983 and 2014) were utilized for this climatological analysis. Sub-daily and monthly precipitation data from TRMM (between 2002 and 2014) were also used to complement the analysis. The major findings are:

1. Contemporary scales of deforestation result in a statistically significant redistribution of dry season precipitation with downwind deforested areas gradually getting wetter and upwind deforested areas getting drier with time. The strength of this dipole has increased between 1983 and 2014 with an annual rate of 345% km year$^{-1}$ and has increased by a factor of 3 to 4 between the 1980s and 2000s.
2. This atmospheric response is found to be markedly different from the regular thermally generated mesoscale circulations which are the dominant response to small scale deforestation prevalent in the early phase of deforestation in the 1980s. The contemporary cloud and precipitation shows a preference of occurrence over downwind regions and suppression over upwind deforested regions despite the deforestation scales being the same in the two regions. This spatial pattern is not explained by the thermally triggered mesoscale circulations suggesting the emergence of a new physical phenomenon at intermediate scales of deforestation (discussed in Chapter 3).

3. Most importantly, unlike the non-precipitating shallow cumulus response to small scale deforestation, contemporary deforestation results in statistically significant dry season precipitation changes in the downwind and upwind regions of the deforested area. Satellite precipitation datasets show that this precipitation change is roughly ±25% of the deforested area mean precipitation in the downwind and upwind deforested areas respectively.

This atmospheric response, which is different from both thermal mesoscale circulations and downwind convection observed over much smaller urban areas (see Shephard (2005) for a review) is a novel finding which can influence our understanding of deforestation triggered physical phenomenon and the interpretation of the studies of climatic impacts of future, patchy deforestation (Saad et al., 2010; Walker et al., 2009) in the Amazon rain forest. The physical processes behind this phenomenon will be investigated and put in to perspective in the next chapter.
Chapter 3

Attribution of Observed, Regional Hydroclimatic Changes to Physical Processes Induced by Contemporary Deforestation

3.1 Motivation

Cloud and precipitation observations presented in Chapter 2 show that in the contemporary times, there is a statistically significant tendency of more clouds and rainfall in the downwind and suppressed clouds and rainfall in the upwind deforested areas. It is argued in Chapter 2 that this phenomenon cannot be explained by thermally generated mesoscale circulations, which are the dominant atmospheric response at small scales of deforestation. Moreover, this phenomenon affects a deforested region which is ~400 km across in the ambient wind direction and is predominantly pasture - and so the driving mechanism is likely different from the regular downwind convection observed over an order of magnitude smaller urban areas (see review by Shephard).
Hence it is argued, in this chapter, that if this redistribution is caused by deforestation, then the causal physical mechanism is not exclusively thermal in nature. A deforested area induces other kinds of surface heterogeneities as well which can trigger a systematic response by the atmosphere. The possibility of such mechanisms is explored in this chapter.

Surface roughness is one of the factors that can impose a major control on the atmospheric response to deforestation. On a local scale, deforestation can result in a 2-orders-of-magnitude change in surface roughness (Wright et al., 1996b), with implications for the surface energy budget (Lee et al., 2011). For example, decreases in surface roughness reduce turbulent mixing and thus the redistribution of energy between the land and the atmosphere. Second, surface roughness also imposes a purely dynamical control on the atmosphere through its impact on the lower momentum boundary condition at the land-atmosphere interface. It is unclear how these thermodynamic and dynamic implications of changes in surface roughness scale with the characteristic size of deforested patches.

On the other hand, the possibility of this redistribution of precipitation being a result of climate variability cannot be discounted either. It is known that decadal global SST changes can affect the basin-wide Amazonian hydroclimate (Yoon and Zeng, 2010; Fernandes et al., 2015; Marengo et al., 2011, 2008a; Zeng et al., 2008). In particular the dry season hydroclimate of the southern and western Amazon rainforest has been shown to be correlated with tropical North Atlantic sea surface temperatures (Yoon and Zeng, 2010; Zeng et al., 2008). Incidentally, the contemporary time period has been plagued by severe droughts (in 2005 and 2010; Lewis et al., (2011)) and floods (2009 and 2012; Marengo et al., (2012); Satyamurty et al., (2013)) which have been correlated with anomalous sea surface temperatures in either the tropical North Atlantic or South Atlantic oceans. The possibility of a larger scale atmospheric control on the the observations reported in Chapter 2 will also be explored in this chapter.
The overall objective of this study is to understand and separate the roles played by decadal climate variability and the effects of deforestation-induced surface roughness changes on the observed hydroclimatic change in Rondônia. The investigation is conducted in two parts. The first, ‘Contemporary’ study, published in the Journal of Geophysical Research-Atmospheres (Khanna and Medvigy 2014a), explores the possibility of the generation of mesoscale circulations due to surface roughness variations between pasture and forest vegetation and analyzes the physical features of such a circulation. The following questions are addressed in this study: (1) Can changes in surface roughness induce mesoscale circulations, by changing the lower frictional boundary condition on the atmosphere (section 3.3.1)? and (2) do the thermodynamic effects of deforestation amplify or weaken the dynamical effects of surface roughness changes (sections 3.3.3, 3.3.4 and 3.3.8)? Standardized settings of a climatological average sea surface temperature and contemporary deforestation are used in these experiments. In the second part, the ‘Multidecadal’ study, we explain the full three decadal development of the hydroclimatic response to increasing scale of deforestation observed in Rondônia (Chapter 2). The numerical model is set up gaining insights from the exploratory ‘Contemporary’ study and according to field observations before performing the ‘Multidecadal’ study. The following questions are addressed: (3) Does the decadal climate variability play a role in the observed trends in spatial patterns of clouds and precipitation (section 3.3.6)? and (4) can the dynamical effect, induced by decrease in surface roughness due to increasing deforestation, explain the temporal transition observed in the satellite data (section 3.3.7)? Finally, the chapter closes with a ‘compositing’ of the observational and numerical results to quantify the hydroclimatic change over the three decades of deforestation (sections 3.4 and 3.5).
3.2 Methods

3.2.1 Numerical Model

The Ocean-Land-Atmosphere-Model (OLAM) (Walko et al., 2000a; Walko and Avis-sar, 2008a,b, 2011) was used to carry out the numerical experiments. A successor of the Regional Atmospheric Modeling System, OLAM is a variable resolution global circulation model which uses finite volume discretization of the full non-hydrostatic, compressible Navier Stokes equations on a hexagonal grid. Such formulation is essential for the modeling of convective processes in mesoscale phenomena such as those studied in this paper. Moreover, while enabling the resolution of small scales at desired locations without greatly increasing the overall computational burden, the variable resolution of OLAM also facilitates interactions between large scale atmospheric dynamics with mesoscale processes without introducing errors due to lateral boundary conditions. These features of OLAM make it a suitable tool to study the mesoscale phenomena which are the subject of this investigation. The microphysics parameterization was obtained from Walko et al. (1995, 2000b), the cumulus parameterization from Grell and Devenyi (2002), and the radiative transfer from Harrington and Olsson (2001). Subgrid-scale turbulence is parameterized according to Lilly (1962) and Hill (1974). OLAM has been evaluated for the Amazon region in several previous studies (Medvigy et al., 2008, 2010, 2011, 2012). The land surface is represented using the Land-Ecosystem-Atmosphere-Feedback model (Walko et al., 2000a). The customization of the model for this study, model version and relevant land surface parametrization relations are described in Appendix B. Biophysical parameters relevant for this study are listed in Table 3.1.
Table 3.1: Biophysical parameters used to parametrize the pasture and evergreen forest vegetation in OLAM. The relevant model parametrization equations and biophysical parameters are reported in Appendix B.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Forest</th>
<th>Pasture</th>
<th>Percentage change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rooting Depth (m)</td>
<td>5</td>
<td>1</td>
<td>-80%</td>
</tr>
<tr>
<td>Vegetation Height (m)</td>
<td>32</td>
<td>0.32</td>
<td>-100%</td>
</tr>
<tr>
<td>Min. Stomatal Resist. (sm$^{-1}$)</td>
<td>500 (OLAM default, used in ‘Contemporary’ study)</td>
<td>100 (used in ‘Multi-decadal’ study)</td>
<td>-80%</td>
</tr>
<tr>
<td>Emissivity</td>
<td>0.95</td>
<td>0.96</td>
<td>1%</td>
</tr>
<tr>
<td>Green Albedo</td>
<td>0.12</td>
<td>0.18</td>
<td>50%</td>
</tr>
<tr>
<td>Max. Veg. Fractional Cover</td>
<td>0.9</td>
<td>0.8</td>
<td>-11%</td>
</tr>
<tr>
<td>Max. Total Area Index</td>
<td>7</td>
<td>3</td>
<td>-57%</td>
</tr>
<tr>
<td>LAI calculated using NDVI$^d$</td>
<td></td>
<td></td>
<td>Updates every month.</td>
</tr>
</tbody>
</table>

$^a$ Wright et al. (1996b)
$^b$ Freitas (1999), Gandu et al. (2004)
$^c$ Culf et al. (1995)
$^d$ DAAC (2013)

3.2.2 Numerical Design

This modeling study is divided into two parts. Numerical experiments performed in the first part explore if contemporary intermediate scales of deforestation can induce any systematic mesoscale circulations and if so, what are the dominant mechanisms inducing such a response. The characteristics of such a circulation are also investigated. This study is referred to as the ‘Contemporary’ study in the text as it serves to explore the nature of the atmospheric response to contemporary scales of deforestation. The second part focuses on explaining the temporal transition in cloud cover and precipitation observed over three decades of deforestation in Rondônia reported in Chapter 2. The possibility of the observed transition in the hydroclimate to be induced by increasing scales of deforestation as opposed to changing climate will be
investigated. The physical mechanism responsible for the observed transition will also be explored. This study is referred to as the ‘Multidecadal’ study in the text.

Simulation Design for ‘Contemporary’ Analysis

As stated before, the numerical experiments in this analysis are designed to understand if surface roughness variations caused by contemporary scales of deforestation can cause systematic mesoscale circulations or not. Systematic mesoscale effects of small scale deforestation on boundary layer dynamics have been shown previously to be strong during early to mid afternoon. Because this study focuses on exploring the boundary layer dynamics resulting from contemporary scale deforestation, we focus on early afternoon times for the analysis. As such, the simulation output is taken and analyzed between 1200 LT and 1300 LT. Also all of the numerical simulations performed for the ‘Contemporary’ study are done for the dry season month of July because this is one of the months (between July and August) when the observed cloud cover patterns have the strongest spatial correlations with the JJAS averaged cloud cover field (Table 2.1) and because this is a time when land-atmosphere coupling is observed to be the strongest in Rondônia (Wang et al., 2000). Also, because this
study is focused only on the effects of deforestation, inter-annual climate variability is neglected by using climatological sea surface temperatures (Reynolds et al., 2002), averaged between 1971-2012, to drive the simulations. The analysis of the effects of deforestation on the full afternoon, evolving over three decades will be performed in the ‘Multidecadal’ study.

The atmosphere is initialized using National Centre for Environmental Prediction (Kalnay et al., 1996) atmospheric fields for June 2004. The soil energy and moisture are initialized using a 15 year model spin up (Medvigy et al., 2013). Time lagged techniques of ensemble generation as described in Hoffman and Kalnay (1983) are used to calculate sample statistics in the experiments. In this technique, a sample of statistically similar experiments is generated by initializing the atmosphere with states which lag in time by some amount. Using this technique an ensemble of 24 simulations is generated initialized at intervals of 1 day starting at 0000 UTC, 8th June 2004 and ending 0000 UTC, 1st July 2004.

The numerical experiments differed according to the land surface properties prescribed for Rondônia. To test the effects of intermediate-scale deforestation the following simulations were carried out: (1) a DEF experiment which has contemporary land cover characteristics (Figure 3.1b) and (2) a FOR experiment which uses the characteristics of pristine vegetation cover over Rondônia. The grid resolution over Rondônia was chosen to be 32 km because mechanisms which result from only intermediate (tens of km) scale deforestation were to be captured. The grid resolution increased to 64 km over the Amazon (necessary to resolve the thermo-dynamical effects of the Andes as shown by Medvigy et al. (2008)) to 256 km outside the Amazon (Figure 3.1a). Consequently, a full resolution of thermally generated mesoscale circulations which are strongest at scales around 10-20 km (Avissar and Schmidt, 1998) was not expected. The vertical resolution was set to 200 m near the surface gradually increasing up to 2 km near the model top at 45 km.
Table 3.2: Numerical experiments for the ‘Contemporary’ analysis. The minimum stomatal resistance used in these experiments is 500 $\text{sm}^{-1}$. All experiments in rows 1 to 3 are performed at a 32 km horizontal resolution. Compare these experiments with the ‘Multidecadal’ experiments (Table 3.3) which use a minimum stomatal resistance of 286 $\text{sm}^{-1}$ and are performed at an 8 km horizontal resolution.

<table>
<thead>
<tr>
<th>Experiment &amp; FOR various resolutions</th>
<th>Land Cover</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEF &amp; FOR various resolutions</td>
<td>Forested Rondônia</td>
<td>DEF - FOR to capture the atmospheric response due to contemporary deforestation.</td>
</tr>
<tr>
<td>DEF-dyn</td>
<td>2004, pasture vegetation as high as evergreen forest</td>
<td>DEF-dyn - FOR to separate out the role of horizontal surface roughness variations.</td>
</tr>
<tr>
<td>DEF-sr</td>
<td>2004, pasture minimum stomatal resistance equal to evergreen forest’s.</td>
<td>DEF-sr - FOR to separate out the role of horizontal sensible heat flux variations.</td>
</tr>
<tr>
<td>DEF</td>
<td>2004</td>
<td>To test the robustness of results at different spatial resolutions.</td>
</tr>
<tr>
<td>FOR</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Additional simulations were carried out to differentiate the impacts of the changes in roughness length from impacts due to changes in other biophysical parameters. Of particular importance is the DEF-dyn ensemble experiment. DEF-dyn is exactly the same as DEF except that its deforested grid cells have the vegetation height of broadleaf evergreen forest (Table 3.1). For comparison, ensemble experiments with changes in other biophysical parameters were also carried out. The DEF-sr experiment is the same as DEF except the minimum stomatal resistance of the deforested vegetation is the same as that of broadleaf evergreen forest. Default parametrizations in OLAM (Table 3.1) for pasture and forest vegetation were used in the ‘Contemporary’ study. It should be noted that the ‘Contemporary’ study was performed with a minimum stomatal resistance of 500 $\text{sm}^{-1}$ (default for OLAM) for forest vegetation as opposed to 286 $\text{sm}^{-1}$ (Freitas 1999, Gandu et al. 2004, Da Silva et al. 2008) used in the ‘Multidecadal’ analysis (Table 3.1). Several tests were also performed.
Figure 3.2: (a) and (b) respectively show land covers in 1986 and 2006 used in the simulations for the ‘Multidecadal’ analysis. The LBA forest and pasture sites are also displayed.

to evaluate the robustness of the results to model resolution. For this purpose the DEF and FOR experiments were repeated for spatial resolutions of 256 km, 128 km, 64 km, 16 km and 8 km over Rondônia. All the simulations for the ‘Contemporary’ exploratory study are summarized in Table 3.2.

**Simulations Design for ‘Multidecadal’ Analysis**

This analysis is performed to capture the multidecadal variability of clouds and precipitation observed in satellite data (Chapter 2) and to test if decrease in surface roughness due to increasing scales of deforestation can explain the multidecadal variability. The two main technical differences or improvements between these experiments and the ones performed for the ‘Contemporary’ study are the use of 1) forest minimum stomatal resistance of 286 $\text{sm}^{-1}$ based on in situ measurements from Amazonia (Freitas 1999) and 2) the resolution of mesoscale effects on a model resolution of 8 km. The specific differences in the experimental design will now be presented.

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Table 3.3: Numerical experiments for the ‘Multidecadal’ analysis. The minimum stomatal resistance used in these experiments is 286 $\text{sm}^{-1}$. All experiments are performed at an 8 km horizontal resolution. Compare these experiments with the ones for the exploratory ‘Contemporary’ study (Table 3.2) which use a minimum stomatal resistance of 500 $\text{sm}^{-1}$ and are performed at a 32 km horizontal resolution.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Land Cover</th>
<th>SST</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEF86SST80</td>
<td>1986</td>
<td>1980-1989 avg.</td>
<td>DEF86SST80 versus FORprSST80 and DEF06SST00 versus FORprSST00 - capture the combined roles of SST variability and land cover change in the observed transition in cloud cover.</td>
</tr>
<tr>
<td>DEF06SST00</td>
<td>2006</td>
<td>2000-2009 avg.</td>
<td></td>
</tr>
<tr>
<td>FORprSST80</td>
<td>Forested Rondônia</td>
<td>1980-1989 avg.</td>
<td></td>
</tr>
<tr>
<td>FORprSST00</td>
<td>Forested Rondônia</td>
<td>2000-2009 avg</td>
<td></td>
</tr>
<tr>
<td>DEF06SSTcl</td>
<td>2006</td>
<td>1971-2010 avg.</td>
<td>Capture the atmospheric response due just to a change of land cover between 1986 and 2006.</td>
</tr>
<tr>
<td>DEF06SSTcl</td>
<td>1986</td>
<td>1971-2010 avg.</td>
<td></td>
</tr>
<tr>
<td>FORprSSTcl</td>
<td>Forested Rondônia</td>
<td>1971-2010 avg</td>
<td></td>
</tr>
<tr>
<td>DEF06SSTcl-dyn</td>
<td>2006, pasture vegetation as high as evergreen forest</td>
<td>1971-2010 avg.</td>
<td>DEF06SSTcl-dyn - FORprSSTcl to separate out the role of horizontal surface roughness variations.</td>
</tr>
<tr>
<td>DEF06SSTcl-sh</td>
<td>2006, all properties of pasture vegetation same as evergreen forest except vegetation height</td>
<td>1971-2010 avg.</td>
<td>DEF06SSTcl-sh FORprSSTcl to separate out the role of horizontal sensible heat flux variations.</td>
</tr>
<tr>
<td>DEF06SSTcl-topo</td>
<td>2006, average topography between 68°W to 57°W and 16°S to 5°S</td>
<td>1971-2010 avg.</td>
<td>Separate the coupled effect of topographical variations from vegetation variations on the regional hydroclimate.</td>
</tr>
<tr>
<td>FOR06SSTcl-topo</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
To simulate the observed multidecadal variability of the hydroclimate, 11 different numerical experiments were carried out (Table 3.3). Three different land cover maps were used: simulations prefixed with DEF86 and DEF06 used the land cover observed in Rondônia [Roberts et al. 2013] in 1986 and 2006, respectively (Figure 3.2); simulations prefixed with FORpr represent pristine forest and replace all pasture in the region with evergreen forest. To reduce the number of degrees of freedom which are introduced by an interactive ocean, OLAM was ran as an atmospheric general circulation model with prescribed monthly averaged sea surface temperatures (SSTs) [Rayner et al. 2003]. Three different SST forcings were used. Simulations suffixed SST80, SST00 and SSTcl are forced with monthly SSTs averaged between 1980-1989, 2000-2009 and 1971-2010 respectively. The Hadley Centers SST time series [Rayner et al. 2003] used for these simulations are available as monthly averages which are further averaged over the periods mentioned above to produce 3 averaged annual cycles. These annual cycles are used for the respective experiments. A simulation that controlled roughness length by running deforestation-like simulations in which the height of pasture vegetation in Rondônia was set to be the same as for evergreen forest (‘dyn’ in the simulation name) was also performed. This simulation is analogous to the DEF-dyn simulation done for the exploratory ‘Contemporary’ study at 32 km resolution. A similar deforested simulation was performed to achieve a minimum possible horizontal variation of surface sensible heat flux while maintaining the roughness differences between the two vegetation types. In this experiment the pasture vegetation had the same properties as evergreen forest except vegetation height (‘sh’ in the simulation name). Note that this simulation is different from the DEF-sr simulation performed for the ‘Contemporary’ study which controlled for minimum stomatal resistance only. Finally, a deforested experiment with no regional topographic variations was also performed (‘topo’ in the simulation name) by applying the area averaged topography within 68°W to 57°W and 16°S to 5°S. The biophys-
ical parameters used for the ‘Multidecadal’ study are the same as that used in the exploratory ‘Contemporary’ study except the minimum stomatal resistance due to reasons discussed in subsection 3.3.5 (Table 3.1).

Deforested experiments DEF86SST80 and DEF06SST00 were performed to analyze the role of changing scales of deforestation and SSTs in the observed decadal changes in the hydroclimate of Rondônia. Experiments DEF86SSTcl and DEF06SSTcl were performed to separate the hydroclimatic effects of changing scales of deforestation from the effects of observed decadal variability of SSTs. Comparing DEF06SSTcl-dyn and DEF06SSTcl-sh to DEF06SSTcl allowed the isolation of the impacts of roughness length. Lastly, the DEF06SSTcl-topo experiment allowed the isolation of the coupled effects of regional topography on the deforestation-induced hydroclimatic changes. The difference fields (DEF-FOR experiments) show the net effect of vegetation cover change from pristine forest to pasture removing spatial features common to both experiments.

Each experiment consists of a time-lagged ensemble of 24 simulations. The ensemble is generated by initializing 24 simulations at intervals of 1 day - intervals starting at 0000 UTC, 8 June 2004 and ending 0000 UTC, 1 July 2004. All simulations end at 0000 UTC, 1 September. All simulation results presented in this study are averaged over the respective 24 ensemble members. Only the months of July and August were simulated due to computational constraints. The month of August was specifically chosen for the ‘Multidecadal’ analysis because observations show that this is one of the months (amongst J, J, A and S) which presents the highest resemblance with the JJAS averaged values. This is summarized in Tables 2.1 and 2.2 which show that in observations amongst all months analyzed 1) the trend in the August dipole moment is the closest to the trend in JJAS dipole moment and 2) the spatial correlation between the August averaged and JJAS averaged cloud cover is the largest.
The initial conditions are obtained from the National Centre for Environmental Prediction (Kalnay et al., 1996) atmospheric fields for June 2004. Soil energy and moisture are initialized using values obtained at the end of 15-year OLAM spinup for June 2004. The initialization is made with these values averaged over a 15°x15° area around Rondônia. For both simplicity and lack of available data, a uniform, constant clay loam soil type was prescribed around Rondônia for reasons described in Appendix B. However, soil characteristics can vary as a function of time over deforested areas (Martinez and Zinck, 2004) due to continual grazing and poor management and can also vary on small spatial scales. Despite this simplification, this simple prescription gave an adequate representation of the observed sensible heat fluxes (Table 3.6).

As mentioned previously, the grid resolution used in all the experiments is ∼8 km over Rondônia, which gradually increases up to 256 km over the whole globe. This resolution was chosen because both the thermally generated vegetation breezes and the atmospheric response to contemporary scales of deforestation can be well captured at this resolution (Avissar and Schmidt, 1998; Patton et al., 2005). The same vertical grid setup is used as in the investigatory climatological simulations.

3.3 Results and Discussion

3.3.1 A Mesoscale Circulation in the Investigatory ‘Contemporary’ Study

In the ‘Contemporary’ study the atmospheric effects of change in land cover in Rondônia were determined by comparing ensemble averaged quantities in the DEF and FOR simulations. For all variables, the variations in the atmospheric state averaged between 1200 LT and 1300 LT was analyzed for all days in July because the atmospheric effects of deforestation were found to be strongest during afternoon hours in a preliminary analysis.
Figure 3.3: The mesoscale circulation represented by DEF-FOR horizontal (arrows) and vertical wind (shading) fields averaged between 1200 LT and 1300 LT for all days in July at altitudes (a) 515 m, (b) 736 m, (c) 967 m, (d) 1207 m and (e) 1456 m. (f) The DEF horizontal winds averaged over the deforested area.

The difference between the wind fields of DEF and FOR reveals a mesoscale circulation (Figure 3.3) marked by a strong region of ascent in the northwest and a strong region of subsidence in the southeast of Rondônia. The vertical structure of the circulation shows that there is an increase in the horizontal wind speed near the surface within the deforested region and a weak return flow aloft. This circulation also veers counter-clockwise (south to southeasterly near the surface and easterly at an altitude of about 1 km). A signature of the mesoscale circulation is also visible in the difference potential temperature (Figure 3.4), where cold surface air temperatures over the deforested areas have been advected aloft by the mesoscale circulation in the northern parts of the domain and vice versa in the southern regions. Although these simulations show a colder near surface air temperature as compared to observations
Figure 3.4: The mesoscale circulation represented by DEF-FOR potential temperature field averaged between 1200 LT and 1300 LT for all days in July at altitudes (a) 736 m, (b) 967 m, (c) 1207 m and (d) 1456 m. Note the non-linear color scaling.

which show surface warming due to deforestation, the dipole structure in Figure 3.4d shows that the mesoscale circulation in Figure 3.3 can cause systematic vertical mixing hence modulating the thermal structure of the atmosphere in the downwind and upwind deforested regions.

### 3.3.2 A Dynamical Origin of the Mesoscale Circulation

Maps of horizontal wind divergence (Figure 3.5) suggest the origin of the mesoscale circulation. It was found that changes in surface roughness generate the observed mesoscale circulation by creating horizontal divergence at the transition between forest and pasture and horizontal convergence at the transition between pasture and forest. These areas of horizontal divergence and convergence are generated because
horizontal winds accelerate while blowing from a rough surface like forest to a smooth surface like pasture. Such regions of convergence and divergence are found to occur in the northwestern and southeastern parts of the deforested domain in DEF-FOR (Figure 3.5 a), leading to vertical motion in DEF (Figure 3.3) following the continuity equation. A further confirmation was made that surface roughness changes initiated the observed mesoscale circulation by comparing the winds in DEF-dyn and FOR. Figure 3.6 shows the near surface and upper air difference wind fields between DEF-dyn and FOR averaged between 1200 LT and 1300 LT. The circulation dominant over the deforested area in DEF is absent in DEF-dyn. Moreover, a map of the column integrated divergence of the DEF-dyn - FOR horizontal winds shows no paired regions of divergence and convergence, but instead a weak and widespread area divergence (Figure 3.5 b).

The physical and thermal features of the mesoscale circulation were analyzed to evaluate changes in the thermal structure of the atmosphere due to deforestation. First, it is found that the mesoscale circulation is contained within the deforested region. This is unlike thermally generated mesoscale circulations which are expected to be strong at the forest-clearing interface and have a downward branch over the
Figure 3.6: DEF-dyn - FOR horizontal winds (arrows) and vertical winds (shading) averaged between 1200 LT and 1300 LT for all days in July at an altitude of (a) 515 m and (b) 967 m.

forest (Avissar and Schmidt, 1998). Secondly, the simulated mesoscale circulation is present at night as well, although with varying intensity (compare Figure 3.7 with Figure 3.3). This again contrasts with the typical thermally generated mesoscale circulation, which subsides at night. Thirdly, in this model set-up, the area averaged sensible heat fluxes between 1200 LT and 1300 LT are lower in DEF by 37 W m$^{-2}$ as compared to FOR (Figure 3.8 and Table 3.5). Thermally generated mesoscale circulations, in contrast, are characterized by increases in sensible heat fluxes in the deforested regions. Taken together, these findings indicate that this mesoscale circulation has a dynamical origin and is not a product of changes in the thermal structure of the atmosphere, although its strength maybe modulated by it. Therefore, these mesoscale circulations are reffered to as Dynamically dominated MesoScale Circulations and henceforth abbreviated as DMSC. Similarly, hereafter the Thermally dominated MesoScale Circulations are abbreviated as TMSC.

The decrease in sensible heat fluxes in DEF with respect to FOR was unexpected because numerous previous studies have found an increase in sensible heat fluxes as a result of deforestation (Nobre et al., 1991; Gash and Nobre, 1997; Souza et al., 2000; Roy, 2009). There have also been some studies that have reported a decrease in sensible heat following large scale deforestation in South America (Da Silva et al., 2000).
Figure 3.7: The night-time monthly mean mesoscale circulation represented by DEF- FOR horizontal (arrows) and vertical wind (shading) fields averaged between 0000 LT and 0100 LT for all days in July plotted at altitudes (a) 515 m, (b) 736 m, (c) 967 m, (d) 1207 m and (e) 1456 m. (f) The horizontal winds in DEF averaged over the deforested area.

2008; Lee and Berbery, 2012; however, the mechanism behind this reduction in sensible heat was not articulated in those studies. In our experiments, this reduction is caused by the stomatal resistance parametrizations and is discussed in subsection 3.3.3.

In our simulations the DMSC is not found to have caused any significant changes in the precipitation over the deforested region (Figure not shown). The largest changes are found to occur around the northernmost areas of the deforested region and nearby forested areas, but these changes are not significant at the 90% confidence level. This suggests that roughness generated ‘vegetation breezes’ are not strong enough to cause convective precipitation, at least with our chosen convective parametrization.
3.3.3 Robustness of the Simulated ‘Dynamical’ Mesoscale Circulation

The sensitivity of the DMSC to model resolution was investigated by comparing the DEF and FOR experiments at resolutions of 256 km, 128 km, 64 km, 32 km, 16 km and 8 km. Vegetation breezes or deforestation-induced mesoscale circulations are found to develop only in the 32 km, 16 km and 8 km simulations (Figure 3.9). The northwestern regions are dominated by increased updrafts and the southeastern regions by strong downdrafts, which is a feature of the DMSC. A horizontal return flow, associated with the DMSC, is also found to occur. The difference fields at 8 km and 16 km resolution however show several strong small scale circulations embedded in the DMSC which are possibly triggered by the resolved heterogeneities. The difference potential temperature field (not shown in figure) also has the dipole structure characteristic of a DMSC, with negative anomalies in the northwest and positive anomalies in the southeast.

The sensitivity of the DMSC to minimum stomatal resistance is also investigated by comparing the results from the simulations DEF-sr and FOR. Minimum stomatal
resistance is found to strongly influence sensible heat fluxes in the 32 km simulations (Table 3.4). It is apparent from the difference horizontal and vertical wind fields in DEF-sr - FOR (Figure 3.10) that the triggering of the DMSC is not dependent on the horizontal gradient in sensible heat flux because the DMSC develops in DEF-sr, which has similar sensible heat fluxes as FOR (the dependence of the DMSC on the magnitude of sensible heat fluxes will be discussed in subsection 3.3.8).

It is expected that the robustness of the DMSC will be influenced by the synoptic scale circulation. Because synoptic states with relatively weak ambient winds are generally more permitting of mesoscale circulations than synoptic states with strong winds [Wang et al. 2000], it is expected that the DMSC will be strongest during times of weak synoptic-scale winds. Thus, it may be that the DMSC is strongest during
Table 3.4: Monthly and area averaged (standard deviation) components of the surface energy balance.

<table>
<thead>
<tr>
<th>Component (W m$^{-2}$)</th>
<th>DEF</th>
<th>DEF-dyn</th>
<th>DEF-sr</th>
<th>FOR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Radiation</td>
<td>113 (1.3)</td>
<td>115 (1.7)</td>
<td>112 (1.2)</td>
<td>118 (1.7)</td>
</tr>
<tr>
<td>Sensible Heat</td>
<td>33 (2.6)</td>
<td>33 (3.2)</td>
<td>39 (2.7)</td>
<td>38 (3.6)</td>
</tr>
<tr>
<td>Latent Heat</td>
<td>78 (1.4)</td>
<td>81 (1.5)</td>
<td>72 (1.2)</td>
<td>78 (1.6)</td>
</tr>
<tr>
<td>Ground storage</td>
<td>1.5 (1.6)</td>
<td>1.5 (1.6)</td>
<td>1.3 (1.5)</td>
<td>1.4 (1.7)</td>
</tr>
<tr>
<td>Incoming Solar Radiation</td>
<td>244 (4.2)</td>
<td>243 (4.9)</td>
<td>246 (2.9)</td>
<td>244 (3.9)</td>
</tr>
<tr>
<td>Outgoing Solar Radiation</td>
<td>32 (0.6)</td>
<td>32 (0.7)</td>
<td>32 (0.4)</td>
<td>30 (0.5)</td>
</tr>
<tr>
<td>Incoming Terrestrial Radiation</td>
<td>295 (5.5)</td>
<td>294 (6.7)</td>
<td>293 (4.6)</td>
<td>292 (4.3)</td>
</tr>
<tr>
<td>Outgoing Terrestrial Radiation</td>
<td>394 (4.1)</td>
<td>391 (4.3)</td>
<td>394 (4.6)</td>
<td>389 (4.7)</td>
</tr>
</tbody>
</table>

Figure 3.10: The mesoscale circulation in DEF-sr-FOR as represented by difference horizontal and vertical wind fields averaged between 1200 LT and 1300 LT for all days in July at altitude 1207 m. The shading shows the difference vertical wind and the arrows show the difference horizontal wind vectors.

dry years and dry season, when the lower level winds get weakened [Marengo et al., 2008b; Yoon and Zeng, 2010]. The DMSC may be weaker (if it is present at all) when winds are relatively strong, as is typical during wet years [Marengo et al., 2012] and the wet season [Garreaud et al., 2009]. The ‘generalizability’ of the DMSC to seasons other than the dry season and locations other than Rondônia will be investigated in greater detail in Chapter 4, which is devoted to this issue.
Table 3.5: Area averaged components (standard deviation) of the surface energy balance between 1200 LT and 1300 LT for all days in July.

<table>
<thead>
<tr>
<th>Component (W m$^{-2}$)</th>
<th>DEF</th>
<th>DEF-dyn</th>
<th>FOR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Radiation</td>
<td>592 (3.2)</td>
<td>598 (3.6)</td>
<td>603 (2.5)</td>
</tr>
<tr>
<td>Sensible Heat</td>
<td>190 (10.0)</td>
<td>196 (12.5)</td>
<td>227 (10.3)</td>
</tr>
<tr>
<td>Latent Heat</td>
<td>286 (8.2)</td>
<td>301 (10.6)</td>
<td>286 (9.0)</td>
</tr>
<tr>
<td>Ground storage</td>
<td>116 (3.0)</td>
<td>101 (2.8)</td>
<td>89 (2.3)</td>
</tr>
<tr>
<td>Incoming Solar Radiation</td>
<td>814 (10.2)</td>
<td>816 (11.2)</td>
<td>821 (6.8)</td>
</tr>
<tr>
<td>Outgoing Solar Radiation</td>
<td>105 (1.4)</td>
<td>106 (1.6)</td>
<td>102 (1.0)</td>
</tr>
<tr>
<td>Incoming Terrestrial Radiation</td>
<td>317 (6.6)</td>
<td>313 (7.9)</td>
<td>311 (5.7)</td>
</tr>
<tr>
<td>Outgoing Terrestrial Radiation</td>
<td>434 (4.8)</td>
<td>426 (5.0)</td>
<td>427 (5.5)</td>
</tr>
</tbody>
</table>

Sensitivity of the Surface Energy Balance to Biophysical Parameters

In this section the effects of surface roughness changes and stomatal resistance changes on the local surface energy balance of the deforested region are investigated. Table 3.5 shows the differences in the area-averaged components of the surface energy balance temporally averaged between 1200 LT and 1300 LT for all days in July for DEF, DEF-dyn and FOR. Using the default parametrizations of OLAM, the forest sensible heat fluxes are simulated much higher than the pasture vegetation and latent heat fluxes almost the same as pasture vegetation throughout most of the afternoon (Figure 3.11) which is opposed to most in situ observations (Gash and Nobre, 1997; von Randow et al., 2004). This overall reduction in the turbulent transfer of heat between land and atmosphere is consistent with a reduction of surface roughness in DEF relative to FOR and results in an increase in daytime surface temperatures (+0.81 °C) in DEF relative to FOR. Consistent with this increase in daytime temperature, an increase in ground energy storage and outgoing long wave radiation is also found in DEF relative to FOR. The role of reduction in surface roughness on the reduction in turbulent transfer of energy between land and atmosphere is further emphasized by the increase in both sensible and latent heat fluxes in DEF-dyn with respect to DEF.

These results, from the default parametrization setup of OLAM, show that a reduction in surface roughness can cause a reduction in turbulent heat transfer between
Figure 3.11: Diurnal cycle of DEF-FOR area averaged surface energy fluxes averaged for all days in July. The variables are also averaged over one-hour periods.

land and atmosphere. The reduction in sensible heat fluxes due to deforestation is opposite of what is observed on field and will be addressed in detail while setting up OLAM for the ‘Multidecadal’ study (Section 3.3.5). However, some inferences regarding the characteristics of the DMSC can still be made with these simulations. These reductions in turbulent energy fluxes due to a deforestation have two important implications for the DMSC and TMSC. First, because a reduction in turbulent mixing can cause an increase in the stability (or decrease in the instability) of the overlying atmosphere, this reduction can interfere with the capability of the DMSC as a convective triggering mechanism. Second, because the decrease in sensible heat fluxes is observed throughout the deforested area, a reduction in surface roughness due to deforestation may have an adverse effect on TMSCs.

However, a comparison between the turbulent fluxes of energy in DEF-dyn and FOR in Table 3.5 indicates that not all of the reduction in sensible heat in DEF relative to FOR is contributed by surface roughness changes. This table shows that an increase in surface roughness in DEF-dyn relative to DEF results in an increase
in daytime sensible fluxes; however, these fluxes still remain lower in DEF-dyn as compared with FOR. Through several sensitivity tests with rooting depth, fractional area coverage of vegetation, NDVI etc, it was found that the minimum stomatal resistance parametrization used in this model set-up caused this decrease of sensible heat fluxes in DEF and DEF-dyn with respect to FOR. The monthly- and area-averaged components of the surface energy balance in the experiments DEF, DEF-dyn, DEF-sr and FOR have been reported in Table 3.4. The monthly averaged sensible heat flux in DEF-sr is very close to that of FOR, but much larger than in DEF or DEF-dyn. Also the latent heat fluxes are lowest in DEF-sr. These results indicate that changes in stomatal resistance due to deforestation have a strong control on the partitioning of turbulent fluxes of heat and can cause a much larger reduction in sensible heat fluxes than the reduction due to changes in surface roughness alone.

Sa et al. (1996) and Wright et al. (1996a) have modeled maximum stomatal conductance based on in situ measurements from paired forest-pasture sites in the Amazon. They have shown that maximum stomatal conductance for pasture is generally larger than that of evergreen forest. This difference between forest and pasture is indeed captured by the parametrization used in our study (Table 3.1). But our simulation results (comparing DEF, DEF-sr and FOR) indicate that sensible heat fluxes are very sensitive to the current stomatal resistance parametrization. Because ‘vegetation breezes’ can be modulated by sensible heat flux magnitudes and horizontal gradients, the sensitivity of the DMSC to stomatal resistance parametrizations will be explored further in section 3.3.8.

3.3.4 ‘Dynamical’ Mesoscale Circulation and Atmospheric stability

In this section we combine our understanding of the dynamical and thermal effects of surface roughness changes on the atmospheric response to deforestation. Figure 3.12
Figure 3.12: Vertical cross sections of difference potential temperature (shading) and difference Brunt-Väisälä frequency (contours with units $\mu$ Hz) averaged between 1200 LT and 1300 LT for all days in July in (a) DEF-FOR and (b) DEF-dyn - FOR along the transect shown in the inset. Note the logarithmic color scaling for potential temperature. Distance between the points NW and SE is 400 km.

shows the vertical structure of the difference potential temperature and difference Brunt-Väisälä frequency along the transect shown in the inset of the same figure. This transect was chosen because the DMSC was found to be strongest approximately along this direction. The vertical structure of the difference potential temperature field in DEF-FOR shows that the DMSC causes increased mixing of the colder surface air with the atmosphere aloft. On the other hand the potential temperature on the downwelling side of the DMSC is found to be warmer in DEF. No such dipole structure of strong cooling or warming is present in DEF-dyn because of the absence of the DMSC.

The vertical structure of the difference potential temperature fields indicates that the DEF atmosphere is generally more stable than the DEF-dyn atmosphere which in turn is more stable than the FOR atmosphere. This ordering is also supported by the positive difference in the Brunt-Väisälä frequency in both DEF and DEF-dyn with respect to FOR. The increased stability in both DEF and DEF-dyn relative to FOR
Figure 3.13: Vertical cross sections of difference specific humidity (shading) and diabatic heating (contours with units milli W m$^{-3}$) averaged between 1200 LT and 1300 LT for all days in July in (a) DEF-FOR and (b) DEF-dyn - FOR along the transect shown in the inset. Note the logarithmic color scaling for specific humidity. Distance between the points NW and SE is 400 km.

occurs because the daytime sensible heat fluxes are smaller in DEF and DEF-dyn than in FOR (Table 3.5). This makes the DEF and DEF-dyn atmospheres less conducive to convection than the FOR atmosphere. But strikingly the DEF atmosphere is not more stable than FOR everywhere over the deforested region. The atmosphere around the upwelling branch of the DMSC (northwest) is actually less stable than FOR, as indicated by the negative difference of the Brunt-Väisälä frequency in DEF with respect to FOR in this region. The opposite is true for the downwelling branch of the DMSC, as expected because of lower sensible heat fluxes in DEF than in FOR.

Whether the DMSC can make the DEF atmosphere more conducive to convection in its upwelling branch can be further evaluated by considering the changes in the atmospheric humidity profiles in the deforested experiments relative to FOR. The vertical cross sections of specific humidity and diabatic heating in DEF - FOR and DEF-dyn - FOR are plotted in Figure 3.13. It is seen that the upwelling branch of the DMSC fosters more water vapor and diabatic heating in the atmosphere. These
features are not observed in DEF-dyn despite it being less stable than DEF. Moreover reductions of a much larger magnitude in both specific humidity and diabatic heating in DEF - FOR, as compared with DEF-dyn - FOR, are found to occur around the downwelling branch. This indicates that the DMSC can potentially suppress convection in the southeast of Rondônia.

This analysis shows that despite the decrease in sensible heat fluxes throughout the deforested region (Figure 3.8), the DMSC is strong enough to break the stability barrier and cause the atmosphere to become more conducive to convection in the northwestern parts of the experimental domain. Hence the DMSC, as a convective triggering mechanism, is not overwhelmed by the increase in the stability of the atmosphere. In fact it has a larger control on the thermal structure of the atmosphere in the northwestern parts of the domain than the sensible heat fluxes. The DMSC can therefore emerge as an important convective triggering mechanism in Rondônia for contemporary scales of deforestation. This can have important implications for the dry season hydroclimate of this region, suggesting the possibility of more cloudiness and rain in the northwest and a reduction in the southeast.

3.3.5 Correcting the Forest Sensible Heat Fluxes

In the exploratory ‘Contemporary’ study, the forest sensible heat fluxes are much higher than the pasture vegetation throughout most of the afternoon (Table 3.5 and Figure 3.11) which is opposed to most in situ observations (Gash and Nobre, 1997; von Randow et al., 2004). Upon investigation the forest minimum stomatal resistance parametrization is found to result in less transpiring trees increasing their sensible heat fluxes to maintain the surface energy balance. As discussed in section 3.3.3 the sensible and latent heat fluxes are most sensitive to the stomatal resistance parametrization. Hence, in order to improve the representation of evaporation by evergreen forests in the model as compared to observations, a newer value of minimum

64
stomatal resistance (286 s m$^{-1}$ from Freitas (1999)) was used in the ‘Multidecadal’ analysis. The midday surface sensible heat fluxes and their spatial patterns were also found to be affected by the soil texture parametrizations as discussed in detail in Appendix B section B.2. A uniform soil type of silty clay loam was applied in a 15° by 15° area around Rondônia. A model evaluation against in situ observations was also performed which is now presented.

The model was evaluated for the 8 km resolution experiment, DEF06SSTcl, using a forest minimum stomatal resistance of 286 s m$^{-1}$ primarily against the in situ LBA-ECO CD-32 Flux Tower Network Data Compilation (Saleska et al., 2013). The eddy covariance, meteorology and radiation data collected at two eddy flux tower sites in Rondônia - Fazenda Nossa Senhora (pasture site at 62.36°W, 10.76°S) and reserve Jaru (forest site at 61.93°W, 10.08°S) (see Figure 3.2) were utilized for the comparison. These sites have been a part of both the Anglo-Brazillian Amazonian Climate Observational Study (ABRACOS) (Gash et al., 1996b; Gash and Nobre, 1997) and Large-Scale Biosphere-Atmosphere Experiment in Amazonia (LBA) (von Randow et al., 2004) providing valuable data for climate studies of the impacts of deforestation, model evaluation and parametrization. Most of the model surface parametrizations used in this work also come from the data collected from these and similar sites during ABRACOS. The ABRACOS campaign was active between 1990 and 1994 and the LBA-ECO CD-32 data was collected between March, 1999 and September, 2002. As the current study is focused on analyzing climatic effects to contemporary deforestation, the LBA data was used for model evaluation. However, it should be noted that the data from these campaigns cannot be used to detect signals of spatial redistribution of clouds or precipitation over the whole deforested region because such an analysis would require simultaneous measurements from more than one pasture site.
Owing to the fact that in situ measurements provide data for a very limited area which is bound to be affected by local, site specific conditions, some model fields were also evaluated against satellite data. Simulations are evaluated against precipitation data from the monthly TRMM satellite data product 3B43 (Huffman and Bolvin [2014]) (resolution 0.25°x0.25°) and surface radiation fluxes obtained from the CERES surface EBAF product (Kato et al., 2013) (resolution 1°x1°). Satellite data were averaged between 2000 and 2014 and over the deforested boundary of 2005 due to their coarse resolution and because the ‘dynamical mechanism’ can especially affect the spatial precipitation patterns. Hence the simulated precipitation reported in Table 3.6 is also averaged over the 2005 deforested boundary. Because of this reason it is also not appropriate to compare simulated precipitation with rain gauge measurements from an earlier time period.

Observed data averaged over the month of August is used for comparison in accord with the time period simulated with OLAM (see numerical design for ‘Multidecadal’ analysis in section 3.2.2). Model evaluation is performed for the numerical experiment DEF06SST00 because this simulation has land cover and SST boundary conditions closest to the LBA-ECO CD-32 field data. The comparison is presented in Table 3.6 and Figure 3.14. In the table all variables (except precipitation) reported from the numerically simulated data are averages over a 0.5° by 0.5° area around the LBA-ECO pasture site (62.36°W, 10.76°S) or the LBA-ECO forest site (61.93°W, 10.08°S). The simulations are labeled respectively ‘DEF06SST00 pas’ and ‘DEF06SST00 for’ in Table 3.6 and Figure 3.14.

Boundary layer processes were evaluated during the afternoon hours as the mesoscale circulations studied here are primarily afternoon phenomenon. The simulated diurnal cycle of surface latent and sensible heat fluxes are shown in Figure 3.14. Over the pasture these fluxes have a reasonable agreement with observations. The forest latent heat flux also agrees reasonably with observations although with a
Table 3.6: Comparison of numerical experiments to field data (Saleska et al., 2013) and satellite data (Ashouri et al., 2015; Kato et al., 2013). Model evaluation is done by comparing data from in situ and satellite measurements with the numerical experiment DEF06SST00. The comparison is performed by calculating averages of simulated results over a ∼0.5° by 0.5° area around the LBA-ECO pasture site (62.36°W, 10.76°S) and over a ∼0.5° by 0.5° area around the LBA-ECO forest site (61.93°W, 10.08°S). The two experiments are respectively named as DEF06SST00 pas and DEF06SST00 for. Only the simulated precipitation is averaged over the whole deforested area in 2005. The values reported from other numerical experiments are not provided for model evaluation but only to document the respective surface energy components. All values presented are averaged over the month of August. In situ data are averaged between 1999 and 2002. Satellite data are averaged over the deforested area between 2000 to 2014. Sensible heat (Sens Heat), latent heat (Lat Heat) and near surface air temperature (Temp) are averaged between 1300 LT and 1800 LT. Net radiation (Net Rad), incoming short wave radiation (Incom SW) and precipitation (Precip) are averaged over the whole day in August.

<table>
<thead>
<tr>
<th></th>
<th>Sens Heat W/m²</th>
<th>Lat Heat W/m²</th>
<th>Net Rad W/m²</th>
<th>Incom SW W/m²</th>
<th>Temp K</th>
<th>Precip mm/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pasture Site</td>
<td>152.9</td>
<td>157.9</td>
<td>109.0</td>
<td>-</td>
<td>31.1</td>
<td>2.01</td>
</tr>
<tr>
<td>Forest Site</td>
<td>99.3</td>
<td>274.1</td>
<td>144.7</td>
<td>-</td>
<td>30.5</td>
<td>0.51</td>
</tr>
<tr>
<td>TRMM</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CERES</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DEF06SST00 pas</td>
<td>156.9</td>
<td>160.6</td>
<td>122.5</td>
<td>284.5</td>
<td>27.0</td>
<td>1.38</td>
</tr>
<tr>
<td>DEF06SST00 for</td>
<td>107.7</td>
<td>223.2</td>
<td>134.9</td>
<td>284.4</td>
<td>25.7</td>
<td>-</td>
</tr>
<tr>
<td>DEF06SST80</td>
<td>129.0</td>
<td>201.9</td>
<td>130.5</td>
<td>283.6</td>
<td>25.5</td>
<td>1.42</td>
</tr>
<tr>
<td>DEF06SSTcl</td>
<td>128.9</td>
<td>202.9</td>
<td>130.5</td>
<td>282.6</td>
<td>25.7</td>
<td>1.45</td>
</tr>
<tr>
<td>DEF06SSTcl-dyn</td>
<td>157.0</td>
<td>161.0</td>
<td>122.2</td>
<td>284.4</td>
<td>27.0</td>
<td>1.25</td>
</tr>
<tr>
<td>DEF06SSTcl-thrm</td>
<td>167.1</td>
<td>158.4</td>
<td>126.3</td>
<td>283.5</td>
<td>24.8</td>
<td>1.38</td>
</tr>
<tr>
<td>DEF06SSTcl-topo</td>
<td>149.3</td>
<td>170.6</td>
<td>124.0</td>
<td>280.9</td>
<td>26.3</td>
<td>0.92</td>
</tr>
</tbody>
</table>

lag of 1 hour. The forest sensible heat fluxes are in disagreement with observations during the morning hours. One possible reason for this disagreement can be that the LBA forest site, reserve Jaru, falls almost inside the deforested boundary of the simulations (Figure 3.2) because the deforestation extent in 2006 (used in the simulations) is larger than that when the LBA-ECO CD-32 data were collected. So possibly some of the forest signal is getting corrupted by this. However, the afternoon averaged fluxes (both latent and sensible) over both pasture and forest sites are in
good agreement with observations (Table 3.6). Because the response time of the planetary boundary layer to surface processes is an hour or less, model output was compared with site observations in the afternoon only.

The near surface air temperature in the LBA-ECO CD-32 data is measured at heights (from ground) of 60 m and 8 m over the forest and pasture canopies respectively. It should be noted that there is no analogue of this measurement in the simulations as the lowest prognosed level in the model is at 100 m altitude. Hence, in the table comparison is made between observed near surface temperature and the closest model analogue - canopy air temperature. Canopy air is defined as that part of the near surface air that is directly in contact with and is affected by soil, snow, surface water and vegetation. Turbulent fluxes of heat and moisture are transferred between these components and the canopy air and between canopy air and the atmospheric boundary layer.

The effect of simulated surface heat fluxes on the boundary layer characteristics during afternoon hours was also compared with observations. For this purpose the
simulated boundary layer height was calculated following prescriptions of previous studies (Fisch et al., 2004). Averaged between 1500 LT and 1600 LT the boundary layer height for pasture is 1270 m ± 150 m and that over forest is 1177 m ± 81 m. Averaged between 1700 LT and 1800 LT the boundary layer height for pasture is 1323 m ± 195 m and that over forest is 988 m ± 97 m. The values represent ensemble mean and standard deviations. These values are comparable to boundary layer heights measured between 14 and 25 August 1994 at the LBA pasture and forest sites which are respectively: 1471 m ± 479 m and 902 m ± 307 m at 1400 LT; and 1641 m ± 595 m and 1094 m ± 385 m at 1700 LT (Fisch et al., 2004). It is however noted that the average difference between the simulated pasture and forest boundary layer height is smaller than the observed difference.

It is noted that the dipole in simulated relative humidity is observed at all model levels close to the boundary layer top (figures not shown) but is strongest slightly above the boundary layer top. Hence, the simulated data presented in this study is reported at ~1717 m altitude.

### 3.3.6 Understanding Observed Multidecadal Variability with Simulations

The numerical analysis of the observed trend in spatial patterns of clouds and precipitation reported in Chapter 2 is now presented. The corresponding numerical design for ‘Multidecadal’ analysis is presented in section 3.2.2. The variable resolution capability of OLAM allows the resolution of climatologically important scales of deforestation around Rondônia on an ~8 km grid (Avissar and Schmidt, 1998; Patton et al., 2005). However, this resolution is still too coarse to adequately resolve clouds. Hence, following previous studies (van Heerwaarden and de Arellano, 2008), relative humidity (RH) near the top of the boundary layer and precipitation are used as indicators of changing hydroclimate.
Figure 3.15: Effect of mesoscale circulations on simulated relative humidity in the early and contemporary time periods. 1717 m altitude relative humidity averaged between 1300 LT and 1800 LT in (a) DEF86SST80, (b) DEF06SST00 (c) DEF86SSTcl (d) DEF06SSTcl (e) DEF86SST80-FORprSST80, (f) DEF06SST00-FORprSST00 (g) DEF86SSTcl-FORprSSTcl and (h) DEF06SSTcl-FORprSSTcl. All results are averaged over all days in August and over all ensemble members. (a), (b), (c) and (d) show percentage difference of the field from deforested area average. Stippling show differences significant at the 1% level.
Figure 3.16: Effect of mesoscale circulations on simulated precipitation in the early and contemporary time periods. (a) DEF86SST80, (b) DEF06SST00, (c) DEF86SSTcl and (d) DEF06SSTcl precipitation totaled between 1600 LT and 2000 LT. All results are averaged over all days in August and over all ensemble members. Figures show percentage difference of the field from deforested area average. Stippling show differences significant at the 1% level.
Figure 3.17: Simulated mesoscale circulations in the early and contemporary time periods. Horizontal cross sections of vertical and horizontal wind averaged between 1500 LT and 1600 LT at (a), (b) 967 m, (c), (d) 1207 m and (e), (f) 1457 m for (a), (c), (e) DEF86SSTcl - FORprSSTcl and (b), (d), (f) DEF06SSTcl - FORprSSTcl. The data is averaged for all days in August and over all ensemble members. The horizontal wind vectors are not to scale.
It is found that simulations forced with 1980s conditions have more convection over the deforested patches as compared to nearby forests, manifest as positive anomalies in Relative Humidity (RH) and precipitation (Figure 3.15 a and Figure 3.16 a) relative to deforested area mean. Simulations forced with 2000s conditions reveal the emergence of a dipole in RH and precipitation (Figure 3.15 b and Figure 3.16 b) with positive anomalies in the downwind deforested areas. The difference between these deforested and the corresponding pristine forest experiments (replacing pasture with forests) also captures the transition (Figure 3.15 e, f), confirming the significant role of increasing deforestation in the emergence of the dipole. These late period results also conform with the DEF-FOR results found in the ‘Contemporary’ exploratory analysis suggesting the absence and presence of the DMSC in the early and late periods respectively.

Model runs with changing land use but identical, climatological global SSTs give very similar results (Figure 3.15 c, d, g, h and Figure 3.16 c, d). These results are supported by the transition in the vegetation-generated mesoscale circulations between the two decades (Figure 3.17). Hence, it is concluded that decadal global SST changes, which affect the basin-scale Amazonian hydroclimate (Yoon and Zeng 2010; Fernandes et al. 2015), are of secondary importance to the observed, smaller-scale hydroclimatic changes reported here (also see discussion in section 3.4).

3.3.7 Transition from a ‘Thermally Dominated’ to ‘Dynamically Dominated’ Convective Regime

Finally, we evaluate whether the simulated dipole is associated with convection modulated by surface roughness variations (the ‘dynamical mechanism’ or DMSC) caused by deforestation. The experiment with 2006 land cover and climatological SSTs is repeated, but with pasture vegetation height set to that of evergreen forest and other pasture parameters at their standard values (DEF06SSTcl-dyn). The absence
Figure 3.18: Effects of sensible heat variations, surface roughness variations and topographical variations in the ‘late’ period. 1717 m altitude relative humidity averaged between 1300 LT and 1800 LT in (a) DEF06SSTcl-dyn, (b) DEF06SSTcl-sh (c) mean(DEF06SSTcl-dyn,DEF06SSTcl-sh), (d) DEF06SSTcl-topo, (e) DEF06SSTcl-dyn - FORprSSTcl (f) DEF06SSTcl-sh - FORprSSTcl, (g) mean(DEF06SSTcl-dyn,DEF06SSTcl-sh) - FORprSSTcl and (h) DEF06SSTcl-topo - FORprSSTcl-topo. All results are averaged over all days in August and over all ensemble members. (a), (b), (c) and (d) show percentage difference of the field from deforested area average. Stippling shows differences significant at the 1% level.
of the east-west dipole in this experiment shows that changes in surface roughness are essential for the simulation of the dipole (Figure 3.18 a, e). When ‘pasture’ is parameterized with pasture height but otherwise as evergreen forest, which in this model setup evapotranspires more and releases lower sensible heat fluxes as compared to the forest in the ‘Contemporary’ analysis (DEF06SSTcl-sh), the model produces only a weak dipole (Figure 3.18 f), revealing the importance of deforestation-induced increase in atmospheric instability for enhanced convection over the deforested areas. An average of these two deforested experiments shows that it is the dynamical mechanism that causes the east-west dipole (Figure 3.18 c, g) suppressing convection in the upwind deforested regions and vice-versa. Lastly, results from the experiment DEF06SSTcl-topo show that regional topography is inconsequential for the existence of the dipole, although it may modulate its strength or orientation (Figure 3.18 d, h). Overall, this transition in the deforestation-triggered convective regime, consistent with cloud and precipitation observations (Chapter 2), illustrates a shift from a thermally-dominated (Roy and Avissar 2002) (at small scales) to a dynamically-dominated (at contemporary scales of deforestation) convective regime.

### 3.3.8 Sensitivity of the ‘Dynamical Mechanism’ to Surface Sensible Heat Fluxes

The DEF06SSTcl-sh experiment shows that although surface sensible heat fluxes are not the triggering process for the cloudiness dipole, they still play a significant role in making the atmosphere conducive to any type of convection. This experiment shows that a background increase in the instability of the atmosphere, induced by deforestation, is required in order to generate the dipole spatial patterns in clouds and precipitation characteristic of the ‘dynamical’ mechanism. Although the DEF-sr and DEF06SSTcl-sh experiments are designed to achieve the same effect, of minimum horizontal sensible heat variations, but they show very different results (compare Fig-
ures 3.10 and 3.18). On the one hand DEF-sr shows a clear signature of the dipole, on the other DEF06SSTcl-sh shows only a weak signal. To understand these differences sensitivity tests were performed with respect to surface sensible heat fluxes by essentially experimenting with minimum stomatal resistance parametrization in these two experiments (Table 3.7). Basically, the DEF-sr experiment was repeated with a minimum stomatal resistance of 286 s m$^{-1}$ both at 8 km resolution (DEF06SSTcl-sr) and 32 km resolution (RES32SR286-sr). And the DEF06SSTcl-sh experiment was repeated with minimum stomatal resistance of 500 s m$^{-1}$ (RES08SR500-sh).

The three additional experiments were performed to test the sensitivity of the results to surface sensible heat fluxes (Table 3.7). These experiments were performed to achieve different levels of surface sensible heat fluxes by regulating pasture minimum stomatal resistance (MSR) and horizontal sensible heat flux variations. These experiments use the 2006 land cover and SSTs averaged between 1971 and 2010 (same as in DEF06SSTcl). Together with DEF-sr and DEF06SSTcl-sh, these experiments will be used to explore the effect of varying surface sensible heat fluxes on the strength of the atmospheric signals. Similar to DEF-sr, experiment DEF06SSTcl-sr captures the atmospheric response when pasture vegetation has the MSR of an evergreen forest. But the value of forest MSR is 286 s m$^{-1}$ and the simulation is performed at 8 km resolution. Similarly RES32SR286-sr is similar to DEF06SSTcl-sr but performed at a resolution of 32 km to correspond it with the ‘Contemporary’ study’s DEF-sr but with forest MSR equal to 286 s m$^{-1}$. Lastly, RES08SR500-sh is the same as DEF06SSTcl-sh but with a forest MSR of 500 s m$^{-1}$.

Figure 3.19 shows the correlation between daytime 1700 m altitude RH dipole strength and sensible heat fluxes that emerges from these experiments. It is clearly observed that a higher magnitude of pasture sensible heat fluxes results in a higher dipole strength or stronger DMSC. This relationship is independent of model resolution (8 km or 32 km). The experiments which control for horizontal sensible heat
Table 3.7: Numerical experiments to test the sensitivity of the dipole strength to surface sensible heat fluxes. MSR is minimum stomatal resistance. FMSR is MSR for forest vegetation. All experiments use 2006 land cover with climatological SSTs. Suffix -sh represents experiments that approximately control for sensible heat fluxes by changing only vegetation height between forest and pasture. Suffix -sr represents experiments that control for MSR between forest and pasture.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Res.</th>
<th>FMSR s m⁻¹</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEF06SSTcl</td>
<td>8</td>
<td>286</td>
<td>Original deforested exp. (Table 3.3).</td>
</tr>
<tr>
<td>DEF06SSTcl-sh</td>
<td>8</td>
<td>286</td>
<td>DEF06SSTcl but controlled for sensible heat fluxes (Table 3.3).</td>
</tr>
<tr>
<td>DEF06SSTcl-sr</td>
<td>8</td>
<td>286</td>
<td>MSR of pasture is same as that for forest.</td>
</tr>
<tr>
<td>RES32SR286-sr</td>
<td>32</td>
<td>286</td>
<td>Same as DEF06SSTcl-sr but performed at 32 km resolution.</td>
</tr>
<tr>
<td>RES08SR500-sh</td>
<td>8</td>
<td>500</td>
<td>DEF06SSTcl-sh but with a MSR of 500 s m⁻¹.</td>
</tr>
</tbody>
</table>

Figure 3.19: Effects of surface sensible heat fluxes on simulated dipole strength. 1717 m altitude relative humidity averaged between 1300 LT and 1800 LT in the experiments shown in the legend. All results are averaged over all days in August and over all ensemble members.
fluxes (-sh in experiment name) show the lowest values of pasture sensible heat fluxes resulting in the lowest values of dipole strength.

It should be pointed out that in the ‘Contemporary’ exploratory analysis, the presence of the dipole in DEF-sr was because the pasture minimum stomatal resistance was set equal to that of forest’s, which wrongly had a higher sensible heat flux as compared to the pasture, resulting in the sustenance of the DMSC even in DEF-sr. But when the forest sensible heat fluxes were made close to in situ observations the dipole disappeared in DEF06SSTcl-sh because the sensible heat fluxes had now reduced.

This analysis clearly shows that the strength of the DMSC is dependent on the pasture sensible heat fluxes and in turn on the regional atmospheric conditions. The variability of the dynamical mechanism and its effects on precipitation are a topic of great interest and will be duly addressed in Chapter 4.

3.4 Quantifying the Hydroclimatic Changes Due to Three Decades of Deforestation - Putting Observations and Simulations Together

Both observations presented in Chapter 2 and numerical results presented in this chapter point at a gradual redistribution of clouds and precipitation during the past three decades of deforestation in Rondônia. Here, the findings from different sources of data, both numerical and observational, are summarized to quantify this transition. To quantify this change the dipole moment vector metric is used to calculate the JJAS average dipole strength for the early (1980s) and the late periods (2000s). A comparison between the two will give a measure of the increase in the ‘dipolarity’ of clouds and precipitation.
Figure 3.20: Emergence of the cloud and precipitation ‘dipoles’ over three decades as captured by observed and simulated data. (see section 3.4 for details on the simulated and observed data used to calculate the dipoles). Individual points represent ensemble mean dipole strength in the corresponding dataset and time period. Error bars represent one standard deviation. The data are scaled so that the mean of each variable in 1980s is equal to 1. The means from the 1980s are used to scale the corresponding variables in the 2000s. The original mean and standard deviation (in brackets) of each variable have the units of % km and are reported below each data point. Arrows represent the dipole moment vectors calculated with ensemble averaged scaled magnitude and direction. The dipole moment mean and variance are expected to differ between the datasets owing to different spatial resolution and data units; however, the scaling of 3 to 4 times between the 1980s and 2000s is observed across all datasets.

Figure 3.20 shows the comparison between average dipole moment strengths and direction between the ‘early’ and ‘late’ periods. Simulated data used to calculate dipole strength include the 1717 m relative humidity averaged between 1300 LT and 1800 LT and precipitation averaged between 1600 LT and 2000 LT. Simulated data are obtained from the month of August from DEF86SST80, DEF06SST00, DEF86SSTcl
and DEF06SSTcl. Observed data used to calculate dipole strength include 1400 LT and 1700 LT averaged GridSat cloud cover and daily PERSIANN precipitation. The ‘early’ observational period includes JJAS 1983 to 1994 (except 1987 and 1988 due to unavailable data) and ‘late’ period includes JJAS 1997 to 2008 (except 1998 due to unavailable data). The dipole metric is calculated using percentage deviations of cloud and precipitation from the deforested area mean. The arrows show the direction of each dipole. The standard deviation in simulated data represents variability between 24 ensemble members. The standard deviation in observational data represents inter-annual variability.

The scaling of 3 to 4 times between the ‘early’ and ‘late’ period dipole strengths is remarkably observed across all datasets. This suggests a common underlying physical phenomenon present in all datasets despite the differences in datatypes, the quantities and periods they represent. This robust scaling is the main result from the observational and numerical analysis presented in this thesis and gives context for re-evaluating our understanding of deforestation-induced physical mechanisms.

3.5 Conclusions

This numerical study was conducted to understand the role played by increasing scales of deforestation in Amazonia in the observations of a gradual spatial redistribution of clouds and precipitation over the past three decades (reported in Chapter 2). First, some numerical experiments were conducted to explore the hydroclimatological effects of contemporary deforestation (of the order of a few hundred kilometers) in Rondônia focusing particularly on the coupled thermal and dynamical atmospheric response to changes in surface roughness. The important findings from this ‘Contemporary’ exploratory study were:
1. Contemporary scales of deforestation gave rise to a mesoscale circulation spanning the whole deforested region of Rondônia in the model. This circulation was found to be strongest during the daytime with its upward branch in the northwest (downwind region) and the downward branch in the southeast (upwind region) of Rondônia. This circulation was triggered as a dynamical response of the atmosphere to the reduction in surface roughness caused by the conversion of evergreen forests to pasture at contemporary spatial scales of deforestation. This is unlike the thermally generated vegetation breezes triggered by the increase in sensible heat fluxes over small scale (of the order of 1 km) forest clearings observed in previous studies.

2. Changes in the surface energy balance suggest that deforestation at contemporary scales, which triggers the dynamically dominated mesoscale circulation (DMSC), also causes a reduction in the turbulent heat fluxes hence implying a weakening of the thermally dominated mesoscale circulations (TMSC). The DMSC was found to cause increased mixing of potential temperature and humidity hence decreasing the atmospheric stability in the northwest of Rondônia and suppressing convection in the southeast.

Gaining insights from these results, numerical simulations were conducted to capture the multidecadal transition of the hydroclimate in Rondônia. It was found that:

1. Global scale decadal climate variability plays only a secondary role in the observed multidecadal transition in the dry season hydroclimate of Rondônia.

2. The causal mechanism for the occurrence of the dipole structure in clouds and precipitation in observations and numerical simulations was found to be dynamical in nature - related to a reduction in the surface roughness due to the replacement of rough forest with smooth pasture. Hence, conforming with the cloud and precipitation observations from Chapter 2, the numerical simulations
Figure 3.21: Transition in the dominant convective regime with increasing scales of deforestation. In the early period (top), convection over the deforested region is enhanced by thermal triggering alone. In the contemporary period (bottom), horizontal variations in surface roughness result in a suppression of convection in the upwind sector and enhancement of convection in the downwind sector.

indicate a transition from a thermally to a dynamically dominated convective regime associated with changing scales of deforestation (Figure 3.21).

3. Additionally, the strength of the DMSC was found to be sensitive to the magnitude of the midday pasture sensible heat fluxes. The increase in surface sensible heat fluxes due to ‘pasturization’, also observed in situ, decreases the stability of the boundary layer air hence becoming supportive of the DMSC. At least in the model, the DMSC lost its strength in the absence of this deforestation-induced decrease in atmospheric stability.

This study provides an integrated perspective on how three decades of deforestation in Amazonia have affected the regional hydroclimate. The generalizability of the
physical mechanisms presented here will be tested for seasons other than the dry sea-
son and regions other than Rondônia in the next chapter. The generalizability of this
mechanism should also be tested for deforested regions in other tropical rainforests,
which is left as future work. Such studies will provide context for thinking about
the climate of a future, more patchily forested Amazonia (Walker et al., 2009), by
articulating relationships between climate and spatial scales of deforestation.
Chapter 4

Spatio-temporal Variability of the
Dynamical Mechanism

4.1 Introduction

The dynamical mechanism emerges as a consequential convective triggering mechanism during the regional dry season of Rondônia (Chapters 2 and 3; Khanna and Medvigy (2014a); Khanna et al. (submitted)). But, to underpin the general relevance of this mechanism for the hydroclimatic changes induced by present day Amazon-wide deforestation, a complete analysis of the ‘generalizability’ of this mechanism to seasons other than the dry season and regions other than Rondônia is necessary. This chapter focuses on the ‘relevance’ of the dynamical mechanism at different temporal and spatial scales and analyzes its relative importance as compared with random thermal triggering caused by warm land surfaces. To achieve this goal the following characteristics of the ‘dynamical’ mechanism will be investigated: 1) its temporal variability and the physical processes controlling this variability and 2) if the dynamical mechanism is observed in deforested areas other than Rondônia.
The dynamical mechanism is a boundary layer land-atmosphere interaction, so it is expected to show a dependence on the regional atmospheric conditions similar to that of the thermally triggered mesoscale circulations (Wang et al., 2009, 1996) i.e. the dynamical mechanism is expected to be consequential during periods of stable atmospheric conditions. Due to this dependence the dynamical mechanism is expected to affect regional clouds and precipitation during the dry season and none during the wet season. But, the sensitivity analysis of the dynamical mechanism to midday surface sensible heat fluxes, presented in Section 3.3.8, suggests that on a subseasonal or monthly time scale the dynamical mechanism weakens under conditions of low surface sensible heat fluxes which are expected to increase the stability of the overlying boundary layer air. Hence, a highly stable boundary layer is expected to suppress any kind of convective triggering including dynamical. Such dependence on the atmospheric thermal structure suggests that the dynamical mechanism may affect the hydroclimate only in some favorable conditions.

On the daily scale, the dynamical mechanism is expected to be inconsequential on days with spatially uniform convection because it is observed through its effects on cloud and precipitation spatial patterns. Such periods occur in atmospheric conditions that are more buoyant than average and supportive of any type of convective triggering. Hence, the presence of the dipole pattern in less buoyant or more stable conditions as compared to days with active, spatially uniform convection, would be a testament of the strength of the dynamical mechanism as a convective triggering mechanism over other types of land-atmosphere convective triggering processes. Hence, it is hypothesized that the dynamical mechanism should be consequential during periods or at locations with more stable atmospheric conditions, than the temporal or spatial average, as compared to periods or places with buoyant conditions supportive of uniform cloudiness. Due to this reason, the dynamical mechanism is expected to be consequential during the dry season relative to the wet season. Also for this
reason, large scale (a few hundreds of kilometers) contiguously deforested areas away from the coasts are expected to have a higher chance of showing the dipole signal as compared to deforested areas closer to the coasts because of the strong influence of the land-ocean contrast in the latter.

By analyzing the day-to-day, inter-seasonal, inter-annual and spatial variability of cloud and precipitation dipole, the following questions will be addressed to test the hypotheses posed above:

1. Is the dynamical mechanism observable throughout the year? If not, what are the atmospheric conditions that are supportive of this mechanism?

2. Is the relationship between the dipole strength and the controlling physical processes ‘general’? Does the relationship vary on different time scales (daily, inter-seasonal and inter-annual)?

3. Is the dipole mechanism dependent on regional or large-scale (seas surface temperature or SST conditions) atmospheric conditions? In other words, can inter-annual variability of the dynamical mechanism be explained using large scale climate state variables quantified by various SST indices?

4. Is cloud or precipitation redistribution, a signature feature of the dynamical mechanism, observed over large scale (a few hundreds of kilometers) deforested areas that have been turned into pasture land like Rondônia?

The above questions will be primarily addressed using more than a decade of annual daily scale cloud and precipitation data sets of the Rondônian hydroclimate, which will be complemented by numerically simulated data (section 4.2.3). Temporal variability on the daily (4.3.2), inter-seasonal (subsection 4.3.1) and inter-annual scales (subsection 4.3.3) will be analyzed. Spatial dependence of the dynamical mechanism will be analyzed by considering the three decadal dry season cloud cover variability over a deforested area in southeast of the Amazon rainforest (subsection 4.3.4).
and comparing it with cloud cover characteristics over Rondônia found in Chapter 2. Finally, the findings from this study, its limitations and future work will be summarized in section 4.4.

4.2 Methods

This study is performed in two parts: 1) Temporal variability of the dynamical mechanism in Rondônia and 2) Spatial variability of the dynamical mechanism by considering a deforested region in southeast Amazonia. The reader should note that this section describes the data used in both the studies, but the analysis of the results in Section 4.3 is performed sequentially.

4.2.1 Region and Period of Study

Two different deforested regions in the Amazon rainforest are considered to analyze the temporal and spatial variability of the dynamical mechanism.

The temporal variability of the dynamical mechanism is analyzed in the deforested regions of Rondônia (section 2.2.1). Land-atmosphere interactions can vary at different time scales. Temporal variability in this study is analyzed at the daily, inter-seasonal and inter-annual time scales at midday hours. The regional atmospheric conditions are quantified by using area averages over the region -63.5°W, -61.5°W, -11.5°S and -9.5°S shown with a red box in Figure 4.1. This area will be referred to as AREA-1 henceforth. Inferences were found not to be sensitive to the choice of the size and location of this area in Rondônia. Although deforestation is an ongoing process, resulting in an increase of deforestation scales every year, a large multi-year time period had to be considered to identify statistically significant relationships between the dipole strength and atmospheric conditions. The period between 2001 and 2014, representing contemporary large scale deforestation in Rondônia, is chosen for
Figure 4.1: Area ‘AREA-1’ (red box) in Rondônia used for the analysis of temporal variability. This is the area over which the atmospheric variables are averaged to quantify the regional atmospheric state for studying the relationships between the dipole and the atmospheric conditions.

the analysis. Hence, for the purpose of the analysis of temporal variability, deforestation rate in this period is assumed to be negligible, which is not a particularly bad assumption given the annual deforestation rates have been on a steep decline since 2004 (see Figure 1.1 for deforestation rates in the whole rainforest and Figure 4.2 for deforestation rates in Rondônia). 1700 LT precipitation data and the average of 1400 LT and 1700 LT cloud cover data are employed to estimate dipole strength. Precipitation data is analyzed during the evening because, as reported in Chapter 2, the precipitation signal caused by the dynamical mechanism is observed with a time lag of a couple of hours with the cloud signal.

Spatial variability of the dynamical mechanism is analyzed by considering a large scale (about two hundred kilometers) deforested region located towards the southeast of the rain forest in the Brazilian state of Pará (Figure 4.2). Similar to Rondônia, this region has been continuously deforested at least since the 1980s. Southeastern Pará is a heavily deforested region of the Amazon rain forest with annual deforestation rates ∼3 times larger than those in Rondônia (Figure 4.2a). Amongst all the other deforested regions in the Amazon rainforest this is one of the main regions where forests are primarily converted to pasture (Sparovek et al., 2012), making it similar
Figure 4.2: (a) Time series of annual deforestation rates in the Brazilian states of Rondônia and Pará. Data obtained from INPE’s PRODES project (INPE-PRODES, 2015). (b) Land cover map of the deforested region in Pará in 2008. Data obtained from INPE’s TERRA-CLASS project (Coutinho et al., 2013).

to the deforested regions of Rondônia in terms of the perturbations to the lower boundary conditions on the atmosphere caused by deforestation. But, as can be seen in Figure 4.2b, the characteristic length scale of deforestation in this region is smaller than that in Rondônia due to which the deforestation in this region is not contiguous. Long time series (three decades) land cover data is not available for this deforested region of the Amazon due to which a complete time series analysis was not possible. The extent of deforestation, or the deforestation boundary, in 1987 and 1995 was obtained from the LBA-ECO LC31 deforestation fraction time series (Leite and Costa, 2013) and the land cover map for 2008 was obtained from the TERRA-CLASS project of INPE (Coutinho et al., 2013). The GridSat cloud cover data, generated between 1983 and 2008 following the methods discussed in Sections 2.2.2 and 2.2.3, was used for signal detection. Only the 1400 LT cloud occurrence maps averaged over the months of June, July and August were used for the analysis of spatial variability.

4.2.2 Prediction Model

The objective of this study is to identify the regional and large, global scale atmospheric constraints on the cloud and precipitation dipole strength (DS) in the defor-
ested regions of Rondônia. For this purpose two types of atmospheric state variables or predictors are utilized 1) which represent regional scale and 2) which represent global scale variability in atmospheric conditions. Metrics used to quantify these atmospheric conditions and the predictive model employed in this study will now be discussed. The data used to calculate these metrics representing regional and large scale atmospheric conditions over AREA-1, are discussed in Section 4.2.3.

The daily scale lifting condensation level (LCL), boundary layer height (BLH) and horizontal wind magnitude just below the boundary layer top (BLW) are used as indicators of regional scale conditions of the boundary layer (BL) which are directly affected by the surface. LCL is the height at which a parcel, dry-adiabatically lifted from the surface, first saturates. The LCL is calculated using a numerical iterative method following a dry adiabat and estimating the saturation water vapour mixing ratio using the surface temperature, specific humidity and pressure. The BLH is obtained following the prescriptions of Fisch et al. (2004). BLH is the height at which the vertical gradient of potential temperature becomes equal to or larger than 2 K km⁻¹. Of these predictor variables, BLH and LCL were found to be highly correlated at the daily time scale (correlation coefficient of 0.93 in the dry season comprising June, July and August) so only LCL was used for most of the analysis. The differences between the forest and pasture atmospheric conditions like differences in LCL and BLW between pasture and nearby forest are expected to modulate the DS on the daily scale as well. But, due to the unavailability of observational data for these ‘difference’ metrics they were estimated with reanalysis data which could not capture any differences between the BL over the two types of vegetation and so resulted in muted correlations with the DS. Hence, such difference metrics could not be used for the analysis. Such an analysis is left as future work dependent on the availability of appropriate data.
The large scale atmospheric conditions are characterized using the convective available potential energy (CAPE) over AREA-1 in Rondônia and two SST indices namely 1) Tropical North Atlantic SST (NATL) (ESRL-PD, 2015a) and 2) Niño 3.4 index (ESRL-PD, 2015b). CAPE is a metric which represents the thermal state of the free troposphere and so is expected to represent larger scale controls on the potential for precipitating convection over a region. CAPE is calculated using a modified version of the metpack MATLAB package developed by George H. Bryan at NCAR using area averaged atmospheric profiles of pressure, potential temperature and dew point temperature. NATL index is the monthly and area average SST in the region between 57.5°W, 15°W, 5.5°N and 23.5°N and represents the thermal state of the Tropical North Atlantic which has been correlated with precipitation variability in western and southern Amazon rainforest especially during the basin’s dry season (Marengo et al, 2008a; Zeng et al. 2008; Yoon and Zeng, 2010; Fernandes et al., 2015). Niño 3.4 represents the thermal state of central tropical Pacific ocean between 5°S to 5°N and 170°W to 120°W and has been shown to affect the Amazon’s hydroclimate especially during the region’s wet season (Marengo, 2004; Liebmann and Marengo, 2001; Ronchail et al., 2002).

To test the hypotheses posed in the introduction, the following multiple linear regression model will be tested to understand some of the underlying physical controls on DS or the dynamical mechanism:

\[
DS = \text{intercept} + \alpha_1 \text{BLW} + \alpha_2 \text{LCL} + \alpha_3 \text{CAPE}. \tag{4.1}
\]

The effects of multicollinearity between the predictor variables at different time scales will also be addressed.
4.2.3 Metrics and Data Used for Analysis

Data sets used to derive the DS, BLH, LCL, BLW and CAPE metrics, to test the statistical correlations between observed or simulated dipole strength in Rondônia and atmospheric conditions, are discussed in this section.

Cloud and Precipitation Dipole Metric

The east-west redistribution of precipitation and cloudiness over deforested regions in Rondônia is inferred from 1700 LT TRMM 3B42, daily PERSIANN and 1400 LT and 1700 LT average GridSat data sets described in Section 2.2.2. To remind the reader, the two precipitation datasets, TRMM 3B42 and PERSIANN, are both at a 25 km spatial resolution and the cloud dataset GridSat is at an 8 km spatial resolution. The spatial redistribution is quantified by the dipole metric defined in Section 2.2.4 using the deforested boundary in Rondônia corresponding to the year 2010.

The dipole moment metric is very sensitive to partial cloudiness or precipitation over the deforested area. In extreme cases, when only a few pixels within the deforested area are cloudy or rainy on the daily time scale, the dipole metric can assume very large or small values which can be significant outliers. Such days can affect the statistics of both the real high dipole days (which have half of the deforested area cloudy) and uniform cloudiness days with a small value of the metric. As cloud occurrence or precipitation occurrence, which are both binary variables, are used for the calculation of this metric, the chances of assigning a wrong dipole strength value to such extreme days are high. For this reason, the pixel-wise time series of the daily precipitation and cloud data is smoothed with a 5 day moving box filter before calculating the daily DS. Also, the days with no or minimal cloudiness and DS over the deforested area are not included in the regression analysis to remove their effect on the statistics of other days. These ‘no cloudiness’ days are in which only 5% or less of all the pixels contained within the deforested boundary are cloudy or rainy.
A not-a-number (nan) value is assigned to the DS for such days to distinguish them from the other days. Such days are referred to as the ‘zero’ dipole days in the text.

The DS and atmospheric metrics have significant variability on the daily scale. Hence, constraining the relationships between these variables using data from all days did not reveal any significant correlations. Moreover, some of the relationships between the DS and metrics of atmospheric conditions are nonlinear further complicating the regression analysis. It was found that the relationships between model variables are best constrained in an ‘end member analysis’ in which only some of the highest and lowest DS days are considered to find the favorable atmospheric conditions which result in a high or low DS. This approach ensures that only the days which have a high chance of active dynamical mechanism or otherwise are chosen for the analysis. This is done because as previously mentioned some of the variability in the DS metric is because of its high sensitivity to partial cloudiness. This end member classification helps capture the first order relationships between model variables and reduces some variability in the data giving an insight of the basic driving mechanisms.

Under this procedure the days are divided into two types: 1) high DS days and 2) low DS days with roughly uniform cloudiness. These days are recognized based on the following criteria: 1) high dipole days are the top \(\sim 15\%\) dipole days in the sample with the highest DS. 2) Similarly, uniform cloudiness days are the top \(\sim 15\%\) days with the smallest DS. It will be seen later in the analysis that the ‘zero’ dipole days occur under markedly different atmospheric conditions than the ‘high’ or the ‘low’ dipole days and so it is important to distinguish these days from one another.

As mentioned, the DS in Rondônia was quantified using either of the three data sets: TRMM 3B42, PERSIANN or GridSat. The correlations between model variables were found to be strongest with the TRMM data although the general inferences were the same irrespective of the dataset. The good correlation of the statistics of the atmospheric state with the TRMM 3B42 data is possibly because this dataset has
been shown to perform better than PERSIANN at capturing the spatial locations of precipitation generated by mesoscale convective systems (Demaria et al., 2011). In the main text, results mostly from the analysis using TRMM 3B42 have been reported. For corresponding results using PERSIANN or GridSat see Appendix C. Also, in the main text dipole strength calculated using TRMM 3B42 data is referred to as DS. Results with PERSIANN or GridSat are reported with appropriate suffixes (PERSIANN-DS or GridSat-DS). It should be noted that because the GridSat data is available only up to 2008, the analysis time period using GridSat data (2001 to 2008) is shorter than the TRMM 3B42 or PERSIANN analysis period (2001 to 2014). The shorter time series of GridSat might be a possible reason for its under-performance as compared to TRMM 3B42.

**Constraining Regional Scale Atmospheric Conditions with In Situ Radiosonde Data**

Ideally, it would be informative to use in situ local scale measurements separately on pasture and forest and the differences between them to understand the local conditions in which the dipole develops. As such, radiosonde data from the LBA pasture and forest sites in Rondônia (Figure 3.2 and subsection 3.2.2) would best serve the purpose of this study. But, radiosonde data at these sites have not been collected after the end of the LBA campaign in 2002. The latest data available from these sites that could be used for this study was collected during the Large-Scale Biosphere-Atmosphere Experiment in Amazonia-Smoke, Aerosols, Clouds, Rainfall and Climate (LBA-SMOCC) between 18 to 29 September 2002. It was generously made available through Dr Gilberto Fisch of the Brazilian Department of Aerospace Science and Technology and Dr Theomar Trindade de Araújo Tiburtino Neves of the National Institute for Space Research, Brazil. The 14 day 1400 LT atmospheric soundings at the pasture site Fazenda Nossa Senhora are used for the analysis as the forest 14 day
time series are partially incomplete. It should be noted that the LBA-SMOCC 14 day radiosonde data could only be used to cross check the relationships obtained using the long time period satellite and reanalysis data in Rondônia.

**Satellite Observations of the Atmospheric Boundary Layer**

A satellite data product which could have been very useful in the present analysis is NASA’s Atmospheric Infrared Sounder (AIRS) data (Texeira, 2013) which collects midday atmospheric soundings over the Amazon while its northward ascent and equatorial crossing around 1350 Rondônia LT. This dataset available at 1° horizontal and 1 km vertical resolution in the troposphere is probably the only daily scale, satellite observational dataset of vertical profiles of the atmospheric state. Some analysis of this dataset revealed a cold and dry bias close to the surface of the Earth because of which it could not be used to derive boundary layer properties. This bias is a known discrepancy in the AIRS data as discussed with Dr Thomas J Hearty at the Goddard Space Flight Center, Greenbelt, Maryland, USA and also partly discussed in Hearty et al. (2014). This bias will probably be corrected some time in the future, but it renders the data set not useful for the current study.

Due to the unavailability of directly or indirectly observed long time period, complete data time series of the atmospheric conditions in Rondônia, most of the data used for statistical analysis of temporal variability in this study is coarse resolution data obtained from reanalysis products ensuring a large data sample size and a temporally complete analysis.

**Constraining Regional and Large Scale Atmospheric Conditions in Rondônia with Reanalysis Data**

Regional and large scale atmospheric conditions are quantified using the 0.7° resolution ERA-interim reanalysis data (ERA-Interim, 2009) which has been shown to
perform the best in the Amazon amongst three state-of-the-art reanalysis products (Lorenz and Kunstmann [2012]). Some of the analysis presented in the results section was also repeated with the NCEP reanalysis 2 (Kanamitsu et al. 2002) which reveals similar relationships as obtained with ERA-interim (figures not shown). The daily 1400 LT ERA data was averaged over the region -63.5°W, -61.5°W, -11.5°S and -9.5°S (AREA-1 in Figure 4.1) to obtain daily resolution midday atmospheric conditions. This area averaged ERA-interim data was also smoothed with a 5 day moving average before using it for the analysis.

**Numerically Simulated Data**

OLAM (Section 3.2.1) was used to generate simulated dry season daily scale data to verify inferences made with observations. The model setup and numerical simulation design is exactly the same as that used for the ‘Multidecadal’ study in Chapter 3 (Section 3.2.2). The simulation DEF06SSTcl (Table 3.3) is run for the months of July and August at 8 km horizontal resolution. July is discarded as spinup and the daily data from August is used. The analyzed data is an average between 1500 LT and 1600 LT because this period falls between the time period of observed cloud measurements (1400 LT and 1700 LT). A total of 12 time-lagged ensemble members are generated initialized at intervals of 1 day starting at 0000 UTC, 8th June 2004 and ending at 0000 UTC 19th June 2004. All simulation results presented here are averages over this ensemble.

**4.2.4 Statistical Tools**

The multiple linear regression model, where ever used, is estimated using the MATLAB function fitlm. The results presented are for a simple linear model without interaction terms. The regression, where ever used, is performed with standardized data with zero mean and unit variance.
Some multicollinearity exists between the predictor variables. It will be shown in the next section that this multicollinearity is stronger between the monthly averaged predictors as compared to five day averaged predictors. The effect of multicollinearity on the multiple regression model will be evaluated using correlation coefficients and the Variance Inflation Factor (VIF) which is a measure of how much the standard error or variance of the $i^{th}$ predictor increases between a linear and a multilinear regression which includes correlated predictors. It is calculated as:

$$VIF_i = 1/(1 - R_i^2)$$

where, $VIF_i$ is the VIF score for the $i^{th}$ predictor and $R_i^2$ is the $R^2$ value obtained by regressing the $i^{th}$ predictor on the remaining predictors. The effect of multicollinearity can be ignored if the VIF score for a predictor is smaller than 5 (Belsley et al., 1980).

A quantile regression was also performed, only for the daily scale data, with the model presented in Equation 4.1, using the MATLAB package quantreg. This function uses the Nelder-Mead simplex method to find the parameter values that minimize the quantile weighted residuals and applies 200 bootstrap samples to generate the probability distributions for the parameter values to estimate their standard errors.

### 4.3 Results and Discussion

The results in this section are presented in two parts: 1) Sections 4.3.1 through 4.3.3 focus on the analysis of the temporal variability of the corresponding dynamical mechanism in Rondônia (Figure 4.1) and the driving mechanisms and 2) Section 4.3.4 focuses on analyzing the spatial variability of the dynamical mechanism by analyzing the cloud cover features in Pará (Figure 4.2).
4.3.1 Inter-Seasonal Variability

The seasonal cycle of the atmospheric conditions are expected to have the strongest correlations with the dynamical mechanism, hence, the analysis initially focuses on seasonal variability of the DS. The 14 year average seasonal cycle of TRMM precipitation (Figure 4.3b), averaged over Rondônia, shows that the months of June, July and August (JJA) consist of the peak dry or winter season when the daily precipitation is at its minimum. December, January and February (DJF) consist of the peak wet or summer season. The climatological seasonal cycle of DS (Figure 4.3 a) reveals that the dipole strength is strongest during the dry season and weakest during the wet season.

The transition seasons of Autumn and Spring occur during the months of March, April, May (MAM) and September, October and November (SON) respectively. The observed climatological seasonal cycle of cloud cover (Figure 4.4) and TRMM precipitation (Figure 4.5) show that the dynamical mechanism affects regional clouds and precipitation during the dry season months of JJA but also the hydroclimate in parts of the Autumn and Spring transition seasons during the months of May and September respectively. These observations show that the dynamical mechanism is not restricted to the dry season but also affects some parts of the transition seasons especially in the beginning of Spring. Such an impact on spring season precipitation can be important for wet season arrival in the region which has been previously shown to be correlated with regional latent heat fluxes [Fu and Li 2004, Li and Fu 2004].

The DS seasonal cycle is found to be out of phase with CAPE which is an indicator of the changing large scale atmospheric conditions in the region. A correlation and regression analysis was performed with monthly averaged data for all years between 2001 and 2014 i.e. with 14×12 data points. A moderately high correlation (Table 4.1) between the monthly averaged DS with monthly averaged CAPE, BLW and LCL is found (similar relations are observed using seasonally averaged data for 14 years in
Figure 4.3: Annual cycles of daily scale 1700 LT (a) TRMM-DS (b) TRMM 3B43 monthly average daily precipitation, 1400 LT (c) wind magnitude just below boundary layer top (BLW) (d) Lifting condensation level (LCL) and (e) CAPE. The variables BLW, LCL and CAPE are obtained using the ERA-interim reanalysis data averaged over AREA-1 (Figure 4.1). DS is obtained using TRMM 3B42 data over the deforested area in Rondônia and Precipitation seasonal cycle is obtained using TRMM 3B43 monthly averaged data in the 5° by 5° area around Rondônia. The variables, except panel (b), are daily resolution smoothed with a 5 day moving window. The variability is inter-annual variability of the smoothed daily data between 2001 and 2014. Shading represents one standard deviation of this inter-annual variability.

Figure 4.6). But the high cross-correlations between these monthly averaged model variables (Table 4.1) corroborate that the driving factor behind the seasonal cycle of these variables is the seasonal cycle of the sun. A linear regression model with BLW or LCL or CAPE as predictors and a multiple linear regression model with all the three as predictors were performed (Table 4.2). The linear regression models
Figure 4.4: Seasonal variation of the dynamical mechanism as captured by the GridSat cloud clover data in Rondônia. Average of 1400 LT and 1700 LT percentage cloud occurrence between 2001 and 2008 in (a) April, (b) May (c) June, (d) July and August average (e) September and (f) October. Note that panel (d) is average over two months which have a very strong dipole signal hence combined. The data is presented as percentage deviations from the deforested area mean (shown at the top of each panel). Arrows show the average horizontal winds at the boundary layer top in the corresponding months.
Figure 4.5: Seasonal variation of the dynamical mechanism as captured by the TRMM 3B42 precipitation data in Rondônia. 1700 LT hourly precipitation averaged between 2001 and 2014 in (a) April, (b) May (c) June, (d) July and August average (e) September and (f) October. Note that panel (d) is average over two months which have a very strong dipole signal hence combined. Data is presented as percentage deviations from the deforested area mean (shown at the top of each panel). Arrows show the average horizontal winds at the boundary layer top in the corresponding months.
Figure 4.6: Relationships between seasonally (DJF, MAM, JJA and SON) averaged model variables - the response variable TRMM Precipitation DS and predictor variables CAPE, Lifting Condensation Level (LCL) and wind magnitude just below the boundary layer top (BLW). The predictor variables are calculated using ERA-interim data averaged over AREA-1 (Figure 4.1). The variables are averaged each year between 2001 and 2014. 1400 LT average wind magnitude at the boundary layer top, Lifting condensation level and CAPE are used as predictor variables and 1700 LT TRMM precipitation DS (color coded) is used as the response. The seasons are represented by different symbols (legend). The correlation coefficients between each pair of predictor variables is reported at the bottom left of each panel.

show significant and high regression coefficients for all the three predictors suggesting their correlations with the seasonal cycle of the sun. The multiple linear regression however shows that both BLW and CAPE can explain about 57% of annual variance in the monthly averaged DS. But the regression coefficient for LCL drops to ∼0 with a $p$-value of 0.9 showing that once BLW and CAPE are included in the model, LCL does not improve the model prediction. This is also observed through the relatively high VIF score for LCL as compared to BLW and CAPE showing multicollinearity of LCL on the other two predictors. The results, including $R^2$, remain the same if LCL is removed from the model.

We include both BLW and CAPE in the regression model although they are moderately correlated because 1) their individual VIF scores are not larger than 5
Table 4.1: Correlation coefficients between model variables derived from monthly averaged data between the period 2001 to 2014 (12×14 data points). TRMM-DS is at 1700 LT. Rest of the variables are at 1400 LT. TRMM-DS stands for TRMM Precipitation dipole strength, BLW stands for boundary layer top wind magnitude, LCL is Lifting Condensation Level and CAPE is Convective Available Potential Energy. All correlation coefficients are significant with \( p \)-value < 10^{-4}.

<table>
<thead>
<tr>
<th>Variables</th>
<th>TRMM-DS</th>
<th>BLW</th>
<th>LCL</th>
<th>CAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS (% km)</td>
<td>1</td>
<td>0.74</td>
<td>0.66</td>
<td>-0.7</td>
</tr>
<tr>
<td>BLW (m s(^{-1}))</td>
<td>0.74</td>
<td>1</td>
<td>0.83</td>
<td>-0.81</td>
</tr>
<tr>
<td>LCL (m)</td>
<td>0.66</td>
<td>0.83</td>
<td>1</td>
<td>-0.83</td>
</tr>
<tr>
<td>CAPE (J kg(^{-1}))</td>
<td>-0.7</td>
<td>-0.81</td>
<td>-0.83</td>
<td>1</td>
</tr>
</tbody>
</table>

so the multicollinearity can be neglected, 2) both contribute to increase the model \( R^2 \), 3) their regression coefficients from the multiple linear regression model (0.48 and -0.31 respectively) are robust to the addition of additional correlated variables to the model like BLH, BLW direction etc (these other predictors were not included in the model because either they are highly correlated to the other model variables or they do not contribute to the predictive capability of the model on the monthly and daily time scale) and 4) because BLW and CAPE represent the control of two different types of physical processes on the DS. CAPE represents large scale thermal control and BLW represents regional scale dynamical control on the DS.

Hence, it is proposed, from the multiple linear regression analysis of the monthly averaged annual cycles of DS, LCL, BLW and CAPE, that the seasonal cycle of the DS is controlled by the seasonal cycle of the large scale thermal control represented by CAPE and is not dependent on the local scale variable LCL, although they both have a strong correlation with DS. This finding, however should not be interpreted as a control of CAPE on DS through a physical process. The high positive regression coefficient of DS with BLW supports the dynamical origin of the precipitation dipole. In conclusion, the dynamical mechanism is found to be weak or inconsequential during the wet season, atmospheric conditions during which are quite conducive to convection. This supports the hypothesis proposed in the introduction.
Table 4.2: Linear regression models of the monthly averaged data between the response variable TRMM-DS and predictor variables BLW, LCL and CAPE estimated over AREA-1 in Rondônia using ERA-interim reanalysis data. Results from 3 linear regression models each performed with either BLW, LCL or CAPE and a multiple linear regression model including all three predictors are presented. 12 data points are available for each year between 2001 and 2014. The coefficient of determination ($R^2$) is also shown. The 4 models are indicated in the first column. The respective VIF scores are also presented.

<table>
<thead>
<tr>
<th>Model</th>
<th>Coeff</th>
<th>p-value</th>
<th>$R^2$</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLW only</td>
<td>0.74</td>
<td>e-29</td>
<td>0.54</td>
<td>–</td>
</tr>
<tr>
<td>LCL only</td>
<td>0.66</td>
<td>e-22</td>
<td>0.44</td>
<td>–</td>
</tr>
<tr>
<td>CAPE only</td>
<td>-0.7</td>
<td>e-26</td>
<td>0.49</td>
<td>–</td>
</tr>
<tr>
<td>BLW, LCL and CAPE</td>
<td>0.48</td>
<td>e-6</td>
<td>0.57</td>
<td>3.8</td>
</tr>
<tr>
<td></td>
<td>-0.31</td>
<td>2e-3</td>
<td>0.57</td>
<td>3.8</td>
</tr>
</tbody>
</table>

4.3.2 Variability on the Daily Scale

Inferences from Satellite and Reanalysis Datasets

We find a strong correlation between the seasonal cycle of monthly averaged DS and monthly averaged synoptic atmospheric conditions in Rondônia (Figure 4.6, Table 4.2). These relations represent the control of the seasonal cycle of the large scale climate on the dynamical mechanism. On a daily scale however, it is expected that the regional atmospheric conditions will have a more profound effect on the DS. This is because the dynamical mechanism is essentially a boundary layer phenomenon and the boundary layer is itself defined as that part of the atmosphere which is affected by the land surface properties at a time scale of hours. Hence in this section the daily scale variability of the dynamical mechanism and its dependence on measures of BL thermal structure and dynamical conditions will be investigated. For this purpose, the midday, regional scale characteristics of the boundary layer, averaged over the pasture area ‘AREA-1’ in Rondônia (Figure 4.1), are analyzed in the months of April-May (AM), June-July (JJ) and August-September (AS) to understand prevalent physical
Table 4.3: Correlation coefficients between model variables derived from daily data between the period 2001 to 2014 for the individual periods AM, JJ and AS in Rondônia. TRMM-DS is at 1700 LT. Rest of the variables are at 1400 LT. All correlation coefficients are significant with $p$-value<$e^{-4}$.

<table>
<thead>
<tr>
<th>Periods</th>
<th>Variables</th>
<th>DS</th>
<th>BLW</th>
<th>LCL</th>
<th>CAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM</td>
<td>DS</td>
<td>1</td>
<td>0.49</td>
<td>0.47</td>
<td>-0.24</td>
</tr>
<tr>
<td></td>
<td>BLW</td>
<td>0.49</td>
<td>1</td>
<td>0.63</td>
<td>-0.4</td>
</tr>
<tr>
<td></td>
<td>LCL</td>
<td>0.47</td>
<td>0.63</td>
<td>1</td>
<td>-0.54</td>
</tr>
<tr>
<td></td>
<td>CAPE</td>
<td>-0.24</td>
<td>-0.4</td>
<td>-0.54</td>
<td>1</td>
</tr>
<tr>
<td>JJ</td>
<td>DS</td>
<td>1</td>
<td>0.47</td>
<td>0.5</td>
<td>-0.45</td>
</tr>
<tr>
<td></td>
<td>BLW</td>
<td>0.47</td>
<td>1</td>
<td>0.67</td>
<td>-0.65</td>
</tr>
<tr>
<td></td>
<td>LCL</td>
<td>0.5</td>
<td>0.67</td>
<td>1</td>
<td>-0.78</td>
</tr>
<tr>
<td></td>
<td>CAPE</td>
<td>-0.45</td>
<td>-0.65</td>
<td>-0.78</td>
<td>1</td>
</tr>
<tr>
<td>AS</td>
<td>DS</td>
<td>1</td>
<td>0.5</td>
<td>0.6</td>
<td>-0.53</td>
</tr>
<tr>
<td></td>
<td>BLW</td>
<td>0.5</td>
<td>1</td>
<td>0.61</td>
<td>-0.62</td>
</tr>
<tr>
<td></td>
<td>LCL</td>
<td>0.6</td>
<td>0.61</td>
<td>1</td>
<td>-0.78</td>
</tr>
<tr>
<td></td>
<td>CAPE</td>
<td>-0.53</td>
<td>-0.62</td>
<td>-0.78</td>
<td>1</td>
</tr>
</tbody>
</table>

mechanisms. Results from other months of the year are not presented here because the average DS in those months is at least five times lower than the selected period and because the predictive power of the regression model for those months is about an order of magnitude lower than the selected period. Moreover, analysis for the individual months between April and September are not presented either because the regression analysis was found to be not robust during individual months as the regression coefficients drastically changed upon addition or removal of other model variables. Also for this reason the months were clubbed into bi-monthly periods of AM, JJ and AS regression analysis during which was found to be robust.

As mentioned in Section 4.2.3 on the daily scale, the multiple linear regression analysis is performed only using end-members i.e. the multiple linear regression analysis is carried out with ‘high’ and ‘low’ dipole days only, to capture the first order relationships between model variables and hence the most dominant atmospheric controls on the DS. The ‘high’ and ‘low’ dipole days for the bi-monthly analysis are selected in the following manner: 1) high dipole days are the 120 days in the 14 year
bi-monthly time series with the highest values of DS, discounting the ‘zero’ cloudiness days. Hence, roughly 14 to 15% of the days in the full time series are selected as ‘high’ dipole days. 2) Similarly, uniform cloudiness days are the 120 days in the 14 year bi-monthly time series with the lowest DS, discounting the ‘zero’ cloudiness days. Hence, 30% of the full data is used. A sensitivity analysis of the multiple linear regression model with respect to the percentage of data used for the analysis is also performed, results from which will be reported.

Apart from BLW, LCL and CAPE, the dependence of DS on some other regional boundary layer characteristics was also tested to identify the variables which explained the daily DS variability the best. These variables include convective inhibition energy (CIN), boundary layer top wind direction, surface pressure and difference in CAPE and CIN between the LBA forest and pasture sites. Of all the regional predictor variables tested for the regression model, LCL and BLW were the least correlated to each other. The other predictors mentioned above could not explain the daily DS variability as well as LCL or BLW. Hence, daily scale BLW and LCL along with CAPE were used to predict DS.

Figure C.1 shows the scatter plots between DS and the predictor variables BLW, LCL and CAPE. The DS occupies different spaces on the predictor phase space in the three bimonthly periods AM, JJ and AS. The analysis is performed separately for the three periods to remove this inter-seasonal variability between the data. Using 120 days to define the ‘high’ and ‘low’ dipole days each, on the daily scale it is found that BLW, LCL and CAPE have similar correlation coefficients with DS (Table 4.3). But there is also some cross correlation between these predictors in all the bimonthly periods which may affect the regression analysis. The regression analyses for individual predictors in Table 4.4 (see Table C.1 for the corresponding PERSIANN and GridSat results) show that the BLW and LCL are, in general, the most important predictors throughout the transition and dry months, with LCL the stronger player.
Table 4.4: Table showing the $R^2$ value of models to explain the daily scale variability in TRMM DS with different combinations of daily scale BLW, LCL and CAPE as predictors. The regression is performed using data using all ‘high’ and ‘low’ dipole days between 2001 and 2014 separately for the four periods: April-May, June-July and August-September. The $R^2$ for the single-monthly regression are also given for reference.

<table>
<thead>
<tr>
<th>Months</th>
<th>BLW</th>
<th>LCL</th>
<th>CAPE</th>
<th>BLW</th>
<th>LCL</th>
<th>CAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM</td>
<td>0.24</td>
<td>0.23</td>
<td>0.06</td>
<td>0.27</td>
<td>0.30</td>
<td></td>
</tr>
<tr>
<td>JJ</td>
<td>0.22</td>
<td>0.25</td>
<td>0.20</td>
<td>0.28</td>
<td>0.28</td>
<td></td>
</tr>
<tr>
<td>AS</td>
<td>0.25</td>
<td>0.36</td>
<td>0.27</td>
<td>0.39</td>
<td>0.39</td>
<td></td>
</tr>
<tr>
<td>May</td>
<td>0.26</td>
<td>0.2</td>
<td>0.07</td>
<td>0.28</td>
<td>0.28</td>
<td></td>
</tr>
<tr>
<td>June</td>
<td>0.30</td>
<td>0.31</td>
<td>0.28</td>
<td>0.34</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td>July</td>
<td>0.16</td>
<td>0.27</td>
<td>0.08</td>
<td>0.27</td>
<td>0.27</td>
<td></td>
</tr>
<tr>
<td>August</td>
<td>0.17</td>
<td>0.41</td>
<td>0.23</td>
<td>0.42</td>
<td>0.45</td>
<td></td>
</tr>
<tr>
<td>September</td>
<td>0.15</td>
<td>0.14</td>
<td>0.00</td>
<td>0.17</td>
<td>0.25</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.5: Standardized coefficients ($p$-value) of the multiple linear regression model between DS and predictors BLW, LCL and CAPE in Rondônia. Standardized coefficients for the regression for each individual predictor is also presented. The regression is performed separately for daily data in the periods AM, JJ, AS between 2001 and 2014.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>AM Coeff.</th>
<th>JJ Coeff.</th>
<th>AS Coeff.</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLW only</td>
<td>0.49 (e-16)</td>
<td>0.47 (e-14)</td>
<td>0.50 (e-16)</td>
</tr>
<tr>
<td>LCL only</td>
<td>0.47 (e-15)</td>
<td>0.50 (e-16)</td>
<td>0.60 (e-24)</td>
</tr>
<tr>
<td>CAPE only</td>
<td>-0.24 (e-4)</td>
<td>-0.45 (e-13)</td>
<td>-0.53 (e-18)</td>
</tr>
<tr>
<td>BLW, LCL and</td>
<td>0.32 (7e-6)</td>
<td>0.22 (4e-3)</td>
<td>0.20 (3e-3)</td>
</tr>
<tr>
<td>CAPE</td>
<td>0.05 (0.4)</td>
<td>-0.11 (0.2)</td>
<td>-0.09 (0.3)</td>
</tr>
</tbody>
</table>
of the two. Considering the TRMM-DS results, CAPE is found to play a negligible role in predicting the DS during this time as adding it to the regression model does not increase the overall R² value. This is probably because CAPE and LCL are strongly correlated at least in JJ and AS (correlation coefficients are -0.54, -0.78 and -0.78 in AM, JJ and AS respectively), so no new information is added to the model if both are used as independent predictors. BLW and LCL are also moderately correlated to each other (Table 4.3) but they are still considered in the multiple regression analysis because 1) their corresponding regression coefficients are found to be relatively robust to the addition or removal of more model variables as compared to regression coefficients for CAPE, 2) their VIF values in all the bimonthly periods are smaller than 3 showing that their multicollinearity is not severe 3) they represent the influence of two different types of physical mechanisms on the dipole - LCL represents a thermal control and BLW represents a dynamical control on DS and 4) they both contribute to increase the model R² as compared to CAPE (Table 4.4).

The corresponding statistics for the linear regression model are presented in Table 4.5 and the predictor phase space in AM, JJ and AS is shown in Figure 4.7 (see Table C.2 and Figures C.2 and C.3 for the corresponding PERSIANN and GridSat results). It is to be noted that the daily scale regression is performed with only the ‘high’ and ‘low’ dipole days neglecting the days with ‘zero’ cloudiness or ‘not a number’ (nan) DS. The standardized regression coefficients of the multiple linear regression models show that out of the three predictors the regional scale variable LCL explains the daily DS variability the most. This shows that on the daily scale regional thermodynamic conditions have a larger control on the dynamical mechanism than the larger scale thermodynamic conditions represented by CAPE. Also, DS is found to be positively correlated with both BLW and LCL. The positive dependence on the daily scale BLW supports the dynamical origin of the cloud or precipitation dipole.
Figure 4.7: Whisker plots showing that the ‘high’ and ‘low’ dipole days occupy different spaces on the predictor phase space. Columns represent different bi-monthly periods: (a,d,g) - AM, (b,e,h) - JJ, (c,f,i) - AS. Blue and red colors represent the top 120 high and low DS days respectively. The yellow color represents days when less than 5% of the total deforested area is covered with clouds. The error bars represent median, 25th and 75th percentiles. The range of the DS on high and low dipole days is also shown at the top of the panels in the bottom row.
Figure 4.8: Sensitivity of the daily scale multiple regression model (Equation 4.1) to the percentage of data used to define ‘high’ and ‘low’ dipole days. The x-axis represents the percentage of the full daily scale data set used for the regression. Per% on the x-axis implies that the ‘high’ and ‘low’ dipole days each comprise Per/2% of the full data. (a, b, c) Regression coefficients, (d, e, f) corresponding p-values and (g, h, i) corresponding R² for multiple regression models in the bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September.
A sensitivity analysis of the daily scale multiple linear regression analysis to the percentage of days used to define the ‘high’ and ‘low’ dipole days is performed and is presented in Figure 4.8. The values of the standardized coefficients for BLW, LCL and CAPE are weakly sensitive to the percentage of days used for regression. These coefficients also show that LCL and BLW are the main influences on daily scale DS (high standardized coefficients and low p-values) as compared to CAPE in all the bimonthly periods, although $R^2$ decreases, as expected, with increasing amount of data used for regression.

A quantile regression was performed between DS and the predictor variables BLW, LCL and CAPE at various percentiles between 10 and 90 for the three bimonthly periods (Figure C.4). LCL again emerges as the most important predictor between BLW, LCL and CAPE with a relatively high standardized coefficient and low p-value. The regression coefficient is higher for higher quantiles conforming with the raw daily scale data presented in Figure C.1. Also, conforming with the multiple linear regression analysis, BLW is found to be the second most important predictor variable at least in JJ and AS with higher standardized coefficients and low p-values as compared to those for CAPE. The regression coefficients for both LCL and BLW are consistently positive as were the multiple regression coefficients for these two variables.

Using 120 days to define ‘high’ and ‘low’ dipoles each, Figures 4.9, C.5 and C.6 show the average cloudiness/precipitation occurrence over Rondônia during the high and low dipole days in the three bi-monthly periods. It should be noted that these maps are not predicted by the model presented in Tables 4.5 and C.2. These are shown just as examples of the average difference in midday cloud or precipitation occurrence between high and low dipole days. The uniform cloudiness/precipitation occurrence observed over the Rondônia region during low dipole days suggests active random thermal triggering which happens preferably over the deforested area during the peak
Figure 4.9: Maps of 1700 LT average TRMM precipitation occurrence for ‘high’ DS days and ‘low’ DS days with corresponding average wind vectors. Rows represent average (a, b, c), ‘high’ dipole (d, e, f) and ‘low’ dipole (g, h, i) days. Columns represent individual bi-monthly periods AM (a, d, g), JJ (b, e, h) and AS (c, f, i). Data is averaged between 2001 and 2014. The average precipitation occurrence in the period within the deforested area is also reported at the top of each panel. Note the different color scales in the different panels.

dry season (panels h and i in Figures 4.9, C.5 and C.6). These distinctions between the ‘bipolarity’ or ‘uniformity’ of cloud/precipitation occurrence over the deforested region respectively during the high and low dipole days is further supported by the angle between the bi-monthly average BLW and dipole vectors reported in Tables 4.6 and C.3. The tables show that during the period AMJJAS the high dipole days have a dipole which is oriented roughly 40° towards the right of BLW following the Ekman spiral in the boundary layer. Whereas during the low dipole days this value is mostly
negative and random. It is also noted that the deforested area mean cloud or precipitation occurrence in Figures 4.9, C.5 and C.6 is consistently higher during low dipole days as compared to high dipole days. These observations indicates that the random thermal triggering results in higher cloud or precipitation occurrence. Combining the insights gained from the regression analysis and these maps, it can be concluded that the ‘low’ DS or the days that support thermal triggering occur under atmospheric conditions which are more conducive to convection as compared to the ‘high’ dipole days. Hence, the dynamical mechanism emerges as a triggering mechanism which is able to break a stronger atmospheric stability barrier which the regular thermal triggering is not able to break. The two mechanisms occur in opposite circumstances, with the one that supports the dynamical mechanism requiring a stronger upward motion. It should be noted that the evidence is not enough to conclude that the dynamical mechanism is the dominant mechanism in all circumstances.

Figure 4.9 also depicts a potential drawback of using the dipole moment metric: that the metric is not able to distinguish between days of high dipole and days which have a area wide southeasterly gradient of precipitation. This problem can contaminate the ‘high’ dipole days as is seen in Figure 4.9e where the positive part of the dipole merges into the high precipitation regions towards the north of Rondônia. However it does not affect the ‘high’ dipole day statistic in every case as can be seen in Figure 4.9f. Some test measures were taken to improve this drawback of the dipole metric, for example the days which had a surface low pressure center right above Rondônia (within 2 degrees of the top of this region) were removed from the analysis, but this reduces the sample size quite a bit rendering poor regression, not particularly improving the results. Similar filtering of the data is work under progress.

Tables 4.6 and C.3 also report the average difference between the daily scale LCL and Boundary Layer Height (BLH) on high and low dipole days. This difference is consistently higher during the period AMJJAS as compared to FM and ON which
Table 4.6: Characteristics of the midday Dipole Strength metric (DS), difference in wind and dipole direction ($\Delta \theta$) and atmospheric conditions ($\Delta H$) during ‘high’ and ‘low’ dipole days in the periods of FM, AM, JJ and AS and ON. Values are obtained using daily scale data between 2001 and 2014.

<table>
<thead>
<tr>
<th></th>
<th>FM</th>
<th>AM</th>
<th>JJ</th>
<th>AS</th>
<th>ON</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>2348 (2130, 2728)</td>
<td>4750 (4169,6051)</td>
<td>11135 (9700,13169)</td>
<td>8267 (7369,10946)</td>
<td>2567 (2370, 2940)</td>
</tr>
<tr>
<td>Low</td>
<td>314 (222, 370)</td>
<td>464 (327,584)</td>
<td>1423 (1131,1778)</td>
<td>586 (451,723)</td>
<td>334 (218, 411)</td>
</tr>
<tr>
<td>$\Delta \theta$&lt;sup&gt;b&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>-2 (-57, 23)</td>
<td>48 (9,86)</td>
<td>32 (-7,79)</td>
<td>47 (16,70)</td>
<td>72 (-22, 187)</td>
</tr>
<tr>
<td>Low</td>
<td>-9 (-91, 93)</td>
<td>-34 (-147,41)</td>
<td>0 (-109,58)</td>
<td>-38 (-148,54)</td>
<td>-3 (-84, 103)</td>
</tr>
<tr>
<td>$\Delta H$&lt;sup&gt;c&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>-46 (-172, 53)</td>
<td>64 (-57,201)</td>
<td>272 (105,378)</td>
<td>450 (306,659)</td>
<td>81 (-32, 244)</td>
</tr>
<tr>
<td>Low</td>
<td>-52 (-119, 55)</td>
<td>-70 (-189,45)</td>
<td>124 (-24,290)</td>
<td>281 (127,522)</td>
<td>58 (-69, 223)</td>
</tr>
<tr>
<td>Zero</td>
<td>nan</td>
<td>nan</td>
<td>298 (178,436)</td>
<td>591 (456,746)</td>
<td>nan</td>
</tr>
</tbody>
</table>

<sup>a</sup>Dipole strength of the TRMM 1700 LT precipitation dipole (% km).

<sup>b</sup>Angle between the 1400 LT BL top horizontal wind and the 1700 LT TRMM-DS vector (degrees).

<sup>c</sup>Difference between 1400 LT LCL and BL height (m)
shows relatively more stable conditions during the dry season as compared to the wet season. Moreover, a marked distinction between the LCL-BLH values on high and low dipole days is also found with the difference being higher during high dipole days. This observation further supports the finding that high dipole days occur during periods in which thermal triggering is suppressed so that the boundary layer can not reach as high as the LCL. This further supports the conclusion that the dynamical mechanism occurs in relatively calm days with high atmospheric stability as compared to low dipole days.

Figures 4.7 and C.2 also show the zero cloudiness days on the predictor phase space. Although not always statistically significant (error bars overlap), the zero cloudiness or precipitation days occur in atmospheric conditions with a higher LCL and BLW and a lower CAPE as compared to both the high and low dipole days. This observation suggests that both thermal and dynamical triggering of convection are weak in days of strong atmospheric stability (regional highs) in which case neither of these land-atmosphere interactions affect the regional clouds or precipitation.

**Inferences from Simulated Data**

Some of the relationships found using satellite observations and reanalysis data are supported by the daily scale numerically simulated data. Multiple linear regression is performed using simulated data averaged between 1500 LT and 1600 LT. Relative humidity at 1700 m altitude is used to calculate DS and is correlated with LCL and BLW averaged between -63.5°W, -61.5°W, -11.5°S and -9.5°S. High and low dipole days are selected from all days in August. The standardized regression coefficients of the multiple regression model are presented in Table 4.7 which shows that the simulated dipole days are also strongly positively correlated with LCL. However, the BLW does not explain the DS variability at all. This also conforms to some extent
Table 4.7: Standardized coefficients (p-value) of the multiple linear regression model between 1700 m altitude relative humidity DS and predictors BLW and LCL calculated using simulated data. The regression is performed separately for daily data at 1600 LT on all days in August in the 12 ensemble simulations. Data for the top 15% high and low dipole days are used for the regression.

<table>
<thead>
<tr>
<th>Simulated Month</th>
<th>BLW</th>
<th>LCL</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>August</td>
<td>-0.015</td>
<td>0.59</td>
<td>0.34</td>
</tr>
</tbody>
</table>

Figure 4.10: Relationships between the simulated DS, LCL and BLW. The DS is calculated with 1600 LT relative humidity at 1700 m altitude and LCL and BLW are calculated at 1600 LT in the month of August. The values are calculated with daily data. Error bars represent median, 25th and 75th percentiles of the predictors during ‘high’ and ‘low’ dipole days.

with observations which show a secondary dependence of DS variability on BLW (Table 4.5). Whisker plots shown in Figure 4.10 also support this finding.

Similiar to observations the high dipole days are characterized by a spatial redistribution of relative humidity between the downwind and upwind regions of the deforested area and the low dipole days are characterized by a uniformly high relative humidity over the deforested region (Figure 4.11). Also the average relative humidity over the deforested area during the low dipole days is slightly higher as compared to nearby forests indicating active thermal triggering over the warm cleared patches. Lastly, conforming with observations the area average relative humidity over the de-
Figure 4.11: Average maps of simulated 1700 m altitude relative humidity for (a) ‘high’ and (b) ‘low’ dipole days. Data is averaged over the month of August over all ensemble simulation. The average 1700 m altitude relative humidity within the deforested area is also reported at the top of each panel.

The BLH in simulated high dipole days is found to be lower than the LCL on the corresponding day as compared to low dipole days (Table 4.8). This result also conforms with the observations (Table 4.6) hence showing that the dynamical mechanism is more effective during days of relatively stable conditions as compared to days when the forested area during low dipole days is higher than the high dipole days. However, the angle between the simulated BLW and the dipole vector is negative for both the high and low dipole days (Table 4.8). It is recalled from the analysis presented in Figure 3.20 that the simulated dipole direction is northeasterly. But the simulated BLW wind direction is easterly (Figure 3.3). This is the reason for a negative difference between the simulated BLW direction and simulated dipole direction. Moreover, the simulated BLW is found to be not different during ‘high’ and ‘low’ dipole days (Figure 4.10) which may explain why the $\Delta \theta$ is negative and similar for both the types of dipole days.
Table 4.8: Characteristics of the Dipole Strength metric (DS), difference in wind and dipole direction ($\Delta \theta$) and atmospheric conditions ($\Delta H$) during ‘high’ and ‘low’ dipole days over the month of August over all ensemble simulations. DS is the 1700 m altitude relative humidity dipole, $\Delta \theta$ is the angle between BLW and the dipole and $\Delta H = \text{LCL-BLH}$.

<table>
<thead>
<tr>
<th>DS (% km)</th>
<th>Median ($25^{th}$, $75^{th}$ percentile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>13789 (11726, 16657)</td>
</tr>
<tr>
<td>Low</td>
<td>1249 (764, 1660)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$\Delta \theta$ (degrees)</th>
<th>Median ($25^{th}$, $75^{th}$ percentile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>-12 (-73, 20)</td>
</tr>
<tr>
<td>Low</td>
<td>-51 (-116, 40)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$\Delta H$ (m)</th>
<th>Median ($25^{th}$, $75^{th}$ percentile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>405 (233, 567)</td>
</tr>
<tr>
<td>Low</td>
<td>70 (-49, 187)</td>
</tr>
</tbody>
</table>

Thermal triggering is active. Hence, it can be concluded from the simulation results as well that the dynamical mechanism is more effective at breaking strong stability barriers in the boundary layer as compared to thermal triggering.

**Supporting Evidence from Site-Level Data**

The positive correlation between DS, LCL and LCL-BLH are also observed in the LBA-SMOCC radiosonde data from the pasture site Fazenda Nossa Senhora in Rondônia. Radiosonde data was collected for 12 days between 18 and 29 September 2002 at different times of the day. LCL and LCL-BLH estimated using 1400 LT atmospheric profiles show a positive correlation with the TRMM 1700 LT DS (Figure 4.12). The TRMM DS is observed to have decreased from 3000 % km during the beginning of this 12 day period to 1000 % km by the end of this period. Although this is a rather short time series to find statistically significant correlations we still find the 1700 LT TRMM-DS and 1400 LT LCL to be correlated with a correlation coefficient of 0.66. LCL-BLH is also found to have higher values in the early part of the 12 day time series as compared to the later part. The correlation coefficient between DS and LCL-BLH is 0.52.
Figure 4.12: Co-evolution of DS, LCL and LCL-BLH from radiosonde data from the pasture site at Fazenda Nossa Senhora collected between 18 and 29 September 2002. (a) Time series of TRMM-DS at 1700 LT between 18 and 29 September 2002. (b) LCL and (c) LCL-BLH at the pasture site at 1400 LT between 18 and 29 September 2002.

Overall, the different types of daily scale data sets, both observational and simulated, used for this analysis suggest that the dynamical mechanism affects the hydroclimate over deforested areas in Rondônia during the regional dry winter months and also some of the transition months. The daily scale analysis suggests that the dynamical mechanism occurs during periods of higher stability as compared to days which support uniform random thermal triggering of convection. Hence, the dynamical mechanism is able to break strong boundary layer stability barriers so much that even the low dipole days during the peak dry season have a high value of DS relative to the transition months and the wet season.
4.3.3 Inter-Annual Variability

The relationships between DS, BLW, LCL and CAPE found on the inter-seasonal and daily time scale in Rondônia will now be analyzed at the inter-annual time scale. The main objective will be to find if large global scale climatic conditions can be used to explain the inter-annual variability in DS.

The inter-annual variability of the precipitation dipole signal is analyzed with 14 years of monthly averaged data for the bi-monthly periods AM, JJ and AS. To remind the reader, the LCL, BLW and CAPE are estimated using the the 1400 LT ERA-interim reanalysis data (ERA-Interim 2009) averaged over AREA-1 in central Rondônia (Figure 4.1) and DS is estimated using TRMM 3B42 data over the deforested regions of Rondônia. Within each bi-monthly period the 15% strongest and 15% weakest DS months show similar dependence on LCL and BL wind magnitude as observed on the daily scale - high winds and high LCL result in higher DS (Figure 4.13). The correlation coefficients between DS and predictor variables calculated using the full dataset for each bimonthly period show similar inter-annual dependence as pointed above (Table 4.9). But the predictor variables are also found to be strongly correlated with each other with correlation coefficients ≥0.75 at least in JJ and AS. The correlation coefficient between LCL and CAPE in AM is -0.58. Hence, the dependence of DS on both CAPE and LCL can be because they are both mutually correlated. The data available for each bi-monthly period (28 sample points for 2 months in 14 years) is used to fit a multiple linear regression model between DS, BLW, LCL and CAPE. None of the regression coefficients were found to be significant at the 5% significance level hence the results are not reported here.

The monthly averaged DS were not found to be significantly correlated with the monthly SST indices NATL (ESRL-PD 2015a) and Niño 3.4 (ESRL-PD 2015b) in the bi-monthly periods of AM, JJ and AS between 2001 and 2014 (Table 4.10). No significant correlations of the monthly averaged DS with SST indices as compared to
Figure 4.13: Applicability of daily scale physical processes (correlations) on the interannual time scale. Correlations between DS, LCL, BLW and CAPE in each bi-monthly period AM, JJ and AS. The values represent monthly averages for each year between 2001 and 2014. Hence each period of each year, for example JJ 2004, contributes two monthly averages. Each period has $2 \times 14$ values. The figures show the predictors during ‘high’ and ‘low’ dipole months in the 14 year period. The low and high dipole months are respectively the top 15% and lowest 15% dipole months of the 14 year data.
Table 4.9: Observed inter-annual correlations between monthly averaged model variables. Correlation coefficients ($p$-value) between DS and predictor variables BLW, LCL and CAPE calculated using monthly averaged data for each bi-monthly period AM, JJ and AS between 2001 and 2014.

<table>
<thead>
<tr>
<th></th>
<th>AM</th>
<th>JJ</th>
<th>AS</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLW</td>
<td>0.62 (0)</td>
<td>0.41 (0.035)</td>
<td>0.6 (0.001)</td>
</tr>
<tr>
<td>LCL</td>
<td>0.69 (0)</td>
<td>0.26 (0.183)</td>
<td>0.66 (0)</td>
</tr>
<tr>
<td>CAPE</td>
<td>-0.53 (0.004)</td>
<td>-0.24 (0.227)</td>
<td>-0.67 (0)</td>
</tr>
</tbody>
</table>

Table 4.10: Correlation coefficients ($p$-value) between DS and SST indices NATL and Niño 3.4 calculated using monthly averaged data for each bi-monthly period AM, JJ and AS between 2001 and 2014.

<table>
<thead>
<tr>
<th></th>
<th>AM</th>
<th>JJ</th>
<th>AS</th>
</tr>
</thead>
<tbody>
<tr>
<td>NATL</td>
<td>0.24 (0.2)</td>
<td>-0.05 (0.8)</td>
<td>-0.07 (0.7)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>0.17 (0.4)</td>
<td>0.04 (0.9)</td>
<td>0.22 (0.3)</td>
</tr>
</tbody>
</table>

Significant correlations with regional scale atmospheric conditions (Table 4.9) suggest that the dipole is more strongly dependent on regional boundary layer conditions than larger scale atmospheric conditions.

4.3.4 Signature of the Dynamical Mechanism in Other Parts of the Deforested Amazon

The spatial dependence of the dynamical mechanism is tested by analyzing the dry season cloud occurrence in the deforested regions of the southern parts of the Brazilian state of Pará (Figure 4.2). The deforested region considered for this analysis is smaller in extent ($\sim$200 km in the direction of near surface winds) as compared to the deforested area in Rondônia ($\sim$400 km in the direction of near surface winds). This deforested region is not a contiguous deforested area as is Rondônia, hence the characteristic length scale of deforestation is also expected to be smaller than that in Rondônia (by visual inspection).
As mentioned in Section 4.2.1 no long time series land cover data of this region is available, which limits a full three decade time series analysis of the changing hydroclimate. Land cover maps for the years 2008, 2010 and 2012 are available from the TERRA-CLASS project of INPE (Coutinho et al., 2013) which is used to estimate the deforested boundary for 2008. Fractional deforestation data is available upto 1995 from the LBA-ECO LC31 data set (Leite and Costa, 2013) which is utilized to estimate the deforested boundary in 1987 and 1995. Owing to the unavailability of data some of the analysis presented here is limited only to the time period between 2001 and 2008. The time series analysis for Rondônia presented in Figure 2.13 could not either be repeated for this deforested region.

The multidecadal time series of the percentage cloud occurrence over Pará for the months of June, July and August (JJA) shows a transition in the hydroclimate with cloud occurrence increasing with the expansion of the deforested boundary between decades the of 1980s and 2000s (Figure 4.14). It is interesting to note that although the deforestation in this region is not as contiguous as that in Rondônia (compare Figures 2.1 and 4.2) a downwind concentration of cloud occurrence is still found in this deforested region of Pará as well (Figure 4.14 c). This signal is different from the cloud occurrence signals in the decades of 1980s and 1990s which show a relatively uniform cloudiness over the deforested area (Figure 4.14 a and b).

The analysis presented in Section 2.3.4 for Rondônia is repeated for this deforested region of Pará in order to test if the increase and decrease in cloudiness respectively over the downwind and upwind deforested areas in the contemporary decade of 2000s is associated with different scales of deforestation in the respective regions or not. For this purpose a map of percentage deviations of 1400 LT JJA cloud occurrence from the deforested area mean between 2001 and 2008 was generated. This map and the land cover map shown in Figure 4.2 are then re-gridded to a 2 km by 2 km grid. These two maps are then used to generate the probability distribution functions
Figure 4.14: Increase in downwind cloudiness with increase in deforestation in southern Pará. 1400 LT average percentage cloud occurrence in JJA between (a) 1983 and 1990, (b) 1991 and 1999 and (c) 2001 and 2008 calculated using GridSat data (Knapp et al., 2011). Data is presented as the anomaly from the 5° by 5° area mean. The 1400 LT, 800 mb, JJA average horizontal wind vectors calculated using the NCEP reanalysis 2 (Kanamitsu et al., 2002) is also shown with the red arrow for the corresponding periods. Dashed line represents deforested boundary in the corresponding period and solid line represents deforested boundary in 2008.

shown in Figure 4.15. Although not a bimodal distribution, as was found in the case of Rondônia (Figure 2.12), the probability distribution of percentage occurrence of cloudiness has a flat top and is multimodal (Figure 4.15 b). This shows that the there is a significant probability of occurrence of ∼5% more and ∼5% less cloudiness than the deforested area mean. Figure 4.15 panel a further shows that the probability of occurrence of more or less cloudiness as compared to the area mean is not dependent on the fraction of deforested area in that grid. In other words, there is no evidence of preferential occurrence of cloudiness over highly deforested grids and suppression of cloudiness over less deforested grids.

This result is a signature feature of the dynamical mechanism which was also found in the case of Rondônia, however in Pará the signal is not as distinct. Some of the reasons for a muted signal can be: 1) the deforested region in Pará is smaller than that in Rondônia so the sample size of grid points is low, 2) the deforested area itself is not contiguously deforested making the dynamical mechanism it self weaker as compared to that in Rondônia and 3) because the size of the deforested area in the
Figure 4.15: Correlations between patterns of cloudiness and scale of deforestation in the contemporary period in Pará. (a) Bivariate probability distribution function (PDF) of 1400 LT JJA percentage occurrence of cloudiness and fraction of deforested area under the corresponding grid cell in 2001 to 2008. (b) Corresponding univariate PDF of % deviations of cloudiness from area mean.

direction of the near surface winds is smaller than that in Rondônia possibly further weakening the dynamical mechanism.

This analysis provides motivation for further investigations into the applicability of the dynamical mechanism to the atmospheric response to deforestation in other large deforested areas of the Amazon rainforest and other tropical regions of the world. The analysis shows that the dynamical mechanism has the potential of being a common atmospheric response to large scale deforestation in the dry season.

4.4 Conclusions

Fourteen years of observed and reanalysis data, complemented by numerical simulations and site level observed data were utilized to understand the spatio-temporal variability of the dynamical mechanism. The temporal variability was analyzed at the daily, seasonal and inter-annual time scales. Spatial variability was tested by consid-
ering a large scale (about one to two hundred kilometers) deforested area in the south of the Brazilian state of Pará. The statistical analysis applied for this investigation resulted in the following conclusions:

1. Like some other land-atmospheric interactions (Shephard, 2005; Seneviratne et al., 2010; D’Almeida et al., 2007), for example urban heat island and thermally triggered mesoscale circulations, the dynamical mechanism is also found to be primarily a winter season phenomenon, however it affects parts of the transition seasons as well. It is found inconsequential under atmospheric conditions which are buoyant or unstable enough to even weak triggering mechanisms. As such the dipole is observed only during the dry and some part of the transition seasons. Also, the daily scale analysis tells us that the dynamical mechanism occurs in days of higher stability and higher winds just below the boundary layer top as compared to periods that support uniform cloudiness characterized by less stable conditions. Also the positive control of magnitude of the boundary layer top winds on dipole strength indicates the ‘dynamical’ origin of these signals.

2. These relationships, between the dipole strength and regional boundary layer thermal and dynamical conditions, are found on the daily (within the dry and parts of the transition season) and seasonal time scales. Inter-annual variability also shows a similar relationship between these variables but the analysis is not statistically significant owing to the small sample size on this time-scale.

3. Data suggests that the dynamical mechanism is a phenomenon controlled by regional scale atmospheric conditions. On a daily scale boundary layer thermal and dynamical conditions contribute to most of the explained dipole strength variability. On a monthly averaged scale regional upper air atmospheric thermal conditions (CAPE) also contribute to the explained dipole strength variability.
Global SST indices representing the states of the tropical North Atlantic Ocean and central Tropical Pacific Ocean (Niño 3.4) are not found to have any significant correlations with monthly averaged dipole strength over the study period.

4. The dynamical mechanism is found to be applicable in the deforested regions of southern Pará, however the signals are weaker as compared to those in Rondônia possibly because this region is not as extensively deforested as Rondônia.
Chapter 5

Summary, Conclusions and Future Work

5.1 Novel Tools, Findings and Their Implications

Amazon deforestation, which currently affects more than 17% of the rainforest, has been a topic of concern amongst climate scientists, ecologists, policy makers and the general public alike. A major part of the ecosystem impacts of deforestation - like increase in fire frequency \cite{Malhi2008, Cochrane2008}, changes in ecosystem adaptation projected by modeling studies \cite{Malhi2008, Malhi2009, Nobre2009} - are largely caused by the ecosystem’s response to the hydroclimatic effects of deforestation. But, despite such important implications, the impacts of present day deforestation on clouds and precipitation has not been well observed nor explained.

The hydroclimatic impact of early stage deforestation, occurring in the 1980s in the Amazon rainforest, is well studied. Several studies have reported an increase in mostly non-precipitating cloud cover due to the small scale (a few kilometers) deforestation occurring in this period (see \cite{DAlmeida2007} and \cite{Lawrence2009}).
Vandecar (2014) for reviews). But contemporary deforestation scales have increased up to several tens to a few hundreds of kilometers. The hydroclimatic impacts of this three decade-long increase in deforestation are not known despite being ecologically important as described above.

This thesis set out to achieve some part of this broad goal of understanding the hydroclimatic impacts, specifically impacts on regional clouds and precipitation, of the present day deforestation in Amazonia by answering the following questions:

1. What is the observed hydroclimatic response to current, intermediate scales of deforestation (several tens to a few hundreds of kilometers)? and how is it different from the hydroclimatic response to small scale (a few kilometers) deforestation which characterized the deforested landscape in Amazonia in the 1980s? What is the impact of this atmospheric response on regional precipitation? (Chapter 2)

2. What deforestation-induced physical mechanism produces this hydroclimatic response? Is it different from the systematic mechanism of ‘thermal’ circulations which were induced due to early period deforestation and resulted in mostly non-precipitating shallow cloudiness? (Chapter 3)

3. How generalizable and hence influential is this physical process both in time and in space at various deforested regions in the Amazon rain forest? What atmospheric conditions are favorable for this atmospheric response? What is the inter-annual variability of the detected atmospheric response? (Chapter 4)

These questions were addressed using both observational and numerical tools making this study probably the first such multidecadal, integrated perspective on this issue. The findings from this thesis in light of the questions posed above will be summarized here. A summary of the novel tools which were developed or used to make this study possible and their broader applicability will be discussed first.
Novel Tools

This study was made possible by the implementation of a customized version of the cloud detection algorithm used by the International Satellite Cloud Climatology Project (ISCCP) and due to the availability of new multidecadal, climate quality geostationary satellite products of brightness temperature and albedo (Gridded Satellite or GridSat) and precipitation (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks or PERSIANN). The ISCCP cloud detection algorithm was simplified because the study regions in this thesis did not have marked land cover contrasts like snow, water and vegetation within one scene. This simplified algorithm applied to the GridSat dataset facilitated the production of a multidecadal, high spatial and temporal resolution time series of cloud occurrence which, along with the PERSIANN precipitation dataset, made the multidecadal study possible.

The use of a variable resolution global circulation model (Ocean-Land-Atmosphere-Model or OLAM) was also a relatively new approach of modeling the regional hydroclimate of the Amazon rainforest at the mesoscale (a few tens of kilometers), which has been a recommended approach to capture mesoscale effects of the land surface without increasing the computational burden. This model was found to be remarkably successful in reproducing the observed signals in cloud and precipitation with the modeled atmospheric relative humidity. The model was customized and evaluated against in situ observations from two forest and pasture sites in the Brazilian state of Rondônia making this model setup particularly useful for similar future hydroclimatic studies, at least in this region of the Amazon rainforest.

The development of the multidecadal high resolution observational tools, customization of the model with in situ observations and their agreement with each other regarding the three decade-long change in deforestation-induced regional hydroclimate make these tools particularly useful for similar studies of the regional hydroclimate in the Amazon rainforest. The questions posed above were addressed,
with the help of these tools, to achieve the aims of this thesis. The major findings are now discussed.

Detection

The detection of the precipitation and cloud cover changes due to contemporary deforestation were mainly analyzed in the deforested regions of southern Amazon rainforest in the state of Rondônia in Brazil. Satellite observations of precipitation and cloud cover in this region show that contemporary large scale (a few hundreds of kilometers) deforestation in the southern parts of the Amazon rainforest results in a redistribution of clouds and precipitation over the upwind and downwind deforested areas particularly during the regional dry season and parts of the transition seasons. As a result, the downwind and upwind deforested areas are receiving respectively 25% more and 25% less cumulative precipitation in the months of June, July, August and September as compared to the full deforested area mean. This phenomenon is also captured by corresponding numerical simulations for the months of July and August. The simulated atmospheric relative humidity just above the top of the boundary layer shows a strong ‘dipole’ signature similar to that observed. The simulated precipitation also captures the dipole but relatively weakly.

Interestingly, no statistically significant multidecadal trends in the precipitation amounts in the upwind and downwind deforested areas were observed in satellite precipitation data. This lack of trend in the total precipitation amount is different from the significant year-to-year trend found in the precipitation redistribution over the deforested area discussed above. The data shows a significant increase in redistribution of precipitation with increasing time but a non-significant increase in the precipitation itself. The trend in precipitation amounts is insignificant probably because high inter-annual precipitation variability masks any trends due to the increase in the dipole strength over time.
This ‘dipole’ response has been the dominant response to contemporary deforestation in the Brazilian state of Rondônia since the late 1990s. The deforestation-induced hydroclimatic impact before this time was characterized by a preferential increase in thermally-induced, mostly non-precipitating cloud cover uniformly over all the highly deforested areas in Rondônia. The ‘dipole’ signature of an increase of clouds and precipitation in the downwind deforested areas and corresponding reduction in the upwind deforested areas is found not to be correlated with the contemporary local deforestation scales in the two areas. This lack of correlation of the cloud patterns with the local deforestation scales is the opposite of cloud cover triggered by thermal mesoscale circulations which occur preferentially and uniformly over deforested areas with subsidence over nearby forests. These results indicate that the ‘dipole’ phenomenon is different from the thermally triggered mesoscale circulations which were observed over small scale (a few kilometers) cleared patches in the early stages of Amazonian deforestation in the 1980s. However, the ‘dipole’ signature is dependent on the size of the full deforested domain because this signal is found only in the contemporary times when the domain size is at least an order of magnitude larger as compared to that in the 1980s.

The dipole phenomenon is characterized using a dipole metric which quantifies the extent and strength of the redistribution of clouds or precipitation over the deforested domain. A remarkable scaling of 3 to 4 times is found to exist between this metric calculated for the decade of 1980s and the decade of 2000s across all datasets used - Satellite cloud cover and precipitation datasets; Simulated relative humidity and precipitation datasets. This scaling, that exists across all the datasets, reconfirms that the same phenomenon is being captured by the three sources of data and that the precipitation redistribution signal is not a chance finding.
Attribution

Numerical experiments were performed using OLAM at 8 km resolution over Rondônia to understand the underlying physical mechanisms driving the observations reported above. Separate sets of experiments were performed to 1) attribute the observed multidecadal transition in clouds and precipitation spatial patterns to decadal climate change or increasing scales of deforestation and 2) explain the physical mechanism responsible for the precipitation redistribution over the deforested area observed in the contemporary period. The model was evaluated using in situ and satellite observations before carrying out the experiments.

An analysis of the first set of numerical experiments shows that the three decade-long evolution of clouds and precipitation, in the form of the ‘dipole’ observed in satellite data, is not explained by decadal climate variability due to changes in sea surface temperatures. On the other hand, simulations show that the increasing scales of deforestation over the past three decades are sufficient to explain the observed multidecadal transition.

A combination of numerical sensitivity tests, performed under Set 2 mentioned above, show that the surface roughness variations caused by the contemporary, almost contiguous deforestation, of the scale of a few hundreds of kilometers, is responsible for the observed ‘dipole’ pattern. The low surface roughness over smooth pasture areas against the surrounding rough forests results in the speeding up of the near surface winds. This results in a low level convergence and corresponding divergence in the downwind and upwind deforested areas respectively triggering a corresponding upwelling and downwelling in the two regions. The regular thermal mesoscale circulation, active in the early phases of deforestation in the 1980s, is not able to explain the dipole phenomenon. Acknowledging the mechanism that gives rise to the cloud and precipitation redistribution, this phenomenon is termed as the ‘dynamical’ phenomenon in the thesis.
Various numerical sensitivity tests performed with OLAM helped pin down some important features of the dynamical mechanism. For example,

- The strength of the dynamical mechanism is found to be dependent on the thermal changes to the boundary layer modulated by an increase in Bowen ratio caused by deforestation.

- This phenomenon is not generated by merely the advection of clouds by the winds above the boundary layer top, as compared to the downwind precipitation observed over urban areas, which is attributed to advection effects. This inference is made because the numerical experiments controlling for surface roughness between forests and deforested areas could not reproduce the dipole pattern.

- The dipole is found not to be generated by local interactions of topography and land cover change, however regional topography may modulate the strength and orientation of the dipole.

- The dynamical mechanism is found to be essentially a boundary layer phenomenon with the resultant vertical wind and relative humidity changes extending a little above the simulated boundary layer height.

- The numerically simulated dynamical mechanism is found to decrease boundary layer instability in the downwind deforested areas and increase it in the upwind deforested areas hence causing a corresponding enhancement and suppression of clouds and rain in the two regions.

**Spatio-Temporal Variability**

A statistical analysis with 14 years of observed and reanalysis data shows that the dynamical mechanism is consequential for the regional clouds and precipitation during
the dry season and some parts of the transition Spring and Autumn seasons. The effect of the dynamical mechanism is strongest during the months of July and August but regional precipitation during the months of May, June and September is also affected by it.

Regression analyses of the dry season daily scale observed data of clouds, precipitation and atmospheric conditions shows that the dynamical mechanism is mostly affected by regional scale thermal and dynamical conditions of the boundary layer. This mechanism is found to be stronger under atmospheric conditions that are more stable as compared to conditions which support uniform cloudiness or rain. Also it is positively correlated with the boundary layer wind speed close to the boundary layer top. The dependence of the dynamical mechanism on boundary layer thermal structure is also captured by daily scale simulated data in the month of August. These findings show that the dynamically triggered mesoscale circulations exist in atmospheric conditions of high stability and winds which are otherwise unfavorable to thermally triggered convection.

The relationships between the daily scale dipole strength and regional boundary layer conditions are found to hold, in a limited way, in the inter-annual timescale as well and explain the corresponding variability of the dipole strength to some extent. But a statistically significant relationship between these variables on the inter-annual time scale could not be obtained due to the limited amount of data. Also, the dipole strength was found not to be significantly correlated with measures of large scale atmospheric conditions represented by indices of sea surface temperatures (SST) namely the Tropical North Atlantic SSTs index and the Niño 3.4 index of central eastern Tropical Pacific SSTs. But the lack of significant correlations of the dipole strength with SST indices can also be a consequence of insufficient data. Although the significance of these results is limited due to the small sample size, these results indicate that
the dynamical mechanism is probably controlled by regional scale boundary layer conditions only.

Two deforested regions towards the south and southeast of the Amazon rainforest were compared to understand the ‘relevance’ of the dynamical mechanism for the hydroclimatic response to present day Amazonian deforestation. One of these regions (Rondônia) is larger (roughly 400 km in the direction of surface winds) and contiguously deforested as compared to the other (southern Pará) which is a smaller deforested area (roughly 200 km in the direction of surface winds). The dynamical mechanism is found to be consequential for both the regions, although the dipole signal in Rondônia is stronger than the dipole signal in southern Pará. This result motivates similar inquiries in large scale deforested areas in the Amazon rainforest and other rainforests in the tropical regions of the World.

5.2 Limitations and Future Work

Improving the Analysis with New Data

Some of the results presented in this thesis are limited by the quality or the sample size of the datasets used. A major improvement to some of the results presented can be made upon the availability of appropriate datasets. This issue is now discussed.

Most observational results in this thesis are based on remotely sensed data. A major improvement of this work will be the use of in situ observed datasets to confirm the signals reported here. In this regard station precipitation, surface wind speed and radiosonde datasets at downwind and upwind locations in the deforested area will be very helpful to elaborate or provide supportive evidence for the analysis presented here. As reported in Chapter 2, a daily scale time series of nearly 8 years of satellite precipitation and cloud cover data was used to statistically detect the dipole signal. Hence, it is expected that in situ data collected in the downwind and upwind defor-
ested areas over a similar period of time should suffice to estimate the dry season precipitation differences between the two regions. Similarly, a few years of radiosonde measurements made at the downwind and upwind locations of the deforested region can provide enough data to detect differences between the boundary layer structures in the two regions and to compare them with the dipole characteristics.

The fact that the limited 14 day time series of radiosonde data from the pasture site, used to understand the daily scale variability of the dynamical mechanism in Chapter 4, conforms with the results obtained using satellite and reanalysis data, motivates a more extensive use of radiosonde datasets, upon availability, for this purpose. Such data sets would facilitate a correlation analysis of dipole strength with metrics representing differences in boundary layer atmospheric conditions between the pasture and forest regions. As such, radiosonde measurements at the LBA pasture and forest sites of Fazenda Nossa Senhora and Reserva Jaru, covering a larger portion of the dry season, would be quite helpful in cross-checking the relationships obtained using satellite and reanalysis data.

Radiosonde measurements of the atmospheric profiles over both the pasture and forest sites in Rondônia have not been collected since October 2002 (based on correspondence with Dr Gilberto Fisch of the Brazilian Department of Aerospace Science and Technology). Most of the radiosonde datasets collected before this time, which could have been useful for the current study, could not be obtained from Brazilian agencies due to various reasons. A proposed future work is to obtain these already existent radiosonde datasets to complement the present analysis. It is also proposed that such site-level precipitation and radiosonde data be collected in future field campaigns to further the analysis presented in this study.

In the same line of argument, a future improved version of the NASA AIRS data, the current version of which was found to have a cold and dry bias close to the surface
of the Earth hence making it not useful for the present study, should also be utilized upon release.

The present analysis of spatial variability of the dynamical mechanism was limited by the unavailability of high resolution multidecadal time series of land cover data for deforested regions other than Rondônia. Even a time series analysis for the deforested areas of southern Pará could not be performed because such a time series of land use change was not available, limiting the analysis only to the contemporary decade. In the future the time series analysis for southern Pará, and similar analysis for other deforested areas of the Amazon can be performed upon the availability of appropriate datasets.

Possible Future and Follow-up Studies

Although OLAM shows a remarkable capability of capturing the observed multidecadal transition in the regional hydroclimate of Rondônia and the observed dipole spatial pattern in the simulated relative humidity changes, the simulated precipitation changes could not capture the dipole signal as effectively. The failure of the convective parametrization scheme to capture precipitation changes due to the dynamical mesoscale circulation could be a major reason for this. Hence, it is proposed that the simulations be repeated with a regional scale model which can explicitly resolve clouds and precipitation at the horizontal resolution of the order of a few hundreds of meters.

It has been shown by previous studies that shallow convection can itself ‘seed’ deep convective activity in suitable background atmospheric conditions (Wu et al. 2009; Gentine et al. 2013; Rio et al. 2009) which usually form as the wet season approaches (Fu and Li 2004; Li and Fu 2004). Hence, the impact of the enhancement and suppression of cloudiness due to the dynamical mechanism can be consequential for the wet season arrival in the upwind and downwind deforested areas. Following this
argument it will be interesting to investigate the effect of the dynamical mechanism on regional precipitation seasonality.

The major finding from this work is that contemporary deforestation affects the dry season precipitation of the downwind and upwind deforested areas in opposite ways. It results in a $\sim25\%$ increase in the precipitation in the downwind deforested areas and a similar decrease in the upwind deforested areas as compared to the deforested area mean. It is also known from previous studies that persistent dry season precipitation changes can cause modifications to the regional ecosystems (see Nobre and Borma (2009) and Malhi et al. (2009)). An interesting future study could be designed around analyzing the effect of this precipitation redistribution on the regional ecology in the downwind and upwind deforested areas. Such ecological impacts can be studied by designing suitable field experiments in future field campaigns in the Amazon or by using ecosystem models coupled with atmospheric general circulation models similar to those described in Nobre and Borma (2009) but by driving the precipitation changes by the dynamical mechanism.

Lastly, the current study did not explore how the effects of the dynamical mechanism will play out under predicted climate change in the next few decades. Deforestation is predicted to continue in the near future with some scenarios predicting the loss of $\sim40\%$ of the forest by 2050 (Soares-Filho et al. 2006). The dynamical mechanism may play an important role in deciding the changes in simulated regional and basin-wide precipitation under future projections of large scale but patchy deforestation (Soares-Filho et al. 2006; Walker et al. 2009). A re-evaluation of such numerical studies analyzing the hydroclimatic effects of future patchy deforestation, under the light of the dynamical mechanism may be performed. Also, numerical studies analyzing the coupled effects of increasing patchy deforestation and the impending climate change can also be of interest.
Appendix A

Implementation and Customization of the ISCCP Cloud Detection Algorithm

A simplified version of the ISCCP cloud detection algorithm described in Rossow and Garder (1993) is used for observational cloud detection in this thesis. A concise description of the detection algorithm is provided here. For a detailed description the reader is referred to the source text.

Obtaining the right clear sky values of reflectances is at the heart of cloud detection. Once the clear sky values of visible and infrared reflectances are obtained, a threshold value is applied to distinguish between cloudy pixels from clear pixels at a time snap. Based on the methodology applied to estimate clear sky reflectances, cloud detection algorithms can be divided into two types - 1) constant threshold methods in which the clear sky reflectances and/or thresholds are obtained from an independent source, and 2) statistical methods, in which the clear sky conditions are obtained using the spatial and temporal statistical properties of the visible and infrared data. The ISCCP algorithm is of the second type. There are certain ad-
vantages of statistical algorithms over threshold algorithms. Although more complex
to implement statistical algorithms are not biased by prescribed surface properties
and thresholds applied on albedo and brightness temperature data which may not
be representative of the time period of study. Also no external information about
the surface reflectance values is needed because these values are estimated by the
algorithm itself. The ISCCP algorithm has been evaluated against other types of
detection algorithms with biases < 10% to 15% (Rossow and Garder 1993).

The version of ISCCP cloud detection algorithm used in this study (taken from
(Rossow and Garder 1993) comprises of five steps which are described below and
presented in the Flowchart A.1. The algorithm performs three tests to decide whether
a pixel has a high chance of being clear.

1. Test 1 - Space Contrast Test: This test captures the spatial variability in the
infrared reflectance from cloudy and bare pixels at a time snap. Within a group
of pixels a pixel is flagged ‘cloudy’ or ‘undecided’ if:

\[
\text{Cloudy} : T_{\text{pixel}} < T_{\text{max}} - \Delta T_1, \\
\text{Undecided} : T_{\text{pixel}} \geq T_{\text{max}} - \Delta T_1. \tag{A.1}
\]

Where, \(T_{\text{pixel}}\) is the brightness temperature of the pixel, \(T_{\text{max}}\) is the brightness
temperature of the warmest pixel in the group and \(\Delta T_1=6.5\) K is a spatial
threshold representing the statistical difference between cloudy and clear pixels
and the uncertainty of the data.

2. Test 2 - Time Contrast Test: This test captures the variability introduced due
to temporal movement of clouds between consecutive days at the same time of
day. A pixel is flagged ‘cloudy’, ‘undecided’ or ‘clear’ based on:

\[
\text{Clear} : |T_j - T_{j-1}| < \Delta T_2,
\]

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STEP 1 (Equation A.1)
Test 1 - Space Test
Clear if, $T_{\text{pixel}} > T_{\text{max}} - \Delta T_1$

STEP 2 (Equation A.2)
Test 2 - Time Test
Clear if, $|T_{\text{yesterday}} - T_{\text{today}}| < \Delta T_2$
and $|T_{\text{tomorrow}} - T_{\text{today}}| < \Delta T_2$

STEP 3 (Table A.1)
Collect 5 day and 30 day statistics of $T_{\text{max}}$, $T_{\text{avg}}$ and $A_{\text{min}}$

STEP 4 (Flowchart A.2)
Form IR and VIS clear sky composites removing pentads with false clear detection

STEP 5 (Equation A.3)
Final detection
Cloudy if, $T_{\text{clear}} - T_{\text{pixel}} > T_{\text{threshold}}$
$R_{\text{pixel}} - R_{\text{clear}} > R_{\text{threshold}}$

Figure A.1: Flowchart of the cloud detection algorithm described in (Rossow and Garder, 1993)

\begin{align*}
\text{Undecided} & : \Delta T_2 \leq |T_j - T_{j-1}| \leq \Delta T_3, \\
\text{Cloudy} & : |T_j - T_{j-1}| > \Delta T_3, \text{ and } T_j < T_{j-1}. \quad (A.2)
\end{align*}

Where, $T_j$ is the brightness temperature of a pixel on the $j^{th}$ day and $\Delta T_2=2.5$ K and $\Delta T_3=8$ K are contrast thresholds. Each pixel’s today’s ($j$) value is compared with its yesterday’s value ($j-1$) and tommorrow’s value ($j+1$).

A pixel that is found either ‘undecided’ or ‘clear’ in both the yesterday and tommorrow time tests and also ‘undecided’ in the space test is flagged ‘likely clear’. In this way an ensemble of ‘likely clear’ pixels is obtained which can be separated in both space and time.
Collecting space/time statistics for clear conditions: In this step of the algorithm the clear sky statistics of visible and infrared reflectances are collected using the ensemble of clear sky pixels obtained in the last step. It is noteworthy that the sample size is increased by collecting the sample over various space and time scales. The space and time scale is selected so that the intra-sample variability is smaller than the natural variability in land surfaces in space and natural variability due to evolution of land surfaces in time. In this study an area of 25 km by 25 km and a time scale of 5 days was chosen to collect statistics. To obtain a statistically significant data those 5 day periods which had data for less than 3 days were discarded. In such cases the statistics were collected over a long time period, but evidently, such an estimation will be an inferior approximation of clear conditions. The statistics for the visible data for clear days was collected only over a 30 day period. The statistics collected in this step are listed in Table A.1.

As expected the sample collected at this step should be affected by the spatial variability in the underlying land cover type. But according to [Rossow and Garder 1993] only stark spatial contrasts like coast lines, snow covered areas have a significant effect. Because the land cover around the study areas in this thesis are relatively uniform, without any large water bodies or snow, no distinction was made on the basis of underlying land cover.

Additionally, any corrections related with seasonal changes in surface properties, applied in the original algorithm by [Rossow and Garder 1993], is bypassed here.

Test 3 - Construction of clear-sky albedo and brightness temperature composites: These composites are prepared using the statistics collected in the last step and following the Flowcharts shown in Figure A.2 and Table A.2 (see [Rossow and Garder 1993] for details about the flowcharts).
IR Clear sky composite

Collect statistics

Is $T_{\text{MAX-it}}/T_{\text{MAX-st}}$ OK?

Yes

Use long term statistics

Is $T_{\text{MAX-st}} \geq T_{\text{MAX-it}} - \text{DEL1}$?

No

Is $N_{\text{CLEAR-it}} \geq \text{MIN}$?

Yes

Is $T_{\text{AVG-it}} \geq T_{\text{MAX-it}} - \text{DEL3}$?

No

$T_{\text{CLR}} = T_{\text{MAX-it}} - \text{DEL3}$

No

Is $N_{\text{CLEAR-st}} \geq \text{MIN}$?

Yes

Is $T_{\text{AVG-st}} \geq T_{\text{MAX-st}} - \text{DEL2}$?

No

$T_{\text{CLR}} = T_{\text{MAX-st}} - \text{DEL2}$

Yes

$T_{\text{CLR}} = T_{\text{AVG-st}}$

VIS Clear sky composite

$R_{\text{CLR}} = R_{\text{MIN-it}} + \text{DEL2}$

Figure A.2: Flowchart to generate brightness temperature and albedo clear sky composites. Infrared values are in Kelvins and visible in percentage scaled radiance. The definitions of the different symbols are provided in Table A.1. $T_{\text{CLR}}$ and $R_{\text{CLR}}$ are the final 5 day clear IR and VIS radiances assigned to a pixel.
Table A.1: Statistics collected with space and time test samples

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{CLEAR-st}$</td>
<td>Number of clear pixels in 5 day period</td>
</tr>
<tr>
<td>$N_{CLEAR-lt}$</td>
<td>Number of clear pixels in 30 day period</td>
</tr>
<tr>
<td>$T_{AVG-st}$</td>
<td>Avg. bright. temp. for clear pixels in 5 day period</td>
</tr>
<tr>
<td>$T_{AVG-lt}$</td>
<td>Avg. bright. temp. for clear pixels in 30 day period</td>
</tr>
<tr>
<td>$T_{MAX-st}$</td>
<td>Max. bright. temp. for all pixels in 5 day period</td>
</tr>
<tr>
<td>$T_{MAX-lt}$</td>
<td>Max. bright. temp. for all pixels in 30 day period</td>
</tr>
<tr>
<td>$R_{MIN-lt}$</td>
<td>Min. albedo for all pixels in 30 day period</td>
</tr>
</tbody>
</table>

Table A.2: Contrast thresholds used for the detection of clear sky values in during different types of cloudy periods in the Flowchart A.2.

<table>
<thead>
<tr>
<th></th>
<th>DEL1</th>
<th>DEL2</th>
<th>DEL3</th>
<th>DEL4</th>
</tr>
</thead>
<tbody>
<tr>
<td>IR thresholds</td>
<td>6</td>
<td>5</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>VIS thresholds</td>
<td>-</td>
<td>3.5</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

The statistics collected in Step 3 are based on clear day observations in consecutive pentads. Now, it is possible that the clear sky ensemble collected for a particular 5 day period does not represent clear conditions at all. This can happen in cases of, for example, extended periods of overcast skies. But the algorithm will still give an ensemble of likely clear pixels. Any cloud mask generated using such an ensemble will be biased. This step of making clear-sky composites checks for such false detection and replaces the 5 day average value of clear sky reflectances with long time period average reflectances. The flowcharts A.2 perform this check on different kinds of ‘false clear day ensembles’.

Note that the flowchart used in this study is a simplified version of the flowcharts in [Rossow and Garder (1993)] based on the approximations listed in step 3.

Final classification: The final step in the cloud detection algorithm is to obtain a classification of each pixel per scene as a ‘cloudy’ or ‘clear’ pixel. This classification is done afresh, independent of any previous classifications but using
the clear sky statistics obtained in step 4. The following albedo and brightness temperature thresholds are applied for the classification:

\[
\begin{align*}
\text{Clear} &: \quad T_{\text{clear}} - T_{\text{pixel}} \leq T_{\text{threshold}}, \text{and} \\
& \quad R_{\text{pixel}} - R_{\text{clear}} \leq R_{\text{threshold}}. \\
\text{Cloudy} &: \quad T_{\text{clear}} - T_{\text{pixel}} > T_{\text{threshold}}, \text{and} \\
& \quad R_{\text{pixel}} - R_{\text{clear}} > R_{\text{threshold}}. \tag{A.3}
\end{align*}
\]

Where, \( T_{\text{clear}} \) and \( R_{\text{clear}} \) are the brightness temperature and albedo of the clear sky for the 5 day period. \( T_{\text{pixel}} \) and \( R_{\text{pixel}} \) are the corresponding values for the pixel for a particular scene. \( T_{\text{threshold}} \) and \( R_{\text{threshold}} \) are the corresponding contrast thresholds each with the value 6.
Appendix B

Ocean Land Atmosphere Model - Customization for this Study

B.1 OLAM and the LEAF model

Version 4.0s of the Ocean-Land-Atmosphere-Model (OLAM) was used for all numerical experiments performed for this thesis. Some newer versions of OLAM were also tested but were found to under perform in simulating the dry season precipitation amounts and the surface energy balance components as compared to OLAM v4.0s, hence this version was used. The sources of various parametrizations used in the model setup have been reported in the main text (Section 3.2.1).

The interactions of the land surface and vegetation with the canopy air and the interactions of the canopy air with the boundary layer air are important for the type of numerical investigations performed for this thesis. These processes are parametrized according to the Land-Ecosystem-Feedback model (LEAF) \cite{Walko2000} and the similarity theory presented in \cite{Louis1981}. LEAF works as a big-leaf model with interactions between vegetation, soil, surface water, snow layers and canopy air. Each atmospheric grid cell interacts with several land grid cells under it itself.
representing distinct land-use types and surface characteristics. The surface turbulent exchanges or fluxes of heat (H), moisture (Q) and momentum (M) between vegetation and its overlying atmosphere are calculated with the following relations:

\[
M = u_*^2 \rho, \quad (B.1)
\]

\[
H = -u_* \rho C_p T_*, \quad (B.2)
\]

\[
Q = -u_* \rho q_*. \quad (B.3)
\]

Where, \( \rho \) is the near-surface atmospheric air density (kg m\(^{-3}\)) and \( C_p \) is the heat capacity of air (J kg\(^{-1}\) K\(^{-1}\)). \( u_* \) is the surface friction velocity (m s\(^{-1}\)). \( T_* \) and \( q_* \) are the surface layer temperature (K) and humidity (kg of vapor m\(^{-3}\)) scales defined as:

\[
u_* = \sqrt{c_1 u_0 f_m}, \quad (B.4)
\]

\[
T_* = \frac{c_1 f_h}{u_*} (T_a - T_c), \quad (B.5)
\]

\[
q_* = \frac{c_1 f_h}{u_*} (q_a - q_c), \quad (B.6)
\]

where, \( u_0 \) is the near-surface wind speed (m s\(^{-1}\)), \( T_a \) and \( T_c \) are respectively near-surface and canopy air temperatures (K), \( q_a \) and \( q_c \) are respectively near-surface and canopy air vapor specific humidities (kg of vapor m\(^{-3}\)). \( c_1 \) is the aerodynamic conductance under neutral conditions given by:

\[
c_1 = u_0 \left( \frac{\kappa}{\log(z/r)} \right)^2. \quad (B.7)
\]

\( z \) is the height above surface where \( u_0 \), \( T_a \) and \( q_a \) are estimated (m), \( r \) is the land cell average surface roughness length for momentum transfer (m) and \( \kappa \) is the Von Kármán constant (0.4). \( c_1 \) is modified under stable or unstable conditions by multiplying it by the appropriate non-dimensional factors \( f_m \) (momentum) and \( f_h \) (heat or moisture).
according to the surface theory of Louis et al. (1981). $f_m$ and $f_h$ for stable conditions are:

$$
\begin{align*}
  f_m &= \left[ 1 + \frac{2b r_i}{\sqrt{1 + b r_i}} \right]^{-1}, \\
  f_h &= \left[ 1 + \frac{3b r_i}{\sqrt{1 + b r_i}} \right]^{-1}.
\end{align*}
$$

(B.8)

(B.9)

$f_m$ and $f_h$ for unstable conditions are:

$$
\begin{align*}
  f_m &= 1 - \frac{2b r_i}{1 + 2c_m}, \\
  f_h &= 1 - \frac{3b r_i}{1 + 3c_h},
\end{align*}
$$

where, $c_m = 7.5 c_2$, \hspace{1cm} (B.12)

$c_h = 5 c_2$, \hspace{1cm} (B.13)

and $c_2 = b a_2 \sqrt{(z/r)|r_i|}$. \hspace{1cm} (B.14)

$b=5$, $d=5$. $r_i$ is the bulk Richardson number given by:

$$
  r_i = \frac{g_0 z (T_a - T_c)}{0.5(T_a + T_c) u_0^2}.
$$

(B.15)

g_0$ is the gravitational acceleration. The average surface roughness height $r$ is calculated according to the equation:

$$
  r = \max(r_{\text{soil}}, r_{\text{veg}}) \times (1 - \frac{r_{\text{snow}}}{r_{\text{soil}}}) + r_{\text{snow}}.
$$

(B.16)

where, the modeled vegetation roughness length $r_{\text{veg}}$, which is dependent on vegetation height $h_{\text{veg}}$ and vegetation total (leaf and stem) area index TAI is calculated as:

$$
  r_{\text{veg}} = h_{\text{veg}} (1 - 0.91 \exp(-0.0075 TAI)).
$$

(B.17)
\( r_{\text{snow}} \) and \( r_{\text{soil}} \) are the surface roughness lengths of snow and soil and their values respectively are: 0.01 m and 0.05 m. \( \text{frac}_{\text{snow}} \) is the fraction of vegetation buried by snow.

### B.2 Sensitivity of the Surface Sensible Heat Fluxes to Soil Texture

As reported under the numerical experiments performed for the ‘Contemporary’ study in Chapter 3, the magnitude of the day time sensible heat fluxes for forest vegetation are simulated higher than those for pasture vegetation (Figure 3.11) and hence also higher than the field observations (Table 3.6). The forest minimum stomatal resistance is reduced from a value to 500 s m\(^{-1}\) to 286 s m\(^{-1}\) (according to Freitas, 1999).

![Figure B.1: DEF-FOR surface sensible heat fluxes at different times of day averaged over all days in August and over all ensemble members. For definitions of the experiments see Table 3.2](image-url)

Figure B.1: DEF-FOR surface sensible heat fluxes at different times of day averaged over all days in August and over all ensemble members. For definitions of the experiments see Table 3.2.
Figure B.2: DEF-FOR Vertical winds at 1700 m altitude at different times of day averaged over all days in August and over all ensemble members. For definitions of the experiments see Table 3.2.

to address this discrepancy (Section 3.3.5). This correction results in a decrease in the forest sensible heat fluxes. A resultant increase in DEF-FOR sensible heat fluxes is found during the midday hours, but this difference is still negative up to 1300 LT (Figure B.1). Moreover, the reduction in the forest minimum stomatal resistance is found to affect the spatial patterns of sensible heat increase in the DEF-FOR simulations (Figure B.1c-g). During the midday hours the DEF-FOR sensible heat fluxes are positive along a central region inside the deforested area and negative in the surrounding deforested pixels. This peculiar spatial pattern in surface sensible heat fluxes also affects the midday local vertical wind patterns which follow this region of high sensible heat flux with subsidence over surrounding deforested areas (Figure B.2c-g) hence suppressing the east-west dipole pattern found in the ‘Contemporary’ study (Figure 3.3) associated with the dynamically triggered mesoscale circulation.
Figure B.3: Abundant soil types around Rondônia. Data obtained from USDA Global Soil Regions.

Table B.1: Prescribed properties for two most abundant soil types in the deforested regions of Rondônia.

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>Sand Fraction</th>
<th>Clay Fraction</th>
<th>Saturated Hydraulic Conductivity (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Silty Clay Loam</td>
<td>0.35</td>
<td>0.59</td>
<td>0.11e-3</td>
</tr>
<tr>
<td>Clay Loam</td>
<td>0.48</td>
<td>0.45</td>
<td>0.22e-2</td>
</tr>
</tbody>
</table>

Some additional numerical experiments showed that this pattern in DEF-FOR sensible heat fluxes resulted from a corresponding pattern in the USDA soil types map that is prescribed in LEAF (Figure B.3). The soil texture map shows that silty clay loam and clay loam are the two abundant soil types in Rondônia. Silty clay loam soils have a larger fraction of clay and smaller fraction of sand as compared to clay loam soils (Table B.1). This results in a lower saturated hydraulic conductivity in the former soil type as compared to the latter. This results in a lower water percolation through the silty clay loam soil as compared to clay loam causing spatial patterns in soil moisture deficit (Figure B.4a) which are the cause of the corresponding spatial patterns in sensible heat fluxes.

Some soil type data sets for Rondônia are available but do not always conform with each other. For example, soil map based on in situ measurements made at different
Figure B.4: August averaged soil moisture in the top 20 cm depth of soil in (a) DEF-FOR and (b) DEF06SScl-FORprSSTcl. For definitions of the experiments see Tables 3.2 and 3.3 respectively.

Forest and pasture sites throughout the Amazon rainforest during the Anglo-Brazilian Amazonian Climate Observation Study (Wright et al., 1996b) shows a uniform soil type in the region of Rondônia. For both simplicity and lack of available data, a uniform, constant silty clay loam soil type was prescribed around Rondônia. Although soil characteristics can temporally modify over deforested areas (Martinez and Zinck, 2004) due to continual grazing and poor management, the uniform soil type is not particularly a poor approximation as it helps us remove the spatial patterns in soil moisture (Figure B.4b) and hence sensible heat fluxes (Figure B.5). It also overall decreases the day time forest sensible heat fluxes (Figure B.5) making the resultant value closer to that observed in situ (Table 3.6).

A survey, of a few soil texture datasets that are available for this region, showed that the soil texture maps are not always consistent with each other. Hence, due to the unavailability of a soil texture map and due to the complications of converting them to the soil parametrization implemented in LEAF, a uniform soil texture map was used for the numerical simulations presented in the ‘Multidecadal’ study (Section 3.3.6) and Chapter 4. Despite this simplification the results in the ‘Multidecadal’
Figure B.5: DEF06SSTcl-FORprSSTcl surface sensible heat fluxes at different times of day averaged over all days in August and over all ensemble members. For definitions of the experiments see Table 3.3.

The study improved (Table 3.6 and Figure 3.14) as compared to the original setup of the model (Figure 3.11), suggesting that this simplification is not inappropriate.
Appendix C

Supplement to Chapter 4

Table C.1: Table showing the $R^2$ value of models to explain the daily scale variability in PERSIANN or GridSat DS with different combinations of daily scale BLW, LCL and CAPE as predictors. The multiple linear regression is performed separately for the four periods: April-May, June-July and August-September.

<table>
<thead>
<tr>
<th>Months</th>
<th>PERSIANN</th>
<th>GridSat</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BLW LCL</td>
<td>BLW LCL</td>
</tr>
<tr>
<td></td>
<td>BLW LCL</td>
<td>BLW LCL</td>
</tr>
<tr>
<td>AM</td>
<td>0.15 0.30</td>
<td>0.06 0.09</td>
</tr>
<tr>
<td></td>
<td>0.30 0.31</td>
<td>0.09 0.12</td>
</tr>
<tr>
<td>JJ</td>
<td>0.12 0.12</td>
<td>0.12 0.14</td>
</tr>
<tr>
<td></td>
<td>0.39 0.42</td>
<td>0.17 0.20</td>
</tr>
<tr>
<td>AS</td>
<td>0.26 0.38</td>
<td>0.26 0.53</td>
</tr>
<tr>
<td></td>
<td>0.39 0.42</td>
<td>0.54 0.54</td>
</tr>
</tbody>
</table>

Table C.2: Standardized coefficients ($p$-value) of the multiple linear regression model between PERSIANN DS or GridSat DS and predictors BLW, LCL and CAPE. The regression is performed separately for daily data in the periods AM, JJ, AS between 2001 and 2014 for PERSIANN and between 2001 and 2008 for GridSat.

<table>
<thead>
<tr>
<th>Pred</th>
<th>PERSIANN</th>
<th>GridSat</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AM Coeff.</td>
<td>JJ Coeff.</td>
</tr>
<tr>
<td>BLW</td>
<td>-0.04 (0.6)</td>
<td>0.05 (0.5)</td>
</tr>
<tr>
<td>LCL</td>
<td>0.53 (1e-9)</td>
<td>0.29 (3e-3)</td>
</tr>
<tr>
<td>CAPE</td>
<td>-0.09 (0.2)</td>
<td>-0.05 (0.6)</td>
</tr>
</tbody>
</table>
Figure C.1: Scatter plots between daily scale TRMM-DS and (a, b, c) BLW, (d, e, f) LCL and (g, h, i) CAPE. Columns represent different bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September.
Figure C.2: Whisker plots showing that the ‘high’ and ‘low’ PERSIANN dipole days occupy different spaces on the predictor phase space. Columns represent different bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September. Blue colors represent the top 120 high DS days and red colors represent the top 120 low DS days. The yellow color represents days when less than 5% of the total deforested area is covered with clouds.
Figure C.3: Same as Figure C.2 but for GridSat data between 2001 and 2008.
Figure C.4: Quantile regression for the model presented in Equation 4.1 between TRMM-DS and predictors BLW, LCL and CAPE. X-axis represents the percentile at which regression is performed. (a, b, c) Standardized coefficients and (d, e, f) corresponding p-values for the three predictors as functions of the quantile. Columns represent different bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September.
Figure C.5: Maps of daily average PERSIANN precipitation occurrence for ‘high’ DS days and ‘low’ DS days with corresponding average wind vectors. Rows represent average (a, b, c), ‘high’ dipole (d, e, f) and ‘low’ dipole (g, h, i) days. Columns represent individual bi-monthly periods: (a, d, g) - April and May, (b, e, h) - June and July, (c, f, i) - August and September. Data is averaged between 2001 and 2014. The average precipitation occurrence in the period within the deforested area is also reported at the top of each panel. Note the different color scales in the different panels.
Figure C.6: Same as Figure C.5 but for GridSat data between 2001 and 2008.
Table C.3: Characteristics of the midday Dipole Strength metric (DS), difference in wind and dipole direction ($\Delta \theta$) and atmospheric conditions ($\Delta H$) during ‘high’ and ‘low’ dipole days in the periods of AM, JJ and AS. Analysis is performed separately for PERSIANN and GridSat. Values are obtained using daily scale data between 2001 and 2014 for PERSIANN and between 2001 and 2008 for GridSat.

<table>
<thead>
<tr>
<th></th>
<th>Median (25$^{th}$ percentile, 75$^{th}$ percentile)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PERSIANN</td>
</tr>
<tr>
<td></td>
<td>AM</td>
</tr>
<tr>
<td>DS</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>$\Delta \theta$</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>$\Delta H$</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>Low</td>
</tr>
</tbody>
</table>

$^a$Dipole strength of the PERSIANN 1400LT precipitation dipole (% km).
$^b$Angle between the BL top horizontal wind and the TRMM-DS vector (degrees).
$^c$Difference between LCL and BL height (m)
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