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The Role of Internal Variability in Climate Change Projections Within an Initial Condition Climate Model Ensemble

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THE ROLE OF INTERNAL VARIABILITY IN CLIMATE CHANGE PROJECTIONS
WITHIN AN INITIAL CONDITION CLIMATE MODEL ENSEMBLE

by

VINEEL YETTELLA

B.Tech., Indian Institute of Technology, Bhubaneswar, 2013

A thesis submitted to the
Faculty of the Graduate School of the
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The role of internal variability in climate change projections within an initial condition climate model ensemble
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has been approved for the Department of Atmospheric and Oceanic Sciences

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The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.
Abstract

Yettella, Vineel (Ph.D., Atmospheric and Oceanic Sciences)

The role of internal variability in climate change projections within an initial condition climate model ensemble

Thesis directed by Assistant Professor Jennifer E. Kay

Unforced internal variability abounds in the climate system and often confounds the identification of climate change due to external forcings. Given that greenhouse gas concentrations are projected to increase for the foreseeable future, separating forced climate change from internal variability is a key concern with important implications. Here, we leverage a 40-member ensemble, the Community Earth System Model Large Ensemble (CESM-LE) to investigate the influence of internal variability on the detection of forced changes in two climate phenomena. First, using cyclone identification and compositing techniques within the CESM-LE, we investigate precipitation changes in extratropical cyclones under greenhouse gas forcing and the effect of internal variability on the detection of these changes. We find that the ensemble projects increased cyclone precipitation under twenty-first century business-as-usual greenhouse gas forcing and this response exceeds internal variability in both near- and far- futures. Further, we find that these changes are almost entirely driven by increases in cyclone moisture. Next, we explore the role of internal variability in projections of the annual cycle of surface temperature over Northern Hemisphere land. Internal variability strongly confounds forced changes in the annual cycle over many regions of the Northern Hemisphere. Changes over Europe, North Africa and Siberia, however, are large and easily detectable and further, are remarkably robust across model ensembles from the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive. Using a simple energy balance model, we find that changes in the annual cycle over the three regions are mostly driven by changes in surface heat fluxes.

The thesis also presents a novel ensemble-based framework for diagnosing forced changes in regional climate variability. Changes in climate variability are commonly assessed in terms of changes in
the variances of climate variables. The covariance response has received much less attention, despite the existence of large-scale modes of variability that induce covariations in climate variables over a wide range of spatial scales. Addressing this, the framework facilitates a unified assessment of forced changes in the regional variances and covariances of climate variables.
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Chapter 1

Introduction

1.1 Uncertainties in climate projections

The Earth’s climate is warming rapidly in response to increasing greenhouse gases (IPCC 2013). Observations and climate simulations are our primary tools for predicting and understanding this response. A climate simulation is a mathematical representation of the temporal evolution of the climate system under specified external forcings and encodes interactions between important climate drivers including the atmosphere, oceans, land and the cryosphere (Gettelman and Rood 2016). By running climate simulations under various greenhouse gas emissions scenarios (Nakicenovic and Swart 2000) and at varying levels of complexity (Held 2005), the scientific community seeks to understand the behavior of the climate system.

While considerable progress has been made in modeling the climate system (Flato et al. 2013), it is impossible to produce perfect future projections of the climate due to fundamental uncertainties that arise from three distinct sources (Hawkins and Sutton 2009). First, unforced variability that is associated with natural fluctuations of the climate system and is independent of any radiative forcing, can lead to considerable uncertainty in future projections. This unforced variability, also termed “internal variability”, has the potential to offset or even reverse trends associated with forced climate change, especially on the regional spatial scales and subdecadal timescales. A striking example is that of the marked reduction in the increase of global mean temperature between 1998 and 2013, known as the “hiatus” (Trenberth 2015). The Pacific Decadal Oscillation (Mantua and Hare 2002), a mode of unforced internal climate variability, has been implicated as a key player in sustaining the hiatus (England et al. 2014). The second source of uncertainty is imperfections in model formulation. These imperfections arise from incomplete understanding and representation of Earth system processes and often lead to differences in projections across models. Finally, imperfect estimation of future greenhouse gas emissions contributes to uncertainty in future radiative forcing (Nakicenovic and Swart 2000) and hence climate projections.
The focus of this thesis is on understanding the role of the first source of uncertainty - internal variability - in model projections of two climate features and on identifying forced changes in these features amidst the noise of internal variability. Before we describe our research goals, we briefly discuss internal variability, its presentation in the climate system and the use of climate model ensembles in separating forced climate change from internal variability.

1.2 Internal variability

Unforced internal variability is ubiquitous in the chaotic climate system. It arises from non-linearities and feedbacks intrinsic to the system and exists independently of any external forcing mechanisms, for example, greenhouse radiative forcing (Mitchell 1976). It manifests on a wide range of time scales (for e.g., see Williams et al. 2017 for a review of internal atmospheric variability occurring on different timescales). For example, atmospheric flows exhibit turbulent fluctuations on the time scales of a few seconds to minutes (Oboukhov 1961). Synoptic scale weather systems lead to weather variability on time scales from days to weeks (Blackmon 1976) and are a prominent feature of extratropical weather. The most widely studied mode of internal variability, the El Niño - Southern Oscillation (ENSO, Rasmusson and Carpenter (1982)), occurs on interannual timescales and is associated with enormous societal and ecological impacts (Kenyon and Hegerl 2008). Internal variability also exists on decadal and even multidecadal timescales. For example, two prominent modes of internal variability, the PDO and the Atlantic Multidecadal Oscillation (AMO, Enfield et al. (2001)) have frequency components at characteristic periods of around 60 years.

Since internal variability can persist on long time scales, the internal and anthropogenic influences on the climate are often confounded, especially on the regional scales and on short timescales (Hawkins and Sutton 2009). A quantitative assessment of the contribution of internal variability is therefore essential to separate forced changes from internal variability. One standard approach of quantifying the uncertainty due to internal variability is to aggregate variability statistics over a period of time long enough to characterize the variability of the statistic under investigation (Leith 1973). When the forced component of
climate change can be sufficiently differentiated from internal variability, the forced component is considered to have been ‘identified’ or to have ‘emerged’. For example, Hawkins and Sutton (2012) estimate the internal variability in annual mean surface temperature as the interannual standard deviation in long pre-industrial control simulations and use the estimate to assess the future point of time at which forced changes in temperature can be identified.

While the above approach of computing variability statistics from a long control simulation or observational record is often useful (e.g. Hawkins and Sutton 2012; Thompson et al. 2015; Li et al. 2016), it is of limited use in the climate change setting. Rapidly increasing greenhouse gases render the climate system non-stationary (Cheng et al. 2014). That is, the probably distributions of climate variables can change in time periods shorter than those that are required to sufficiently characterize the statistics of internal variability.

How can we estimate the role of internal variability in a transient climate change setting? Given that the Earth’s climate system is chaotic and it’s future states exhibit sensitive dependence on its present state (Lorenz 1963), a very useful approach is to run an ensemble of climate simulations, subject to the same external forcing but started from slightly different initial states (Collins and Allen 2002; Kay et al. 2015). After the memory of the initial states is lost, each member of this ‘initial condition’ ensemble evolves independently in a manner characteristic of a random stochastic process (Deser et al. 2012). Sampling across the ensemble member spread then allows for the estimation of internal variability at any desired point in time.

The research presented in this thesis revolves around the identification of forced climate change from internal variability using a large initial condition climate model ensemble - the Community Earth System Model Large Ensemble (CESM-LE, Kay et al. (2015)). The CESM-LE was designed with the explicit goal of enabling the assessment of climate change in the presence of internal variability and consists of 40 simulations of a single climate model (CESM-CAM5, Hurrell et al. 2013a). All simulations begin at 1920 and extend to 2100 under historical (Lamarque et al. 2010) and Representative Concentration Pathway 8.5 (RCP 8.5, Meinshausen et al. (2011)) forcings. The simulations are identical in all model components
except for extremely small differences (of the order of $10^{-14}$ K) in the initial air temperature field. Internal modes of variability lead to growth of these initial errors and consequently spread among the ensemble members. The large number of ensemble members, the length of the simulations that extend from the early twentieth century to the end of the twenty-first century and an accompanying multi-century preindustrial control simulation together provide a comprehensive resource for understanding the influence of internal variability on future projections of the climate. A detailed description of the CESM-LE and applications to illustrative climate problems can be found in Kay et al. (2015).

1.3 Research goals and outline of chapters

This thesis addresses three specific research goals. The first goal pertains to understanding the role of internal variability in and the mechanisms underlying future changes of precipitation within extratropical cyclones. Secondly, the influence of internal variability on the detection of forced changes in the annual cycle of surface temperature is explored and the physical factors driving the forced changes assessed. Finally, recognizing that climate variability is an inherently multivariate problem, a statistical framework is developed to facilitate the detection of forced changes in the variances and covariances of climate variables arising from imposed forcings external to the climate system.

A brief description of each chapter now follows.

1.3.1 Chapter two

Chapter two is titled “How will precipitation change in extratropical cyclones as the planet warms? Insights from a large initial condition ensemble”. This work was produced in collaboration with Dr. Jennifer Kay of the Department of Atmospheric and Oceanic Sciences at the University of Colorado Boulder and has been published in Climate Dynamics (Yettella and Kay 2016).

Precipitation in the extratropics (and in many other parts of the globe) is strongly modulated by the internal variability of the large-scale atmospheric circulation (Shepherd 2015). This variability gives rise to large uncertainty in near-term precipitation projections (IPCC 2013). Motivated to isolate forced changes
in extratropical precipitation from the large noise of internal variability, we investigate extratropical precipitation by analyzing cyclone-centric composites within the CESM-LE. The cyclone compositing procedure reveals that precipitation increases robustly in all cyclone sectors across all CESM-LE members, and rises above the noise of internal variability in both near- and far-futures.

Cyclone compositing not only allows for the robust identification of anthropogenic influence on extratropical precipitation but also facilitates addressing many important aspects of precipitation such as its frequency of occurrence, intensity and timing. Leveraging the large amount of cyclone data yielded by the compositing procedure, we also address the mechanisms underlying the precipitation increases within cyclones. Specifically, we use a simple statistical procedure to decompose future precipitation changes into contributions arising from changes in cyclone moisture, wind speed and frequency of cyclone occurrence. The decomposition shows that precipitation changes are almost entirely driven by increases in atmospheric moisture content with secondary contributions from changes in cyclonic wind speeds and occurrence frequency.

1.3.2 Chapter three

Chapter three is titled “The role of internal variability in 21st century projections of the seasonal cycle of Northern Hemisphere surface temperature” and is under review in the Journal of Geophysical Research: Atmospheres (Yettella and England 2018). This work was produced in collaboration with Mark England, a PhD student in Applied Physics and Applied Mathematics at Columbia University, and took initial inspiration from the Advanced Climate Dynamics Courses summer school 2017, “The Dynamics of the Seasonal Cycle”.

The annual cycle explains a large portion of variance in the Earth’s surface temperature (Mckinnon et al. 2013) and is associated with a number of societal and ecological effects (Schwartz et al. 2006; Carey 2009; Lambert 1971). Yet, few studies have investigated the annual cycle’s response to increasing greenhouse gases and the influence of internal variability on the detection of forced changes in the annual cycle. Motivated by this, we leverage the CESM-LE to understand the impact of internal variability on the
annual cycle over the Northern Hemispheric land masses. We find that future projections of the changes in the annual cycle will be severely limited by internal variability, even by the end of the 21st century.

The study also finds regional exceptions - Europe, Northern Africa and Siberia - where changes in the annual cycle are easily detectable from internal variability and are robust across model ensembles from the Coupled Model Intercomparison Projection Phase 5 (CMIP5) archive. The physical mechanisms underlying these robust changes are explored using a simple energy balance model. Specifically, we decompose annual cycle changes into contributions arising from changes in the physical parameters that set the annual cycle. We find that future changes in the annual cycle over the three regions are mostly driven by changes in surface longwave and turbulent heat fluxes.

1.3.3 Chapter four

Chapter four, titled “An ensemble covariance framework for quantifying forced climate variability and its time of emergence”, was produced in collaboration with Dr. Jeffrey Weiss, Dr. Jennifer Kay of the Department of Atmospheric and Oceanic Sciences at the University of Colorado Boulder and Dr. Angeline Pendergrass at the National Center for Atmospheric Research, and has been published in Journal of Climate (Yettella et al. 2018a).

Modeling studies commonly address changes in variability in terms of changes in the variances of climate variables. The role of covariances has received much less attention than that of variances despite the existence of large-scale modes of variability that couple regional climates across distant locations on the planet. Recognizing the importance of covariances in variability studies, this chapter develops a statistical framework that leverages model ensembles to enable a unified assessment of the regional variances and covariances of climate variables under climate change. Since climatic time series are in general serially correlated and the underlying probability distributions are not always known, the framework utilizes a time-series resampling method to estimate sampling uncertainties in the time-evolving regional variances and covariances. By comparing variance and covariance statistics in climate model
ensembles under evolving external forcings with those in unforced control simulations, the framework further allows for the assessment of the time of emergence of variability statistics.

The chapter also presents two illustrative examples of the framework’s application to the assessment of forced variability in the CESM-LE. First, the variability of annual mean global temperature is partitioned into components arising from the variances and covariance of land and ocean temperatures. In response to increasing greenhouse gases, land temperature variability increases and emerges from its preindustrial state in the 1950s. The land-ocean temperature covariance also increases and emerges from its preindustrial state in the 2000s. On the other hand, ocean temperature variability is found to be remarkably robust to greenhouse gas forcing and stays approximately constant at its preindustrial level. Second, the framework is applied to quantify changes in temperature variability associated with the Arctic region and the Northern Hemisphere midlatitudes. It is found that Arctic temperature variability in most months is greatly reduced by the end of the 21st century, consistent with sea ice loss in the CESM-LE (Jahn et al. 2016).

Chapter four ends with an appendix containing unpublished work that adapts the variability framework to the study of initial-value predictability. Ensemble studies of initial-value predictability often employ a variance based metric, the Potential Prognostic Predictability ($PPP$, Pohlmann et al. 2004) to study the predictability of climate variables. It is demonstrated how the statistical framework developed in chapter 4 can be used to decompose the $PPP$ of a climate variable into predictability components arising from subjectively chosen regions on the globe. As an illustration, the $PPP$ of global average daily surface temperature in the CESM-LE is decomposed into components arising from land variance, ocean variance and land-ocean covariance and the time evolution of these components is investigated.

1.3.4 Chapter five

Chapter five summarizes the above works. We list the main findings and conclusions from each chapter and also provide directions for future research.
Chapter 2

How will precipitation change in extratropical cyclones as the planet warms? Insights from a large initial condition climate model ensemble

2.1 Abstract

The extratropical precipitation response to global warming is investigated within a 30-member initial condition climate model ensemble. As in observations, modeled cyclonic precipitation contributes a large fraction of extratropical precipitation, especially over the ocean and in the winter hemisphere. When compared to present day, the ensemble projects increased cyclone-associated precipitation under twenty-first century business-as-usual greenhouse gas forcing. While the cyclone-associated precipitation response is weaker in the near-future (2016–2035) than in the far-future (2081–2100), both future periods have similar patterns of response. Though cyclone frequency changes are important regionally, most of the increased cyclone-associated precipitation results from increased within-cyclone precipitation. Consistent with this result, cyclone-centric composites show statistically significant precipitation increases in all cyclone sectors. Decomposition into thermodynamic (mean cyclone water vapor path) and dynamic (mean cyclone wind speed) contributions shows that thermodynamics explains 92 and 95% of the near-future and far-future within-cyclone precipitation increases respectively. Surprisingly, the influence of dynamics on future cyclonic precipitation changes is negligible. In addition, the forced response exceeds internal variability in both future time periods. Overall, this work suggests that future cyclonic precipitation changes will result primarily from increased moisture availability in a warmer world, with secondary contributions from changes in cyclone frequency and cyclone dynamics.
2.2 Introduction

Extratropical cyclones (hereafter cyclones) exert a strong influence on extratropical weather and climate. Cyclones control cloud amount and, as a consequence, radiation received by the extratropics. In addition, cyclones transport heat and moisture poleward and are an important part of the global atmospheric circulation. Of specific relevance to this study, cyclones produce a large fraction of extratropical precipitation. For example, Hawcroft et al. (2012) found cyclones contribute more than half of total Northern Hemisphere (NH) winter extratropical precipitation. Similarly, Catto et al. (2012) show that up to 90% of rainfall in the major storm-track regions is associated with fronts.

Recognizing the importance of cyclonic precipitation, an obvious question emerges: how will cyclonic precipitation change in a warming world? Previous work has addressed this question. For example, using an objective cyclone detection and compositing technique, Bengtsson et al. (2009) found that cyclone precipitation increased 11% per track over the twenty-first century, which is about twice the projected increase in global precipitation (Held et al. 2006). Using a feature tracking algorithm, Zappa et al. (2013) investigated the response of North Atlantic and European extratropical cyclones to climate change in the climate models participating in phase 5 of the Coupled Model Intercomparison Project (CMIP5) and ascribed the uncertainty in cyclone precipitation response to the competing effects of increased moisture content and reduced cyclone intensity. Internal variability may be important for explaining precipitation differences amongst climate projections (Power et al. 2012), but internal variability uncertainty has been difficult to separate from model formulation uncertainty in previous studies using ensembles of opportunity such as CMIP5 (Tebaldi and Knutti 2007).

Building upon previous work, we analyze the influence of global warming on cyclonic precipitation in an initial condition ensemble of a global coupled climate model: the CESM Large Ensemble (CESM-LE, Kay et al. 2015). The CESM-LE consists of 30 realizations of a single model (CESM-CAM5, Hurrell et al. 2013b) under the same external forcing. Ensemble spread is generated by small differences in initial conditions alone. The small initial condition differences grow and create spread among the ensemble members. Using the CESM Large Ensemble, we can for the first time robustly quantify cyclone-associated
precipitation change in the presence of internal climate variability, albeit within a single modeling framework.

Our study has three specific goals. First, we quantify future changes in total and cyclone-associated extratropical precipitation in the CESM-LE. Specifically, we compare total and cyclone-associated precipitation in the present with that in the near- and far-futures and assess when the forced signal emerges from the noise of internal climate variability using a simple statistical test. Second, we map precipitation rate changes within cyclones using cyclone-compositing. Finally, and most importantly, we assess the processes underlying projected changes in two quantities: cyclone-associated and within-cyclone precipitation. It is important to be clear about what these two terms mean. Cyclone-associated precipitation refers to the precipitation that accumulates at any grid point of interest due to cyclonic influence and in a sense, is Eulerian in perspective. Within-cyclone precipitation refers to the precipitation occurring within individual cyclone systems and in a sense, is Lagrangian in perspective.

Quantifying cyclone-associated and within-cyclone precipitation first requires identifying cyclones, a topic with a long history which we briefly introduce here. Early cyclone studies were limited by the lack of computing power. With the rise of computing power, and the advent of climate models and gridded analyses, the doors were opened for detailed objective studies of synoptic variability in the extratropics and the structure and evolution of individual cyclones. One of the earliest numerical studies of synoptic variability was done by Blackmon (1976), who used an Eulerian approach based on bandpass-filtered variance of the 500 hPa geopotential height. Feature-based Lagrangian techniques were also developed that identify and track individual cyclones. These techniques provide a more direct and clearer way of studying the structure and evolution characteristics of individual cyclones than provided by an Eulerian approach. These techniques differ in their choice of identification and tracking criteria which can sometimes lead to differences in the results obtained and inferences made (Neu et al. 2013). In this study, we adopt such a Lagrangian technique developed by Serreze (1995) for the identification of cyclone centers in all ensemble members but make no attempt to track them. We then extract the precipitation around identified cyclone centers to estimate the contribution of cyclones to precipitation in the extratropics.
After identifying cyclone centers, quantifying future within-cyclone precipitation rate changes using a cyclone-compositing approach follows naturally and provides useful cyclone-centric information. Cyclone composites of precipitation are produced by averaging the cyclone-center relative precipitation fields of individual cyclones. Averaging smooths the variability in individual cyclone fields and reveals the structure present in a typical cyclone. The compositing approach has been used in a host of studies ranging from the observation-based investigation of precipitation and cloud structure in cyclones (Lau and Crane 1995; Field and Wood 2007; Naud et al. 2012) to the evaluation of the reproduction of certain aspects of cyclones by climate models (Klein and Jakob 1999; Bauer and Del Genio 2006; Field et al. 2008; Bodas-Salcedo et al. 2012). By comparing the ensemble mean composites in the present with those in the near- and far-futures, we unveil the magnitude and pattern of precipitation change in cyclones.

Quantifying precipitation change is the first step, but understanding the mechanisms underlying projected changes in cyclonic precipitation is the most important goal of this study. Such an evaluation is particularly relevant in the context of the expected increase in atmospheric moisture content (Held et al. 2006) and the poleward shift of the cyclone tracks with global warming (Yin 2005). We ask two questions in this context: (1) How do changes in frequency of cyclones affect cyclone-associated precipitation? and (2) What factors cause future changes in within-cyclone precipitation?

We organize the paper as follows: In Sect. 2, we detail our cyclone identification and compositing procedures and decomposition methods. In Sect. 3, we present our results addressing the primary goals of our study: quantifying and explaining. In Sect. 4, we place our results into a broader context and finally, in Sect. 5, we summarize. As we will show, our study highlights the important role that thermodynamics plays in controlling the future precipitation within extratropical cyclones and the negligible effect internal climate variability has on the cyclonic precipitation response to global warming.
2.3 Methods

2.3.1 Initial condition ensemble: the CESM large ensemble

To quantify future changes in the presence of internal variability, we utilize daily averaged output from the CESM-LE: an ensemble of 30 CESM1-CAM5 simulations at 1° x 1° resolution. The 30 CESM-LE simulations were carried out for the period 1920–2100 under identical external forcing but starting from slightly different initial conditions. Historical forcing was applied from 1920 to 2005 and Representative Concentration Pathway 8.5 (RCP 8.5) forcing was used from 2006 to 2100. The first ensemble member was started using January 1 conditions of a randomly selected year (402) of a 1500-year pre-industrial (defined as 1850) control run of CESM1-CAM5 and then integrated forward from 1850 to 2100. The state of the first ensemble member on Jan 1, 1920 was used to initialize the rest of the ensemble members. A small random perturbation (order of $10^{-14}$ K) to the initial air temperature field was added to each ensemble member before integrating them forward from 1920 to 2100. Due to the chaotic nature of the climate system, these perturbations grow until initial condition memory is lost creating spread among ensemble members. A detailed description of the CESM-LE can be found in Kay et al. 2015.

Using the CESM-LE, we compute precipitation responses in two seasons: DJF and JJA. Following the IPCC, we define the present, near-future and far-future as 1986–2005, 2016–2035, 2081–2100 respectively. We compute the precipitation response as ensemble-mean epoch differences between the future epochs and the present. Assuming ensemble members to be independent, we evaluate the 95% statistical significance of the responses against a null hypothesis of zero change using a 2-sided student $t$ test.

2.3.2 Analysis methods used

2.3.2.1 Cyclone identification and compositing

Cyclone centers are identified as minima in the daily averaged sea level pressure ($PSL$) fields following the methodology outlined in Serreze (1995). Keeping in mind the large amount of data to be processed, we have refrained from using other, more computationally expensive cyclone identification methods.
methods, for example, those based on vorticity (Hoskins and Hodges 2005). Prior to the identification, $PSL$ fields are smoothed in space using four passes of a nine-point local smoother. Smoothing eliminates a majority of spurious lows produced near high topography due to incorrect model extrapolation to sea level. Grid points in the extratropical regions (defined as the latitude bands between 30° and 90° in both hemispheres) with a $PSL$ value lower than the values at the surrounding 8 points are then identified as minima. After identification, the central $PSL$ values are compared with $PSL$ values at surrounding grid cells in a series of outwardly expanding shells. Minima are then filtered based on threshold $PSL$ values at these shells. Applying these filtering criteria eliminates weak depressions as well as spurious lows that survive the smoothing procedure. Minima that pass the filtering procedure are considered cyclone centers and their locations, date of occurrence and central pressure are entered into a dataset. The total number of cyclone centers detected globally in all time periods and all ensemble members stood at approximately 6,600,000 which is an average of 10 cyclone centers per day globally in each ensemble member.

No attempt is made to construct cyclone tracks using the identified cyclone centers. Tracking proved difficult using the daily averaged CESM-LE data available to us. In 24 hours, cyclones can travel a distance which is on the same order as the separation between individual systems. This can lead to false associations between cyclone centers on consecutive days. For this reason, each cyclone on each day is treated as an individual system. This approach has been used in other studies as well (Lambert and Fyfe 2006; Finnis et al. 2007).

We now describe the cyclone compositing procedure. Compositing has been used in various studies to calculate the average structure of cyclonic variables (Field and Wood 2007; Bodos-Salcedo et al. 2012; Hawcroft et al. 2012, their appendix). Composites can be produced by simply using the latitude-longitude grid to define cyclonic area around each center. However, this can introduce bias due to grid distortion especially in the extratropics. This problem can be avoided by using a natural radial grid centered on each cyclone center (Bengtsson et al. 2007). We define a radial grid (Appendix I) of great radius 2000 km with 100 km shell spacing. Each shell consists of 360 equally spaced points. Model fields of any desired meteorological variable (in this paper wind velocities, precipitation and $PSL$) at any desired height (in this
paper at the surface) are bilinearly interpolated onto the radial grid. Composites are then produced by averaging these radial fields.

### 2.3.2.2 Decomposition of cyclone-associated precipitation change at grid points

Following Zappa et al. (2015), we decompose cyclone-associated precipitation change at each grid point into contributions from changes in the number of days cyclones are present in the neighborhood of the grid point and average precipitation rate change in those cyclones. The “neighborhood” is defined as a 2000 km radial cap centered on the grid point. The methodology works as follows: Let \( P(x,y) \) be a grid point. Let \( N_1 \) be the total number of days in which cyclones are present in the neighborhood of \( P(x,y) \). The total cyclone contributed precipitation at that grid point can then be represented by:

\[
P_C = N_1 \mu_1
\]

Eq. (2.1)

where \( \mu_1 \) is the mean precipitation that falls at the grid point during the \( N_1 \) days. The change in \( P_C \) in a future time period can then be written as

\[
\delta P_C = (N_2 - N_1) \mu_1 + (\mu_2 - \mu_1)N_1 + (N_2 - N_1)(\mu_2 - \mu_1)
\]

Eq. (2.2)

where \( N_2 \) and \( \mu_2 \) are the equivalents of \( N_1 \) and \( \mu_1 \) for a future time period. The first term on the RHS is interpreted as the contribution from changes in the fraction of time the grid point spends in the neighborhood of cyclones. The second term is interpreted as the contribution from changes in the precipitation rate in cyclones. The third term represents covariation.

As mentioned in Hawcroft et al. (2012), total cyclone-associated precipitation is sensitive to the size of the radial cap that is selected. Hawcroft et al. (2012) chose 12° (1334 km)/10° (1120 km) radial caps for DJF/JJA for extracting cyclonic precipitation based on an investigation into the behavior of average cyclonic precipitation as a function of distance from the cyclone center. We chose a 2000 km radial cap for both seasons based on a similar investigation (not presented in the paper). The larger cap size is a consequence of our choice of cyclone identification method as well as using daily-averaged data which spatially smooths out the precipitation field. In our investigation, we found that the frontal precipitation
band can be offset from the pressure low by as much as five hundred kilometers which meant that a larger cap had to be used to capture all of this precipitation. A sensitivity test using various cyclone radii showed that our results are robust to the choice of cyclone radius (see Appendix III).

### 2.3.2.3 Decomposition of precipitation changes in cyclones

Using a simple mass conservation argument, Field and Wood (2007) showed that the warm conveyor belt (WCB) rain rate \( R_{WCB} \) in a cyclone is proportional to the product of cyclonewide-averaged surface wind speed \( V \) and cyclonewide-averaged column-integrated water vapor (Water Vapor Path \( WVP \)):

\[
R_{WCB} \propto V \cdot WVP
\]

Eq. (2.3)

Pfahl and Sprenger (2016) show that this relationship explains a large fraction of the variance of cyclone precipitation at all latitudes. Because most cyclonic precipitation occurs in the WCB, Equation (2.3) still holds if \( R_{WCB} \) were replaced by the cyclonewide-averaged precipitation rate \( PR \). Since \( PR \) is simpler to calculate, we use it as a substitute for \( R_{WCB} \). We adopt \( V \) and \( WVP \) as measures of the strength and moisture content of a cyclone respectively. We also assume the two quantities to be independent based on the arguments of Field and Wood (2007).\( V, WVP \) and \( PR \) are calculated for each cyclone center on a 2000 km radial grid centered on the cyclone center (see previous section) with cosine weighting to account for the clustering of points towards the center of the radial grid (see Figure 2.14).

We next describe the decomposition procedure. Consider a set of cyclones \( C_P \) detected in a desired region and time period. Let \( C_F \) be the set of cyclones detected in the same region in a future time period. Let \( < PR >_{P(F)} \) be the mean \( PR \) value of cyclones in \( C_{P(F)} \). \( < PR >_F \) minus \( < PR >_P \) then represents future change in the mean of cyclonewide-averaged precipitation of cyclones occurring in that region. The decomposition procedure splits this change into contributions from future changes in the strength and moisture content of cyclones in that region. The first step in the procedure is to construct probability density functions (PDFs) of \( V \) in each set by binning. Let these PDFs be denoted by \( P_v_P \) and \( P_v_F \) corresponding
to $C_P$ and $C_F$ respectively. Each bin represents a distinct cyclone strength regime. Into each bin, $PR$ values from $C_P$ are composited to obtain a distribution of $PR$ conditioned on $V$ and denoted by $F_P$. The conditional distribution $F_F$ corresponding to $C_F$ is obtained in the same way. $< PR >_F$ minus $< PR >_P$ can then be represented:

$$< PR >_F - < PR >_P = \sum_{i=1}^{k} F_{P_i} (P v_{F_i} - P v_{P_i}) + \sum_{i=1}^{k} (F_{F_i} - F_{P_i}) P v_{P_i} + \sum_{i=1}^{k} (F_{F_i} - F_{P_i}) (P v_{F_i} - P v_{P_i})$$

Eq. (2.4)

where $k$ is the number of bins and the index $i$ indicates evaluation in the $i^{th}$ bin.

The first term on the right-hand side of Eq. (2.4) represents the change in $< PR >$ due to future change in the PDF of $V$ with the distribution of $PR$ conditioned on $V$ remaining unchanged. It is interpreted as the result of changes in the average strength of cyclones in the region. The second term is the change in $< PR >$ due to future change in the distribution of $PR$ conditioned on $V$ with the PDF of $V$ remaining unchanged. It is interpreted as the result of changes in the average moisture content of cyclones in the region. The third term represents covariation. This simple decomposition framework was used by Emori and Brown (2005) to split precipitation change into contributions from changes in dynamic and thermodynamic components at individual grid points and by Bony et al. (2004) to infer dynamic and thermodynamic components of cloud response to climate variations.

2.4 Results

2.4.1 Precipitation present day and future changes

We begin by presenting present-day and future changes in extratropical precipitation within the CESM-LE. For ease of comparison with previous work, we examine changes in two seasons: DJF and JJA. We focus on the ensemble mean to minimize noise from internal climate variability. The largest present-day extratropical precipitation rates occur over the ocean basins in the storm track regions where the precipitation rates approach 8 mm/day (Figures 2.1a and 2.1b). The contribution of cyclones to extratropical precipitation generally agrees well with the observations-based results of Hawcroft et al. (2012) (see their Figures 2 and 3). However, we caution that such a comparison could be compromised by differences in
cyclone identification methodologies. For example, the contribution over the continental United States is underestimated, in some places by as much as 30%.

**Figure 2.1.** Ensemble-mean Extratropical Precipitation: a) DJF Present day (1986-2005), b) JJA present day, c) DJF near-future (2016-2035), d) JJA near-future, e) DJF Far-future (2081–2100), f) JJA far-future. Stippling indicates statistically significant change at the 95% confidence level.

Both the near-future and the far-future precipitation responses are statistically significant over the majority of extratropics (Figures 2.1c-f). While the magnitude of the precipitation change is larger in the far-future than in the near-future, both future periods have similar spatial patterns of precipitation change. During both the near-future and the far-future, precipitation increases when compared to the present in most extratropical regions.

We next focus on cyclone-associated precipitation in the CESM-LE. Similar to the total precipitation, the majority of cyclone-associated precipitation occurs in oceanic storm tracks in both DJF and JJA (Figures 2.2a-b). Indeed, similar patterns of total precipitation (Figures 2.1a and 2.1b) and cyclone-associated precipitation (Figures 2.2a and 2.2b) demonstrate cyclonic activity is the dominant control on mid-latitude precipitation in the CESM-LE. Consistent with seasonal variations in NH cyclonic activity, NH cyclonic precipitation is larger in NH winter (DJF) than in NH summer (JJA). While more cyclonic precipitation also occurs in SH winter (JJA) than in SH summer (DJF), the seasonal variations in cyclonic
having demonstrated that cyclones are a primary contributor to present-day extratropical precipitation in the CESM-LE, it follows that the spatial pattern of cyclonic precipitation change (Figures 2.2c-f) closely matches the total precipitation change (Figures 2.1c-f). Also similar to the total precipitation future change pattern, the cyclonic precipitation change pattern intensifies in the far-future with more grid points experiencing statistically significant changes.

### 2.4.2 Decomposition of future changes in cyclonic precipitation at individual grid points

Two factors explain future cyclone-associated precipitation changes in a warming world – contributions from changes in cyclone frequency and contributions from changes in within-cyclone precipitation (see methods in Section 2.3.2.2). We compare these contributions in Figures 2.3 and 2.4. Within-cyclone precipitation change contributions dominate cyclone frequency change contributions in most regions. In most of the extratropics, within-cyclone precipitation change contributions increase cyclone-associated precipitation. Notable exceptions are the decreases seen over the North Atlantic and the Mediterranean region in DJF and over North America and Western Europe in JJA (Figures 2.3c and 2.3d,
Figures 2.4c and 2.4d). While within-cyclone precipitation change contributions are first-order, cyclone frequency change contributions do have a comparable magnitude over a considerable area of the extratropics. Particularly noticeable are the decreases seen over the Pacific storm track in DJF and over the North Atlantic in JJA (Figures 2.3a and 2.3b, Figures 2.4a and 2.4b), consistent with future cyclone frequency changes (Figure 2.5).

2.4.3 Precipitation Composites

Having learned that within-cyclone precipitation changes dominate over cyclone frequency changes throughout most of the extratropics, we next further examine within-cyclone precipitation changes using composites of present-day cyclonic precipitation and future changes. We start with cyclone composites of precipitation by hemisphere and season (Figure 2.6). The comma-shaped precipitation structure associated with the warm conveyor belt is clearly visible in the composites. The comma shape is flipped in the SH composites (Figures 2.6b, 2.6d). In both the SH and NH composites, precipitation reaches its greatest intensity close to the cyclone center. The composites are constructed by averaging the radial precipitation fields from a few hundred-thousand cyclones contributed by all ensemble members. Hence they represent greatly averaged precipitation footprints. The individual precipitation footprints of the cyclones were found to be highly variable. The composites represent the spatial average extent of cyclonic precipitation. The extent found in the composites justifies the selection of a 2000 km radial cap – it captures most of the cyclonic precipitation. The precipitation magnitude in the central regions of the composites agrees well with that in the composites derived from observational data (Hawcroft et al. 2012, their Figure S1; Field and Wood 2007, their Figure 3). The comma shape of the precipitation band matches the composites in Field and Wood 2007 in terms of its spatial spread and orientation.
Figure 2.3. Contributions to Cyclone-associated Precipitation ($C_P$) changes in the far-future (2081 - 2100): a) DJF cyclone frequency change contributions, b) JJA cyclone frequency change contributions, c) DJF within-cyclone precipitation change contributions, d) JJA within-cyclone precipitation change contributions.

We next show precipitation change in cyclone composites of the far-future compared with the present (Figures 2.7, 2.8). In all composites, statistically significant precipitation increases occur at most points on the radial grid. The greatest precipitation increases occur near the composite centers, also where the cyclone precipitation is largest. The rate of change of saturation vapor pressure with change in temperature is highest in NH, JJA. Correspondingly, we see the greatest increases in the NH, JJA composites suggesting a strong role for thermodynamics in cyclone precipitation change.
Figure 2.4. As in Fig. 2.3 but for the near-future (2016 - 2035).

2.4.4 Decomposition of future changes in precipitation within cyclones

Our results thus far reveal that within-cyclone precipitation in both hemispheres increases in the future (Figures 2.7, 2.8). A next obvious question is: Why is precipitation increasing within the cyclone composites in a warming world? To answer this question, we decompose precipitation changes into contributions from the changes in the cyclones’ thermodynamic and dynamic environments. On average, increase in moisture accounts for more than 90% of within-cyclone precipitation increase in both future time periods (Table 2.1). In contrast, the contribution from changes in wind speed are smaller. In agreement with the negligible contribution of changes in dynamics, future cyclonic $V$ PDFs vary little compared with those in the present (Figure 2.10a). In contrast, a clear shift to higher values can be seen in future $WVP$ PDFs (Figure 2.10b). Interestingly, the number of cyclones with extreme values of moisture content increases at the expense of the number of cyclones with moderate moisture content.
**Figure 2.5.** Future changes in the fraction of time that a grid point spends under cyclonic influence: a) DJF near-future (2016 - 2035) changes, b) JJA near-future changes, c) DJF far-future (2081 - 2100) changes, d) JJA far-future changes. Stippling indicates statistically significant change at the 95% confidence level.

**Table 2.1.** Ensemble mean contributions. Standard deviation given in parentheses. Individual member values in Figure 2.9. Methods in Section 2.3.2.3

<table>
<thead>
<tr>
<th></th>
<th>Near-future (2016 - 2035)</th>
<th>Far-future (2081 - 2100)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total $&lt; PR &gt;$ Change (mm/day)</td>
<td>0.0863 (0.0173)</td>
<td>0.4402 (0.0174)</td>
</tr>
<tr>
<td>Thermodynamic contribution (mm/day), % of $&lt; PR &gt;$ change</td>
<td>0.0796 (0.0160), 92%</td>
<td>0.4166 (0.0151), 95%</td>
</tr>
<tr>
<td>Dynamic contribution (mm/day), % of $&lt; PR &gt;$ change</td>
<td>0.0066 (0.0061), 8%</td>
<td>0.0233 (0.0060), 5%</td>
</tr>
</tbody>
</table>

We next map the contributions of moisture content and wind speed to precipitation changes in the two future periods (Figures 2.11a-d, 2.12a-d). Since the decomposition is performed utilizing sets of cyclones in a 2000 km radius around each grid point, the figures display a spatially smoothed map of the contributions. In general, the thermodynamic contributions (Figures 2.11c and 2.11d, Figures 2.12c and
2.12d) increase $< PR >$. In contrast to this general rule, thermodynamic changes reduce $< PR >$ in the lower parts of North America and the Mediterranean region during JJA (Figures 2.11d, 2.12d). Unlike thermodynamic contributions, dynamic contributions have a mixed influence on $< PR >$ (Figures 2.11a and 2.11b, Figures 2.12a and 2.12b). Interestingly, the dynamic contribution changes sign over a major portion of the Northern extratropics between the near- and far-futures. In most regions in the far-future, the dynamic contribution is considerably smaller than the thermodynamic contribution. An exception is in the North Atlantic and in the subsidence regions, where the dynamic and thermodynamic components have comparable magnitudes in both seasons.

We now examine mean within-cyclone precipitation changes (Figure 2.13) that contribute to cyclone-associated precipitation changes (Figures 2.3c and 2.3d and Figures 2.4c and 2.4d). These changes do not always correlate positively with their contributions to cyclone-associated precipitation changes. Within-cyclone precipitation changes are significant in most regions of the extratropics in both epochs and seasons. The contours follow those of the thermodynamic contributions (Figures 2.11c and 2.11d and Figures 2.12c and 2.12d), highlighting the importance of increased moisture content in a warming world for driving increased cyclonic precipitation.

2.5 Discussion

Despite the potential for complexity, we found modeled precipitation changes in extratropical cyclones in a warming world are simple to explain: precipitation increases because water vapor increases. Using the classic warm conveyer belt model and the finding that the cyclone strength change is negligible (Figure 2.10a, Figures 2.11a and 2.11b, Figures 2.12a and 2.12b), most of the increase can be attributed to increased moisture content in a warmer atmosphere. This result agrees with Li et al. 2014 who used recent warm periods in reanalysis data as analogues for future warming and found increased cyclonic precipitation but essentially unchanged cyclone intensity. Cyclone compositing also revealed that increased water vapor availability leads to increased precipitation in the central regions of model cyclones.
Figure 2.6. Present-day (1986 – 2005) ensemble-mean cyclone precipitation composites: a) DJF composite in the Northern Hemisphere (NH), b) DJF composite in the Southern Hemisphere (SH), c) as in a) but for JJA, d) as in c) but for SH. Precipitation is plotted in colored contours. Mean PSL (hPa) is overlaid as black contour lines.
Figure 2.7. Far-future (2081-2100) ensemble-mean cyclone precipitation difference composites. a) DJF difference composite in the Northern Hemisphere (NH), b) as in a) but for the Southern Hemisphere (SH), c) as in a) but for JJA, d) as in c) but for SH. Precipitation difference is plotted in colored contours. Present-day (1986 - 2005) mean PSL (hPa) is overlaid as black contour lines. All regions are statistically significant at the 95% level.
Figure 2.8. As in Fig. 2.7 but for the near-future (2016 - 2035). Stippling indicates statistically insignificant change at the 95% confidence level.
Figure 2.9. Contributions to within-cyclone precipitation change. Near-future (2016 – 2035, dash). Far-future (2081 – 2100, solid). Black, red and green represent total mean cyclonewide-averaged precipitation ($< PR >$) changes, thermodynamic and dynamic contributions to $< PR >$ changes respectively. Horizontal lines represent respective means (See Table 1 for values). Changes are calculated using methods in section 2.3.2.3 for cyclones detected in the entire extratropical region ($30^0$N(S) - $60^0$N(S)) for DJF and JJA combined.

There are regional exceptions to our overall finding that thermodynamics increases within-cyclone precipitation. For example, changes in thermodynamics considerably reduce within-cyclone precipitation over South-Central Europe and over a major portion of the United States in the far-future (Figure 2.12d). This reduction occurs despite of increased average cyclone moisture content and only slightly decreased average cyclone strength in those regions (not shown). This suggests that within-cyclone precipitation simulated by the climate model in these regions is less than that predicted by the WCB model which warrants investigation.
Figure 2.10. Probability distribution functions of a) cyclone-averaged wind speed $V$ b) cyclone-averaged water vapor path $WVP$. Green: present (1986 – 2005), Blue: near-future (2016 - 2035), Red: far-future (2081 - 2100). Individual lines represent ensemble members. The PDFs are derived for cyclones detected in the entire extratropical region (30°N(S) - 60°N(S)) for DJF and JJA combined.

All things considered, changes in cyclone dynamics are often negligible (Figure 2.10a, Figures 2.11a and 2.11b, Figures 2.12a and 2.12b). As argued by Bengtsson et al. 2009b, unchanging cyclone dynamics could be a result of compensation between the strengthening of storms due to increased moisture and an associated greater latent heating and the weakening of storms due to weakened equator to pole surface temperature gradient with a warming climate. We caution that this result might be resolution dependent. Cyclone intensity, in terms of surface wind speed, can increase, albeit modestly, in a warmer climate at finer resolutions (Booth et al. 2013).

This study also investigated the influence of changes in storm-frequency on cyclone-associated precipitation. Changes in storm-frequency in the future are consistent with results from literature. For example, in the far-future (Figures 2.5c and 2.5d), SH cyclone frequency exhibits a dipole behavior by increasing in the Southern Ocean (South of 60°S) and decreasing in the sub-Antarctic ocean (North of 60°S) agreeing with the results of Fyfe 2003. This dipole behavior also agrees with model projections of poleward SH storm track shifts. The dipole is stronger in JJA than in DJF due to the competing effect of ozone recovery in DJF which tends to oppose the poleward shift (Polvani et al. 2011). In boreal winter (Figure 2.5c), the shifts are not necessarily poleward in all regions. For example, a tripolar response, as found in a multimodel assessment by Zappa et al. (2013), is present over the North Atlantic Ocean and Europe, consistent with minimal jet shifts found by Barnes and Polvani (2013) in that region. In the North-
Eastern Pacific however, clear poleward storm track shifts are present, as also noted by. In agreement with
the findings of Chang et al. (2015), the gradient of frequency change over the East Pacific just off the North
American coast suggests a southward shift of cyclones in that region. Contrary to their results however,
cyclone activity is reduced. Consequently, the cyclone-associated precipitation increase over the coastal
East Pacific and California regions (Figure 2.2e) is explained exclusively by the increased precipitation
intensity within cyclones (Figure 2.3c). In boreal summer (Figure 2.5d), cyclone frequency decreases
throughout the extratropics, most prominently over the North Atlantic Ocean and Europe. The gradient of
change is consistent with a clear poleward jet shift in those regions (Barnes and Polvani 2013). On
comparing the contributions of changes in cyclone frequency and precipitation intensity (Figures 2.3, 2.4)
with total cyclonic precipitation change (Figures 2.2c-f), the only regions where contributions by changes
in cyclone frequency dominate are the winter time Pacific Storm tracks and SH low latitudes in addition to
the summer time North Atlantic Ocean. In all other regions, contributions by changes in precipitation
intensity associated with the increased moisture content clearly dominate during both seasons suggesting a
stronger role for thermodynamics in causing cyclone-associated precipitation change. We caution that these
results are specific to CESM-CAM5 and there is intermodel spread in the storm track response (Chang et

In spite of the complex interaction between various physical drivers of change that could result in
cyclone response uncertainty (Zappa et al. 2013, Woollings et al. 2010), our results under RCP 8.5 forcing
show that the dominance of thermodynamics over dynamics rises above internal variability in both time
periods (Figure 2.9, Table 2.1). Even in the near future when internal variability noise can possibly hide
signals from the forced response, the conclusion is very clear: changes in thermodynamics are far more
important than changes in dynamics from a cyclone precipitation perspective. The relative magnitude of
the ensemble spread in the contributions (standard deviations in Table 2.1) suggest that the role of internal
variability is negligible and a small number of ensemble members is sufficient to detect the forced response
in cyclones in an average sense even in the near-future. Ensemble spread in the contributions arising from
internal variability was found to be minimal even on the regional scale (not shown) throughout the
extratropics in both future periods. Our results imply that future cyclone change studies may be best served by focusing on their thermodynamic aspects. However, this does not eliminate the need to study changes in extremes of cyclonic winds due to their relevance to the society.

Like all studies, the methods applied here have limitations. This work assumes that cyclone $V$ and $WVP$ are independent quantities based on the arguments of Field and Wood (2007). Mathematically, this assumption translates to a negligible covariation term in Eq. (2.4). The covariation term was indeed found to be negligible when the decomposition of within cyclone precipitation changes into contributions from changes in cyclone $V$ and $WVP$ in the neighborhood of each grid point was performed taking into account complete sets of identified cyclones. When the decomposition was performed for particular cyclone strength regimes (e.g: the middle tercile of a tercile-by-tercile partition of cyclones based on strength), the covariation term attained a magnitude comparable to the thermodynamic and dynamic terms. Cyclone thermodynamics and dynamics are coupled to each other in such a scenario and as a result the effect of their covariation must be included in the analysis.

Another potential limitation of this work is the use of daily averaged data. Because cyclones evolve on sub-daily timescales, the use of daily data smooths cyclones. Indeed, a side analysis with reanalysis data (see Figure 2.15 in appendix II) shows that the precipitation maximum near cyclone centers was smaller in 24-hourly averaged composites than in 6-hourly averaged composites by as much 6mm/day. Furthermore, Marciano et al. 2015 and Willison et al. 2013 show that cyclone moist dynamics that are well resolved temporally feedback onto the circulation within a 12-hour window. Therefore, using daily averages will act to smooth out the feedback that couples cyclone dynamics and thermodynamics, potentially affecting a key conclusion of the paper that cyclone dynamics remains unchanged in a warmer climate. The results of Li et al. 2014 however strongly suggest that the conclusions are robust to the choice of temporal averaging. Using warm and cold epochs in 6 hourly reanalysis data as analogues for a warmer future climate and the present climate, they investigate changes in cyclone precipitation, moisture and dynamics. They find that as the extratropical climate transitions from a cold epoch to a warm epoch, cyclone precipitation and moisture increase while cyclone dynamics remains essentially unchanged. This lends confidence to the
fundamental conclusion of our work: cyclone thermodynamics dominate over dynamics in a warmer world. Our conclusion that the dynamics changes within cyclones are relatively small is also consistent with idealized model experiments (Booth et al. 2013).

Finally, we use an imperfect model with precipitation biases. Biases in the simulation of present-day precipitation imprint themselves on the projections of precipitation change since precipitation changes associated with warming correlate with the present-day pattern of precipitation (Bony et al. 2013). Although models represent front occurrence frequency well, they overestimate the frequency of frontal precipitation and underestimate its intensity (Catto et al. 2015). These compensating factors add little bias to accumulated precipitation and as a result, frontal precipitation is well represented on average in models (Compare Figures 2.18, 2.19 and 2.20 in appendix IV with Figures 2.1a, 2.1b, 2.2a, 2.2b and 2.6). For example, using a cyclone-compositing approach, Field et al. (2008) have shown that accumulated cyclonic precipitation rate and composite structure over oceans reproduced by CAM are in good agreement with satellite estimates. However, the underestimation of frontal precipitation intensity could impact present-day simulations and future projections of model cyclone strength through the resulting underestimation of latent heat fluxes. Willison et al. (2013) argue that one cause of this deficiency could be the coarse resolution of present day GCMs. Horizontal resolution can have an important impact on storm track response to changes in large scale conditions such as moisture and dynamics.

For example, Willison et al. (2013) show an enhanced positive feedback between cyclone intensification and latent heat release within the cyclone at higher resolutions, resulting in stronger storms relative to coarser simulations. As demonstrated by Field et al. 2008, model resolution can also impact the sensitivity of changes in model cyclonic clouds and precipitation to changes in moisture and dynamics. Specific to our study, Field et al. 2008 argue that Eq (2.3) may not completely explain the variance in the model composite-mean rainfall rates which could potentially affect the decomposition results presented in Table 2.1. While important to consider, we do not think these factors change the essential conclusion of our work: changes in thermodynamics in a warming world explain most of the changes in cyclone precipitation.
Figure 2.11. Contributions to mean cyclone-wide averaged precipitation (<$PR$>) changes in the near-future (2016 - 2035). a) DJF dynamic contributions b) JJA dynamic contributions c) DJF thermodynamic contributions d) JJA thermodynamic contributions. These maps were produced by constructing circles of great radius 2000 km at every grid point and applying the decomposition procedure described in section 2.3.2.3 to the set of $V, WVP$ and $PR$ values of cyclones located within each circle in each ensemble member. The ensemble-mean of the resulting values of the contributions are assigned to the corresponding central grid point.

2.6 Summary

Using a cyclone-compositing approach, we find that precipitation within extratropical cyclones as represented by a state-of-the-art global coupled climate model (CESM1-CAM5) increases in the future. With some regional exceptions, within-cyclone precipitation increases mostly due to increase in the cyclonic water vapor content, not changes in cyclonic wind speeds. Cyclone-associated precipitation increases mostly due to within-cyclone precipitation enhancement. Despite their potential to affect cyclone-associated precipitation, changes in cyclone frequency play only a secondary role with some regional exceptions. In spite of the potential for uncertainty arising from complex interaction of various physical
Figure 2.12. Contributions to mean cyclone-wide averaged precipitation ($<PR>$) changes in the far-future (2081 - 2100). a) DJF dynamic contributions b) JJA dynamic contributions c) DJF thermodynamic contributions d) JJA thermodynamic contributions. These maps were produced by constructing circles of great radius 2000 km at every grid point and applying the decomposition procedure described in section 2.3.2.3 to the set of $V$, $WVP$ and $PR$ values of cyclones located within each circle in each ensemble member. The ensemble-mean of the resulting values of the contributions are assigned to the corresponding central grid point.

drivers of change, internal climate variability has a negligible effect on the dominance of thermodynamic contributions to extratropical cyclone precipitation change over other controls on precipitation in the near- and far-futures.
Figure 2.13. Mean cyclonewide-averaged precipitation $<PR>$ change: a) DJF near-future (2016 - 2035) change, b) JJA near-future change, c) DJF far-future change (2081 - 2100) change, d) JJA far-future change. Stippling indicates statistically significant change at the 95% confidence level.
Appendix I: Construction of cyclone-centric radial grids

The radial grids used in our study are centered on cyclone centers and consist of equally-spaced shells on the sphere with each shell consisting of a desired number of points (Figure 2.14). Such radial grids have previously been used in Bengtsson et al. 2009a for cyclone compositing purposes. Here we give direct formulas for the construction of such grids.

Consider a cyclone center C identified on the globe at latitude $\phi$ and longitude $\lambda$ where the angles are expressed in radians. The unit vectors $\vec{e}_1$, $\vec{e}_2$, $\vec{e}_3$ at C in the zonal, meridional and radial directions (assuming the center of the Earth to be the origin) respectively are given by

$$\vec{e}_1 = -\sin(\lambda) \hat{i} + \cos(\lambda) \hat{j}$$ \hspace{1cm} \text{Eq. (2.5)}

$$\vec{e}_2 = -\sin(\phi) \cdot \cos(\lambda) \hat{i} - \sin(\phi) \sin(\lambda) \hat{j} + \cos(\phi) \hat{k}$$ \hspace{1cm} \text{Eq. (2.6)}

$$\vec{e}_3 = \cos(\phi) \cdot \cos(\lambda) \hat{i} + \cos(\phi) \sin(\lambda) \hat{j} + \sin(\phi) \hat{k}$$ \hspace{1cm} \text{Eq. (2.7)}

where $\hat{i}$, $\hat{j}$, $\hat{k}$ are the unit vectors of a fixed right-handed coordinate system with origin at the center of the globe.

Let $s$ be the desired great-circle distance between the shells of the radial grid centered on C and $m$ be the desired number of shells. Let the desired number of points on each shell be $n$. Then, the projections $x$, $y$, $z$ of the radial vector joining the origin to the $q^{th}$ point on the $p^{th}$ shell are given by

$$x\hat{i} + y\hat{j} + z\hat{k} = R \sin\left(\frac{ps}{R}\right) \cos\left(\frac{2\pi q}{n}\right) \vec{e}_1 + R \sin\left(\frac{ps}{R}\right) \sin\left(\frac{2\pi q}{n}\right) \vec{e}_2 + R \cos\left(\frac{2\pi q}{n}\right) \vec{e}_3$$ \hspace{1cm} \text{Eq. (2.8)}

where $R$ is the radius of the Earth, $p$ can range from 1,2,3...$m$ and $q$ from 1,2,3,...$n$.

The latitude and longitude $\phi_{p,q}$ and $\lambda_{p,q}$ of the point are then given by

$$\phi_{p,q} = \left(\frac{\pi}{2} - \arccos\left(\frac{z}{\sqrt{x^2+y^2+z^2}}\right)\right) \frac{180}{\pi}$$ \hspace{1cm} \text{Eq. (2.9)}

$$\lambda_{p,q} = ((\text{Arg}(x + iy)) \mod (2\pi)) \frac{180}{\pi}$$ \hspace{1cm} \text{Eq. (2.10)}

where $\text{mod}$ is the modulus operator, $\text{Arg}$ stands for complex argument and $i$ is the imaginary unit. $\phi_{p,q}$ and $\lambda_{p,q}$
and $\lambda_{p,q}$ are output in degrees, and lie in $[{-90, 90}]$ and $[0,360)$ respectively. By iterating $p$ and $q$ from 1 to $m$ and 1 to $n$ respectively, the latitudes and longitudes of all radial grid points can be obtained.

Figure 2.14. Illustration of a cyclone-centric radial grid. The green points represent model grid points. The black dot is a sample cyclone center. The red points represent the radial grid.
Appendix II: The effect of temporal resolution on cyclone composite precipitation intensity.

Figure 2.15. DJF (1986 - 2005) cyclone composite precipitation for a) 6 hourly, and b) daily averaged data from NCEP-DOE II reanalysis (Kanamitsu et al. 2002) in the Northern Hemisphere.

Appendix III: Sensitivity of cyclonic precipitation to the choice of cyclone radius

The cyclone radial grids used in our study have a radius of 2000 km. Including all precipitation within a 2000 km radius will capture precipitation that is not associated with cyclones, especially during the early phases of cyclone development. The results could therefore potentially be sensitive to our choice of cyclone radius (see also Rudeva and Gulev 2011). A data-driven strategy of choosing an optimal cyclone radius is to choose a radius from a range of radii to which cyclone precipitation is insensitive. Using this strategy, we find that 2000 km is an appropriate choice because present-day cyclonic precipitation and future changes are robust to changes in radius in the 1800-2200 km range (Figures 2.16 and 2.17).
Figure 2.16. Cyclone-associated Precipitation ($C_P$) for DJF Present day (1986 - 2005) derived using different cyclone radii (radii listed in insets) in ensemble member 1.

Figure 2.17. Cyclone-associated Precipitation ($C_P$) for DJF Far-future (2081 - 2100) minus DJF Present day (1986 - 2005) derived using cyclone grids of different radii in ensemble member 1. Cyclone radii are listed in panel insets.
Appendix IV: Present day (1986 - 2005) precipitation in NCEP-DOE II reanalysis data.

Figure 2.18 Extratropical Precipitation in NCEP-DOE II reanalysis data: a) DJF Present day (1986-2005), b) JJA present day

Figure 2.19. Ensemble-mean Cyclone-associated Precipitation ($C_P$) in NCEP-DOE II reanalysis data: a) DJF Present day (1986-2005), b) JJA present day
Figure 2.20. Present-day (1986 - 2005 cyclone precipitation composites derived from NCEP-DOE II reanalysis data: a) DJF composite in the Northern Hemisphere (NH), b) DJF composite in the Southern Hemisphere (SH), c) as in a) but for JJA, d) as in c) but for SH. Precipitation is plotted in colored contours.
Chapter 3

The role of internal variability in 21st century projections of the seasonal cycle of Northern Hemisphere surface temperature

3.1 Abstract

The seasonal cycle is fundamental to the Earth’s climate system, accounting for the vast majority of temperature variance. Understanding how the seasonal cycle will change in the future, and by when, is a key question with important implications. Here, a forty-member initial condition climate model ensemble is used to investigate the influence of internal variability on the detection of changes in the amplitude and timing of the seasonal cycle of surface temperature over Northern Hemisphere land in response to increasing greenhouse gases. Internal variability renders the detection of these changes challenging; even by the mid-21st century, small ensembles will be insufficient to separate the forced signals from internal variability over many continental regions in the Northern Hemisphere. Despite this, projected changes over Europe, North Africa and Siberia are large and easily detectable, even in a single member. Specifically, amplitude increases over Europe and North Africa while it decreases over Siberia. On the other hand, the timing of the seasonal cycle is delayed over all three regions. It is found that these changes are remarkably robust across model ensembles from the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive. To understand the mechanisms underlying these robust changes, a simple energy balance model is used to partition changes into contributions arising from changes in the physical parameters that control the seasonal cycle. It is found that future changes in the seasonal cycle over the three regions are most strongly controlled by changes in surface longwave and turbulent heat fluxes.
3.2 Introduction

The seasonal cycle of Earth’s surface temperature is a fundamental aspect of climate variability; the annual frequency band contains more temperature variance than any of the well-known modes of circulation variability (e.g: El Nino-Southern Oscillation, Bjerknes (1969); Northern Annular Mode, Thompson and Wallace (2000); Pacific North American pattern, Wallace and Gutzler (1981)). Beyond being a fundamental feature of the climate system, the seasonal cycle in temperature has a number of first-order ecological and societal effects. For example, it has a modulating effect on biological cycles in plants (Schwartz et al. 2006), determines animal migration patterns (Carey 2009), influences agricultural development (Lambert 1971), can affect the estimation of climate trends and variability (Qian et al. 2011), and has even been argued to have played a crucial role in the growth and collapse of civilizations (Patterson et al. 2010).

Anthropogenic emissions, which are projected to increase for the foreseeable future (IPCC 2013), are rapidly changing the Earth’s climate, both in the mean (Madden and Ramanathan 1980; Hawkins and Sutton 2012) and in the variability about the mean (Huntingford et al. 2013; Yettella et al. 2018b). Given the high societal and ecological relevance of the seasonal cycle of surface temperature, it is crucial to understand how increasing anthropogenic emissions might change its climatological characteristics in the coming century. A notable previous study that investigated changes in the annual cycle in a warmer world is that of Dwyer et al. (2012), hereafter referred to as D12. The authors analyzed output from the Coupled Model Intercomparison Project phase 3 (CMIP3, Meehl et al. 2007) suite of models and found that, in the global mean, the models robustly projected a delay in the phase and a decrease in the amplitude of the seasonal cycle of surface temperature. Using a simple energy balance model, they further showed that the changes are largely driven by sea ice loss in a warming climate. Despite the importance of the seasonal cycle, its response to increasing greenhouse gases has been investigated by only a few other model studies (e.g: Mann and Park 1996; Lynch et al. 2016). As such, several fundamental questions about the future seasonal cycle response remain unaddressed.
This paper addresses two specific research goals. Our first and main goal is to understand the influence of internal variability on the ability to detect forced changes in the twenty-first century seasonal cycle of surface temperature over Northern Hemisphere (NH) continental land masses. Unforced internal variability, that arises solely from modes inherent to the climate system, can give rise to year-to-year variations (Ault et al. 2011) and even multidecadal trends (Stine and Huybers 2012; Cornes et al. 2017) in the seasonal cycle adding uncertainty to future projections. Quantifying this uncertainty and assessing its impact on the detection of forced changes is essential for several obvious and important reasons. First, the detection of a statistically significant change is often the first step in attributing change to a particular cause, for example increasing greenhouse gases (Bindoff et al. 2013). Furthermore, detection is essential for informing policy makers and stakeholders to enable near-term risk mitigation and long-term adaptation (IPCC 2013). Finally, given that recent trends in the observed seasonal cycle have been partly attributed to human influence (Stine et al. 2009; Qian and Zhang 2015), it is easy to envisage that anthropogenically forced changes in the seasonal cycle will become even more significant in the future. It is therefore vital to understand how internal variability will influence the detection of these changes. To the best of our knowledge previous studies have not investigated the role of internal variability on seasonal cycle projections at either the global or regional scales. A recent exception is Labe et al. (2017) who use a large ensemble of climate model simulations to investigate the role of internal variability in future projections of spring onsets over the continental United States and demonstrate a large projected increase in the likelihood of early springs.

We address the influence of internal variability on the detection of forced changes in the seasonal cycle using a coupled climate model ensemble. Using the ensemble, we quantify the uncertainty arising from internal variability by addressing two specific questions: 1) how soon can we detect forced changes in the seasonal cycle for a given number of ensemble members? and 2) how many ensemble members would be required to detect forced changes at a future point in time?
Our second goal pertains to addressing the mechanisms underlying future changes in the seasonal cycle leveraging models that participated in the Coupled Model Intercomparison Project phase 5 (CMIP5, Taylor et al. (2012)). For this purpose, we utilize the energy balance model developed by D12, and partition future changes in the seasonal cycle into contributions arising from changes in the physical parameters that control the seasonal cycle. Specifically, we quantify the role of effective heat capacity and surface energy fluxes in driving future changes across different CMIP5 models. Using the energy balance model, we also briefly explore biases in the simulation of the historical seasonal cycle within the CMIP5 models.

We organize the paper as follows: In section 3.3, we describe our methods and data. In section 3.4, we present the climatological structure of the seasonal cycle in the CESM-LE. In section 3.5, we present projected changes and assess the influence of internal variability on the detection of projected changes in the CESM-LE and in several CMIP5 ensembles. We find that internal variability exerts a profound influence on forced changes in seasonality over much of the NH. We also reveal areas where forced changes are strong compared to internal variability and are therefore easily detectable, even in a single realization of the climate system, and further show that these changes are robust across multiple ensembles from the CMIP5 archive. In section 3.6, we utilize the energy balance model to explore the mechanisms underlying future changes in the seasonal cycle, as well as historical biases in CMIP5 models. Finally, in section 3.7, we offer some concluding remarks.

3.3 Methods and data

3.3.1 Definition of the seasonal cycle

Two methods have primarily been used in the literature to define the seasonal cycle of surface temperature (Stine et al. 2009). The first is based on the time of the year when temperatures reach a level of interest, a useful method when one is interested in phenomena that depend on temperature crossing a threshold. Threshold-based definitions confound the description of systematic changes in the seasonal cycle when a warming signal is present in the annual mean (See Figure s1 in Stine et al. 2009). The alternative method of describing the seasonal cycle is based on a decomposition of the yearly temperature time series,
whose annual mean has been removed, into orthogonal sinusoids or harmonics. As such, this method enables a description of the structure of the seasonal cycle that is unaffected by annual mean warming. Since the focus of this paper is on the detectability of systematic changes of the seasonal cycle in a warming climate, without regard to any threshold-based phenomena, we adopt the second definition.

The harmonic structure of the seasonal cycle exhibits a notable geographic dependence. For example, as noted by D12, the sun passes overhead twice in the tropics and as a result the tropical seasonal cycle of insolation and in turn that of temperature has a strong semi-annual character. In contrast, the extratropical seasonal cycle is predominantly annual in nature. The annual and semi-annual sinusoids together capture the vast majority of the variance in the seasonal cycle of surface temperature virtually everywhere on the globe. In this paper, we limit our focus to the annual sinusoid and to the regions where >85% of the variance in the seasonal cycle is explained by the annual sinusoid. Our choice therefore excludes large portions of the tropics. We further limit the scope of this study to the NH.

Adopting the methods of Stine et al. (2009), we compute the annual sinusoid (annual cycle hereafter) for year \( t_0 \) using the Fourier transform:

\[
Y_x(t_0) = 2 \sum_{t=0.5}^{11.5} e^{2\pi i t / 12} x(t + t_0)
\]  
Eq. (3.1)

where \( x(t + t_0), t = 0.5, ..., 11.5, \) are 12 monthly average values of either the surface (skin) temperature or solar insolation. Monthly average values resolve the annual cycle adequately for the purposes of this study (Stine and Huybers 2012; McKinnon et al. 2013). We compute the phase of the annual cycle as \( \phi_x = \tan^{-1}(\text{Im}(Y_x)/\text{Re}(Y_x)) \) and the amplitude as \( A_x = |Y_x| \). To enable a standardized comparison of the timing of the annual cycle across different latitudes, we reference its phase, \( \phi_T \), and amplitude \( A_T \), to the phase, \( \phi_S \), and amplitude, \( A_S \) of the local solar insolation, and define gain \( G_T = \frac{A_T}{A_S} \) and lag \( \lambda_T = \phi_T - \phi_S \). We hereafter quantify changes in the annual cycle in terms of changes in its gain and lag (see methods of Stine et al. (2009)). We note that previous studies have used slightly varying methods to define the annual cycle. For example, Qian and Zhang 2015, rather than investigate gain, examine the amplitude in terms of the range of seasonal mean temperatures within a year; we expect our studies to be broadly comparable.
although caution should be taken for results at lower latitudes where the correspondence of gain and amplitude is weaker.

3.3.2 Data

We assess the influence of internal variability using an initial condition ensemble: the CESM large ensemble (CESM-LE, Kay et al. 2015). The CESM-LE consists of 40 simulations of a single climate model (CESM1-CAM5, Hurrell et al. 2013b) that are all run under the same forcing: historical (Lamarque et al. 2010) from 1920 to 2005 and Representative Concentration Pathway 8.5 (RCP 8.5, Meinshausen et al. 2011) from 2006 to 2100. The ensemble members are initialized identically at 1920 except for small differences (order of $10^{-14}$ K) in the air temperature field. Chaos leads to growth in these initial differences eventually leading to spread among the ensemble members. As such, each member represents an independent realization of the climate system and the spread represents uncertainty arising from internal variability alone. To assess the robustness of the CESM-LE projections, we analyze output from an initial-condition ensemble based on a different model: the CanESM2 (Canadian Earth System Model 2, Aroras et al. 2011) large ensemble (Fyfe et al. 2017) that consists of 50 ensemble members and was run under the same forcing as the CESM-LE, albeit at a lower resolution of 5° x 5°. We also briefly examine the CESM medium ensemble (CESM-ME, Sanderson et al. 2018) which consists of 15 members that are run under RCP 4.5 (Thomson et al. 2011) conditions from 2006 to 2080 to understand the sensitivity of our results to the chosen emissions scenario.

We explore the mechanisms underlying projected changes in the annual cycle in 22 CMIP5 historical and RCP 8.5 model simulations (Table 3.1, Taylor et al. 2012) using a simple energy balance model (section 3.6). This analysis requires temperature, shortwave flux fields at the surface and solar insolation which are all obtained at 2.5° resolution from the CMIP5 Next Generation (CMIP5-ng) database. Monthly data from the first ensemble member (r1i1p1) of each CMIP5 model is utilized for the computation of the annual cycle. We note that all models used in this study prescribe solar insolation based on a
reconstruction of total solar irradiance by Wang et al. 2005. Exceptions are the ACCESS1-0 and ACCESS1-3 models that used a reconstruction by Lean 2000.

In this study, we also explore model biases by comparing model results with observational data. We derive the observational gain and lag using the Berkeley Earth Surface Temperature (BEST, Rohde et al. 2013) dataset available at 1° resolution and historical solar irradiance data based on the Wang et al. 2005 reconstruction. We bilinearly interpolate BEST data to the lower resolution model grids to facilitate comparison. Shortwave fluxes at the surface are obtained from NCEP-DOE Reanalysis II (Kanamitsu et al. 2002).

3.3.3 Detection of forced changes in the annual cycle

The primary goal of this study is to understand the influence of internal variability on the detection of future changes in the annual cycle; for this purpose, we use the statistical approach outlined in Deser et al. (2012). In each ensemble member of the CESM-LE, we quantify future amplitude and lag changes in terms of decadal epoch differences within that ensemble member. We estimate forced change as the ensemble mean epoch difference $\bar{X}$ and internal variability as the ensemble standard deviation of the epoch differences $\sigma$. We consider the forced change $\bar{X}$ to be significantly different from zero at 95% confidence, given $\sigma$, if the following condition based on the standard error of the mean is met:

$$\left| \frac{\bar{X}}{\sigma} \right| \geq \frac{2}{\sqrt{N-1}}$$  \hspace{1cm} \text{Eq. (3.2)}$$

where $N$ is the number of ensemble members. The minimum number of ensemble members ($N_{\text{min}}$) required to detect a significant forced epoch difference at 95% significance is computed as (Sardeshmukh et al. 2000):

$$N_{\text{min}} = \frac{9}{(\frac{2}{\sqrt{N-1}})^2}$$  \hspace{1cm} \text{Eq. (3.3)}$$
3.4 Climatological structure

We begin by presenting the climatological structure of the annual cycle in the CESM-LE in the NH over both land and ocean. Specifically, we look at the long-term (1960-2005) mean gain and lag within member 1 (Figures 3.1a and 3.1b) of the CESM-LE and the standard deviation across the ensemble members (Figures 3.1b and 3.1d). The standard deviations of both gain and lag (Figures 3.1b and 3.1d) are very small compared to the long-term means (Figures 3.1a and 3.1c) indicating little variability across the ensemble members. Two striking spatial features in the annual cycle response to solar insolation are observed. First, gain is generally larger over land compared to that over the oceans, while lag is larger over the oceans, reaching more than 75 days in the lower midlatitudes. These differences in the annual cycle response are consistent with the vastly different effective heat capacities of land and ocean: the larger effective heat capacity of the ocean damps the amplitude of the temperature response to the oscillatory forcing of solar insolation and delays its phase compared to that over land. This dependence of annual cycle characteristics on the effective heat capacity will be made more quantitative in section 3.6. Second, there is a notable zonal gradient in gain and lag, following the direction of the background circulation that carries the tempering influence of the oceans onto land. Specifically, gain generally increases as one moves west to east across the continents while lag exhibits the opposite tendency. A similar spatial structure is also seen in the variability of gain and lag (Figures 3.1b and 3.1d) - the variability of gain increases as one moves to the east across continents while the variability of lag decreases.

In Figure 3.2, we document the long-term mean gain and lag in observations (Figures 3.2a and 3.2d) and associated biases in the CESM-LE (Figures 3.2b and 3.2e). On comparing Figures 3.1a and 3.1c with Figures 3.2a and 3.2d and also with results from previous observational (Stine et al. 2009; Stine and Huybers 2012) and model studies (D12), we find that the CESM-LE is able to reproduce the broad spatial structure of the annual cycle. However, after computing the fractional differences in gain and lag between the model and observations (Figures 3.2b and 3.2e), we find that the model exhibits large biases over many regions. For example, the CESM-LE overestimates gain by more than 30% over the Rocky Mountains and North Africa, and lag by more than 50% over Mexico. When aggregated over land, the CESM-LE
underestimates lag by 8.5% while overestimating gain by 14% compared to BEST observations. Interestingly, the spatial pattern of biases seen in Figure 3.2b, most notably the biases over the sea ice edge, persist to some extent in the CMIP5 models (not shown) and also in the CMIP3 based results of D12.

While the mean state is important, it is crucial to assess model fidelity in simulating the variability of the historical annual cycle. To gain a qualitative understanding of how representative the simulated internal variability is of the real climate system, we show in Figures 3.2c and 3.2f, the ratio of the interannual standard deviations of detrended gain and lag in member 1 of the CESM-LE to those in the BEST observations. Over most land regions, modeled variability is statistically indistinguishable from observed variability. Exceptions are the Tibetan Plateau, the Rocky Mountains and Western Russia where the modeled variability in gain is almost 1.5 to 2 times greater than observed variability and is statistically distinguishable at the 95% confidence level. It is important to note that if future internal variability over these regions is also overestimated by the CESM-LE, then the estimates of the time of detection of forced changes will be biased to later years and the number of ensemble members will be biased to a higher number (see Eq. (3.2) and (3.3)).

3.5 Future changes and the influence of internal variability

Because the impacts of changes in the seasonal cycle on society are largest over land, we restrict our analyses to the large continental land masses. We examine changes in the gain (Figure 3.3a) and lag (Figure 3.3d). To reduce the noise of internal variability and bring out robust forced signals, we focus on the far-future (2091 - 2100) ensemble mean change relative to this past decade (2008 - 2017). By the end of the 21st century, the gain of the annual cycle increases over Europe, Northern Africa, vast portions of the United states and Greenland. The increases seen over Europe are particularly striking with the gain difference reaching more than 12 °C/kW/m² (roughly 2.5 °C in terms of amplitude). There are also regions where the gain decreases, specifically, over Siberia, Alaska and Canada. The largest reductions in gain, upto -10 °C/kW/m² (roughly -3 °C in terms of amplitude), occur over Siberia and Alaska. The spatial pattern of change in lag (Figure 3.3d) is very different to that of gain. Lag increases (i.e., the timing of the annual
Figure 3.1. (a) 46-year (1960-2005) mean gain in member 1 of the CESM-LE. (b) Standard deviation across CESM-LE members of 46-year (1960-2005) mean gain. (c) as in (a), and (d) as in (b) but for lag. Regions where less than 85% of the variance in an average demeaned year (averaged over 1960-2005) is explained by the annual cycle, in one or more ensemble members, have been excluded.

The cycle is delayed) by almost 2 days over most of the NH. Exceptions, however, are lag reductions over the Iberian Peninsula, Mexico and Central Asia. Both the gain and lag projections are statistically significant over most land regions.

We repeat the above analysis with the CanESM2, a different large ensemble consisting of 50 ensemble members (see section 3.3.2) and with 22 CMIP5 models. We find that the CanESM2 large ensemble and the CMIP5 multi-model ensemble project very similar gain (Figures 3.3b and 3.3c) and lag (Figures 3.3e and 3.3f) changes over most regions by the end of the 21st century. While the magnitude of change in the CMIP5 projections is smaller, likely due to averaging across models with compensating changes, the direction and spatial pattern of change is consistent with those in the CESM-LE and CanESM2 and with the CMIP3 results of D12. It is interesting to note that future changes in the amplitude seem to be a continuation of trends in the historical record (Qian and Zhang 2015). The striking similarities between anthropogenically
Figure 3.2. (a) 46-year (1960-2005) mean gain in BEST observations. (b) 46-year (1960-2005) mean gain percentage difference between ensemble mean of the CESM-LE and BEST observations. (c) Ratio of interannual standard deviation of gain (1960-2005) in member 1 of the CESM-LE to that in BEST observations. (d) as in (a), (e) as in (b), and (f) as in (c) but for lag. Regions where less than 85% of the variance in an average demeaned year (averaged over 1960-2005) is explained by the annual cycle, in one or more ensemble members, or in observations, have been excluded. Stippling indicates regions where the interannual variance in member 1 of the CESM-LE is different from that in BEST observations according to a two-tailed F-test at the 95% confidence level.

forced changes in the annual cycle in two different large climate model ensembles with different model physics and in the CMIP5 multi-model mean, increases confidence in the projections.
Figure 3.3. Ensemble mean epoch difference (2091-2100 minus 2008-2017) for gain over land in (a) 40-member CESM-LE, (b) 50-member CanESM2-LE, and (c) CMIP5 multi-model ensemble (Table 3.1). (d) as in (a), (e) as in (b), and (f) as in (c) but for lag. Stippling in (a), (b), (d), (e) indicates changes that are not statistically significant at 95% confidence. Stippling in (c), (f) indicates that the multimodel mean change has the same sign as at least 75% of the models. Regions where less than 85% of the variance in an average demeaned year (averaged over 1920-2100) is explained by the annual cycle, in one or more ensemble members, have been excluded. In (f), bounding boxes numbered 1, 2, 3 correspond to the definitions of Europe, North Africa and Siberia used in this study.

3.5.1 How soon can forced changes in the annual cycle be detected?

We now address the first goal of this study: quantifying the influence of internal variability. We begin by assessing the time of emergence of forced changes in gain and lag. Following the strategy of Deser et al. (2012), we use Eq. (3.2) to compute the decade of emergence of statistically significant forced changes for two ensemble sizes: small ($N = 5$) and large ($N = 40$). Forced changes are computed as decadal-mean ensemble-mean differences for future decades relative to the past ten years (2008 – 2017). With a small ensemble, the detection of forced changes in the gain (Figure 3.4a) and lag (Figure 3.4b) is not possible until mid-21st century over most regions of the NH. Particularly striking are the continental United States and Western Russia where the detection of changes, in either the gain or lag, is not possible even by the
end of the 21st century. Changes in the annual cycle that are detectable with a small ensemble within the next 20 years occur only over a handful of regions - Europe, Eastern Canada and Eastern Siberia being the most prominent examples.

Increasing the ensemble size to 40 leads to earlier detection times for both gain (Figure 3.4c) and lag (Figure 3.4d) consistent with the expectation that a larger ensemble size would lead to stronger signal to noise ratios. Indeed, with 40 ensemble members, forced changes in the gain and lag are detectable within the next 30 years over the majority of the Northern Hemispheric land areas. However, there are also a few regions where the changes are not detectable by mid-century even with 40 ensemble members. For example, changes in gain over the Eastern United States and in lag over the Iberian Peninsula become detectable with a large ensemble only in the second half of the 21st century.

3.5.2 How many ensemble members are necessary to detect forced changes?

An alternate and useful perspective of quantifying the influence of internal variability is to assess the minimum number of ensemble members ($N_{\text{min}}$) required to detect forced signals. We compute $N_{\text{min}}$ for three future epochs in relation to 2008 - 2017: near-future (2026-2035), mid-21st century (2046-2055) and the far-future (2091-2100). The effect of internal variability is strongest in the near-future with changes in gain (Figure 3.5a) and lag (Figure 3.5d) requiring more than 40 ensemble members for detection over most regions. Moving towards 2046-2055, the forced signals strengthen leading to smaller ensemble size requirements for detection (Figures 3.5b and 3.5e). However, even by mid-21st century, there are vast regions where detection of forced signals from the noise of internal variability is not possible even with a large ensemble of 40 ensemble members. For example, detecting mid-21st century changes in gain over most of the United States, and changes in lag over Western Russia requires more than 40 ensemble members. The effect of internal variability on detection is evident even as we move to the end of the 21st century. While far-future forced changes in gain and lag are strong enough to be detectable over many regions using fewer than 10 ensemble members (Figure 3.5c and 3.5f), there are regions, for example Western Russia, where forced changes in either the gain or lag are not detectable even with 40 members.
While Figure 3.5 demonstrates the strong confounding influence internal variability exerts on simulated forced changes in the structure of the annual cycle over many regions in the NH, there are also regions in the CESM-LE where the forced signals are relatively strong compared to internal variability and therefore are easier to detect. For example, forced signals in gain and lag over Europe, Northern Africa and Siberia are detectable with as few as 3 ensemble members by mid-21st century (Figures 3.5b and 3.5e). Consistent with Figures 3.3, the regions with the largest projected changes tend to be the regions where detection with a smaller ensemble size is possible. Since the results in Figures 3.4 and 3.5 are derived from equivalent mathematical expressions (Eq. (3.2) and (3.3)), it should not be surprising that the two figures lead to similar conclusions.

### 3.5.3 Detecting forced twenty-first century seasonal cycle changes in future observational records

While it is useful to view the climate system as an ensemble of independent trajectories, recall that only one of these trajectories is actually realized in the future. Assessing the possibility of detection of forced changes in a single realization, and transferring that knowledge to the future observational record, is therefore of obvious practical interest. This however requires an approach that is slightly different from the
Figure 3.5. Minimum number of ensemble members required to detect change in gain over land at 95% confidence for the periods (a) 2026-2035, (b) 2046-2055, (c) 2091-2100, relative to the period 2008-2017. (d) as in (a), (e) as in (b), and (f) as in (c) but for lag. Grey indicates regions where even 40 members are not sufficient to detect a significant change. Excluded regions are the same as in Figure 3.3.

ensemble-based methods applied thus far (see Eq. (3.2) and (3.3)). A metric that is particularly useful here is the signal-to-noise ratio (S/N, e.g: Hawkins and Sutton (2012)) that quantifies the signals of climate change relative to a baseline noise level in a single realization. Here, we define the noise as the interannual variability of the historical (1960-2005) gain and lag. The signals are obtained by first removing the historical mean from gain and lag and linearly regressing them onto time at each grid point. The year at which S/N exceeds a ratio of one is considered the Time of Emergence (ToE) of the signal, as done in previous studies (Hawkins and Sutton 2012). The ToE can be interpreted as the year in which one can first identify a robust change in the seasonal cycle in the future observed record from internal variability.
We apply the signal-to-noise ratio approach to member 1 of the CESM-LE and show the results for gain in Figure 3.6a. While the signal does not emerge from noise over most land areas in the NH, we are able to detect anthropogenic influence in three previously identified regions (Europe, North Africa, Siberia) as well as Northern Canada, as soon as the coming decade. We further apply the procedure to the remaining ensemble members individually and display the 10th and 90th percentiles of the ToE across the members (Figures 3.6b and 3.6c) with the goal of qualitatively assessing the range of possible ToE. At the 10th percentile, changes emerge by 2025 over the three regions whereas at the 90th percentile, changes emerge by the mid-21st century. These percentiles give crude estimates of the lower and upper bounds of the ToE. This indicates a high likelihood that forced changes in the annual cycle over the three regions will be detectable even in a single realization, and thus the future observed record, by the mid-21st century. We do not include the corresponding lag figure because the internal variability swamps the forced response and so changes in lag are not detectable by the end of the century.

For the ToE estimated from the CESM-LE to be relevant to the real world, one assumption is that the variability simulated by the model is not considerably different to that found in observations. In general, the CESM-LE overestimates the interannual variability of gain over NH land (Figure 3.2c) and therefore the ToE are likely to be overestimates when compared to future observational records. It is conceivable therefore that, in the three regions which this study identifies, the changes in observations are detectable at an earlier year. Even accounting for these differences between the model and observations, it seems unlikely that changes in the annual cycle will be detectable from observations over much of the NH (grey regions in Figure 3.6) by the end of this century. In some regions, mostly over mountainous terrain, the model significantly overestimates variability (Figure 3.2) and we indicate these areas in Figure 3.6 with stippling. These are regions in which the ToE estimated from the CESM-LE is likely biased and so we cannot make robust conclusions over these regions. One should note, however, that these regions have no overlap with the three key regions identified in this study (Europe, N Africa and Siberia).

This study focuses on scenario RCP 8.5 which is used in the CESM-LE projections and is considered to be a ‘business as usual’ scenario. Figures 3.6a-3.6c indicate that forced changes in the annual
cycle in the identified regions will be detectable even in a single realization of the climate system under RCP 8.5 conditions, as soon as the coming decade. If, however, significant efforts are made to reduce future anthropogenic emissions and warming is limited to a further 1.5° or 2° increase (Mitchell et al. 2017), then RCP 4.5 would be a more realistic scenario to investigate. Figures 3.6d-3.6f show the estimated ToE in gain using the fifteen members of the CESM-ME which is run with RCP 4.5 forcing. As one would expect, the signal is larger under RCP 8.5 and so the ToE occurs much earlier. Under RCP 4.5, very few regions, except from Western Europe, exhibit any detectable change in gain by the end of this century. Although these results are not unexpected, we note that the CESM-ME only has 15 members compared to the 40
members of the CESM-LE and so there is additional uncertainty that arises from the use of a smaller sample. Overall, this shows that our findings are sensitive to the choice of emissions scenario.

3.5.4 How robust are projections of the 21st century annual cycle?

Figures 3.4-3.6 indicate the existence of land areas where forced changes in the seasonal cycle are strong compared to the noise of internal variability and are detectable even with small ensembles in the near future. We next test this hypothesis using multiple CMIP5 ensembles. Specifically, we use five CMIP5 models that each contributed at least 4 ensemble members under the RCP 8.5 scenario and quantify forced signals in each model in terms of the gain and lag differences over land. We limit our focus to averages over land areas in three regions where the forced changes are particularly strong compared to internal variability, and therefore may be detected with few ensemble members (see Figure 3.3f for region definitions): Europe (37º N - 55º N, 8º W – 27º E), Northern Africa (20º N - 36º N, 12º W - 35º E) and Siberia (60º N – 71º N, 85º E – 185º E). We assess forced changes for three future time periods: near-future (2026 - 2035), mid-21st century (2046 - 2055) and far-future (2091 - 2100) relative to 2008 – 2017. We present the estimated forced changes in Figure 3.7, along with changes in individual members to convey ensemble spread. All model ensembles project gain increases over Europe and North Africa, and decreases over Siberia, and lag increases over all three regions during the time periods under investigation, although with differing rates. Consistent with the finding from the CESM-LE that the forced signals over the three regions will be detectable with fewer than 10 ensemble members, the forced signals projected by almost all models rise above the noise of internal variability and become statistically significant by the mid-21st century. We note that these findings are insensitive to small variations in the geographical limits used to define the three regions.

Having shown that the direction of forced changes in the structure of the annual cycle over the three regions is highly robust and easily detectable across the models, it is useful to make note of the magnitude of these changes. Forced changes in lag over the three regions are rather small ranging from 2 to 6 days across the model ensembles by the end of the 21st century. In contrast, forced changes in amplitude (not
Figure 3.7. Change in gain (top row) and lag (bottom row) for area averaged regions over Europe (left column), North Africa (middle column) and Siberia (right column) over the coming century from RCP8.5 integrations. See section 3.5.4 and Figure 3.3f for how the three regions are defined. For each region, changes are shown for the two large ensembles (CESM-LE in black and CanESM2 in red) and the five small ensembles from the CMIP5 archive (blue). Each change is relative to the decadal average of the last ten years 2008-2017. Circles represent projected changes by the near future (2026-35 - present), crosses represent projected changes by the mid-century (2046-55 - present) and diamonds represent projected changes by the far future (2091-2100). The lines join the ensemble average for each set of changes. The values are spaced proportionally to time on the x-axis.

... shown) are large and are comparable to annual mean warming, reaching almost 50% of the projected mean temperature increase over Europe.

The direction of change in gain over the three regions in Figure 3.7 matches that of the historical trend in gain (Stine et al. 2009). In combination with annual mean warming, the historical trend in gain has contributed to differing warming rates of summers and winters (e.g: Balling et al. 1998, Qian and Zhang 2015). Specifically, increases in gain over Europe and Northern Africa have manifested as summers warming faster than winters, and decreases in gain over Siberia as winters warming faster than summers. The highly robust results in Figure 3.7 suggest that this observed differential in summer and winter warming rates over the three regions will continue into the 21st century.
3.6 Mechanisms

3.6.1 Energy balance model

We next turn to our second goal of understanding the mechanisms underlying future changes in the annual cycle using multiple models from the CMIP5 archive. We find it useful to leverage the simple surface energy balance model proposed by D12:

\[ C_{\text{eff}} \frac{dT}{dt} = F[t, T] \]

where \( C_{\text{eff}} \) is the effective heat capacity of the surface, \( T \) is temperature, \( F \) is net energy flux into the surface and \( t \) is time. While \( C_{\text{eff}} \), in general, exhibits seasonality due to seasonal changes in surface properties like soil moisture (Carson and Moses 1963), D12 report that results based on Eq. (3.4) are insensitive to seasonal changes in \( C_{\text{eff}} \). We therefore assume \( C_{\text{eff}} \) to be constant within a given year. It must be noted that \( C_{\text{eff}} \) is the heat capacity of a layer of material that the atmosphere can thermally influence on the annual timescale (typically the top one or two meters of soil; Carson and Moses (1963)) and not the heat capacity of some substance per unit mass or of a fixed mass of a substance.

To bring out factors affecting the annual cycle in surface temperature, we follow D12 and partition the net energy flux into the surface layer as \( F[t, T] = Q(t) - \beta T \). \( Q(t) \) represents net shortwave flux at the surface, computed as downwelling minus upwelling shortwave radiation at the surface, and is assumed to be linearly independent of \( T \). \(-\beta T \) represents the sum of longwave and turbulent heat fluxes at the surface layer. \( \beta \) is a constant and may be interpreted as a damping factor that controls the extent to which the surface longwave and turbulent heat fluxes influence the temperature response to solar forcing. Increases in \( \beta \) may be interpreted as these fluxes, in some combination, becoming more effective at maintaining the surface temperature at equilibrium, and vice versa for decreases in \( \beta \).

Diagnostic relationships between the gain and lag of surface temperature and the controlling parameters \( C_{\text{eff}}, \beta \) and \( Q \) may be derived by applying a Fourier transform to Eq. (3.4):

\[ \lambda_T = \lambda_Q + \arctan \left( \frac{\omega C_{\text{eff}}}{\beta} \right) \]

Eq. (3.5)
\[ G_T = \frac{G_Q}{\sqrt{\beta^2 + \omega^2 c_{\text{eff}}^2}} \]  

Eq. (3.6)

where \( G_Q \) and \( \lambda_Q \) are the gain and lag of \( Q \) calculated using the methods in section 3.3.1 and \( \omega = 2\pi \text{ yr}^{-1} \).

In practice, \( C_{\text{eff}} \) and \( \beta \) can be obtained by inverting Eq. (3.5) and Eq. (3.6):

\[ C_{\text{eff}} = \frac{\sin(\lambda_T - \lambda_Q)}{\omega \left( \frac{G_T}{G_Q} \right)} \]  

Eq. (3.7)

\[ \beta = \frac{\cos(\lambda_T - \lambda_Q)}{\frac{G_T}{G_Q}} \]  

Eq. (3.8)

Eq. (3.5) and Eq. (3.6) delineate the relationship between the gain and lag of the annual cycle of surface temperature, and the physical parameters that control them. In particular, the equations show that \( C_{\text{eff}} \) has a direct relationship with \( \lambda_T \) and an inverse relationship with \( G_T \). On the other hand, the equations reveal an inverse relationship of \( \beta \) with both \( \lambda_T \) and \( G_T \). Since \( \beta \) parameterizes the combined influence of longwave and turbulent heat fluxes, it is not straightforward to physically interpret the effect of \( \beta \) on the annual cycle. The effect of \( C_{\text{eff}} \), on the other hand, can be understood more readily: a larger effective heat capacity is expected to result in a smaller and more delayed temperature response to solar forcing. As a simple check, we plot the historical (1960-2005) gain and lag for NH land in 22 CMIP5 models, computed using the definitions in section 3.3.1, against \( C_{\text{eff}} \) (Eq. (3.7)) in Figure 3.12 in the Appendix 1. In line with physical intuition, \( C_{\text{eff}} \) exhibits a strong negative relationship \( (r = -0.52, p = 0.01) \) with gain (Figure 3.8a) and a strong positive relationship \( (r = 0.57, p = 0.01) \) with lag (Figure 3.8b), with most models (20 out of 22) underestimating \( C_{\text{eff}} \) compared to observations.

### 3.6.2 Application of energy balanced model to forced changes

We use Eq. (3.5) – Eq. (3.8) to understand future changes in the annual cycle over the three regions where we earlier identified highly robust changes across a range of ensembles (Figure 3.7). In Figure 3.9, we plot \( C_{\text{eff}} \) and \( \beta \) (computed using Eq. (3.7) and Eq. (3.8)) as a function of time for the three regions. Although there is considerable intermodel spread in all regions, the most pronounced changes in \( C_{\text{eff}} \) and
\( \beta \) occur over Siberia where, in the multimodel mean, \( C_{eff} \) nearly doubles and \( \beta \) increases by about 25% relative to the early 20\textsuperscript{th} century. Eq. (3.6) suggests that increases in \( C_{eff} \) and \( \beta \) should act together to reduce gain. Consistent with this, we previously noted a large projected reduction in gain over Siberia (Figure 3.7). In contrast, Eq. (3.5) suggests that increases in \( C_{eff} \) should act to increase lag while increases in \( \beta \) should have the opposite effect. Despite the 25% increase in \( \beta \) and a 20% decrease in \( \lambda_Q \) (not shown) that contribute to reduce lag, the larger 90% increase in \( C_{eff} \) has the greater influence leading to an increase in lag over Siberia (Figure 3.7).

**Table 3.1.** CMIP5 historical and RCP 8.5 data used in this study.

<table>
<thead>
<tr>
<th>Model</th>
<th>Ensemble member</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACCESS1-0</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>ACCESS1-3</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>bcc-csm1-1</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>bcc-csm1-1-m</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>BNU-ESM</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>CanESM2</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>CCSM4</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>CESM1-BGC</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>CESM1-CAM5</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>FGOALS-g2</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>GFDL-ESM2G</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>GFDL-ESM2M</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>HadGEM2-CC</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>inmcm4</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>MIROC5</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>MIROC-ESM-CHEM</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>NorESM1-M</td>
<td>r1i1p1</td>
</tr>
<tr>
<td>NorESM1-ME</td>
<td>r1i1p1</td>
</tr>
</tbody>
</table>
Over Europe and North Africa, changes in $C_{\text{eff}}$ and $\beta$ are smaller and less robust than those over Siberia. $\beta$ decreases by 12% over Europe and 15% over North Africa, while changes in $C_{\text{eff}}$ are even smaller: $C_{\text{eff}}$ decreases by 4% over Europe and 8% over North Africa. Ascertaining the combined influence of these small changes on changes in the gain and lag of the annual cycle is not straightforward since fractional changes in $\lambda Q$ and $G Q$, while small, are of magnitudes comparable to the fractional changes in $C_{\text{eff}}$ and $\beta$ over these regions, and their influence as such needs to be taken into consideration (see Eq. (3.5), Eq. (3.6)). We address this problem next by explicitly partitioning changes in gain and lag over the three regions into contributions arising from changes in the four controlling parameters $C_{\text{eff}}, \beta, G Q$ and $\lambda Q$.

The partitioning is achieved by linearizing Eq. (3.5) and Eq. (3.6):

$$\Delta \lambda_T = \Delta \lambda_Q + \frac{R}{1+R^2} \frac{\Delta C_{\text{eff}}}{C_{\text{eff}}} - \frac{R}{1+R^2} \frac{\Delta \beta}{\beta}$$  \hspace{1cm} \text{Eq. (3.9)}

$$\Delta G_T = \frac{G_Q}{G_Q} \Delta G_Q - G_T \frac{R^2}{1+R^2} \frac{\Delta C_{\text{eff}}}{C_{\text{eff}}} - G_T \frac{1}{1+R^2} \frac{\Delta \beta}{\beta}$$  \hspace{1cm} \text{Eq. (3.10)}
where $R = \frac{\omega C_{\text{eff}}}{\beta}$. The first terms in Eq. (3.9) and Eq. (3.10) represent contributions from changes in the annual harmonic of $Q$, the second terms, from changes in $C_{\text{eff}}$, and the third terms, from changes in $\beta$. This linearization was found to provide a good approximation; differences between the sum of the contributions and the full changes in the gain and lag were found to be small. Using Eq. (3.9) and Eq. (3.10), we partition future changes in the annual cycle in the three regions on an individual model basis and plot the results in Figure 3.9. We also list the multimodel mean values in Table 3.2. While there is considerable intermodel spread in the magnitude of future changes in gain and lag, the direction of change is more or less the same across the models in all three regions and is consistent with the results from Figure 3.7. Changes in $\beta$ have the largest influence on changes in gain and lag in the multimodel mean except over Siberia where increases in $C_{\text{eff}}$ dominate increases in lag. Interestingly, despite the proximity of the two regions, the gain increases over Europe and North Africa arise in different ways. $\beta$ and $C_{\text{eff}}$ act in opposition over North Africa with $\beta$ dominating and resulting in an increase in gain while they both contribute to an increase in gain over Europe. It is also seen that $G_Q$ has a considerable influence on gain, albeit smaller than that of $\beta$. In contrast, changes in $\lambda_Q$ affect lag to a negligible degree. Overall, Figure 3.9 suggests that $\beta$ is the most important parameter for understanding the highly robust future changes in the annual cycle revealed in Figure 3.7, except for the change in phase over Siberia.

It has previously been suggested that changes in seasonality over the NH are most strongly influenced by changes in atmospheric circulation (Stine and Huybers 2012). We note that atmospheric circulation changes affect the annual cycle primarily by impacting surface fluxes and therefore the effect of these circulation changes are implicitly captured by changes in $\beta$. It is important to acknowledge, however, that changes in atmospheric circulation would predict the opposite response in gain over Europe (Stine and Huybers 2012) and it therefore seems likely that this is not the only factor causing these changes.

Given the abstract nature of the definitions of $C_{\text{eff}}$ and $\beta$, how should our results from the energy balance model be interpreted physically? If we look at the projected changes in Siberia, we hypothesize that the increase in $\beta$ is related to the loss of Arctic sea ice northward of this region which allows for more
Figure 3.9. Changes in gain (left column) and lag (right column) for area averaged regions over Europe (top row), North Africa (middle row) and Siberia (bottom row) partitioned into contributions from changes in effective heat capacity (blue), $\beta$ (red) and net solar insolation at the surface (yellow), across 22 CMIP5 models (see Table 3.1 for list of models). Black dots represent sum of contributions. Changes are calculated for the far-future (2091-2100) relative to the present (2008-2017).

Heat to be fluxed from the newly exposed ocean. It has been shown that, although Arctic sea ice loss peaks in September, the resultant heat flux to the atmosphere is maximum in the winter (e.g. see Figure 2 of Sun et al. (2015), and Figure 2 of England et al. (2018)) which would lead to a reduction in the gain. The energy balance model allows us to weigh the contribution of different processes. For example, this suggests that the possible effect of sea ice loss is more far more important than the effect of the increase in $C_{\text{eff}}$ over Siberia (Figure 3.9), which could be a result of increased soil moisture from snow melt, and changes in $Q$ arising from changes in albedo due to a reduction in the snow season length. Another example that demonstrates the use of the energy balance model is the different signs of the contributions of $Q$ over Europe and North Africa (Figure 3.9). The results clearly show that changes in these two regions are not governed by identical processes; we are unsure of the reason behind this, but we think it could be related to changes in cloud cover (e.g. Tselioudis et al. 2016).
To explore the influence of internal variability on the physical parameters, we next partition future changes in the annual cycle within the CESM-LE and document the results in Figure 3.10. The magnitude of the ensemble mean change in gain and lag in the three regions is comparable to that of the CMIP5 multimodel mean (Figure 3.10). While internal variability leads to spread in the magnitude of changes across the ensemble members, the direction of the changes is, in general, consistent across the members and matches that in Figure 3.10. It is interesting to note that the spread of the contributions across the ensemble members, while small compared to the ensemble mean contributions (Table 3.3), is roughly half that of the CMIP5 multimodel spread (compare standard deviations in Tables 3.2 and 3.3). In other words, to the extent that the CESM-LE represents the variability of the real climate system, internal variability is an important consideration not only for detection but also for understanding the relative roles of the factors that contribute to future changes in the annual cycle.

3.6.3 Application of energy balance model to historical biases

Motivated by the utility of the energy balance model in understanding future changes in the annual cycle, we finally apply the model to explore biases in the simulation of the historical (1960 - 2005) annual cycle by the CMIP5 ensemble. Specifically, we use Eq. (3.9) and Eq. (3.10) to partition CMIP5 model biases in the simulation of the historical annual cycle with respect to BEST observations into contributions from biases in the controlling parameters \(C_{\text{eff}}, \beta, G_Q\) and \(\lambda_Q\). We present these results in Figure 3.11. Despite spread in their magnitude, the sign of the contributions of the biases is largely consistent across the models, suggesting a common origin to the biases in the models. In the multi-model mean, gain is slightly overestimated over Europe and North Africa while it is underestimated over Siberia. Lag on the other hand is underestimated in all three regions. The total multi-model mean bias in gain in the three regions, and in lag over Siberia, are relatively small. It is seen that these small changes are in fact the result of cancellations between large and opposing contributions from biases in the controlling parameters.

It is important to note that biases in the controlling parameters are in many cases larger than future changes in the parameters (compare Figure 3.11 with Figure 3.9), which could introduce uncertainty to the
3.7 Summary and discussion

Consistent with previous studies that documented the influence of internal variability on observed trends in seasonality (e.g: Stine and Huybers 2012), our results show that future projections of the annual cycle will also be strongly modulated by internal variability. In particular, our study suggests that the detection of systematic changes in the annual cycle due to increasing greenhouse gases will be challenging
Figure 3.11. Biases in gain (left column) and lag (right column) for area averaged regions over Europe (top row), North Africa (middle row) and Siberia (bottom row) partitioned into contributions from changes in effective heat capacity (blue), $\beta$ (red) and net solar insolation at the surface (yellow), across 22 CMIP5 models (see Table 3.1 for list of models) and member 1 of the CESM-LE (indicated by the label “LE” on the x axes). Black dots represent sum of contributions. Biases are calculated as 46-year (1960-2005) mean differences between models and BEST observations.

from the observational record, and even with small ensembles, over many NH land regions in the coming decades.

Yet, despite the noise from internal variability, our investigation did find regional exceptions where the forced annual cycle signals are relatively strong compared to internal variability. Indeed, we found regions where changes in the seasonal cycle are detectable with ensembles consisting of ~ 5 members by the mid-21st century. Specifically, our multimodel analysis of annual cycle projections over three such regions (Europe, Northern Africa, Siberia) leveraging five CMIP5 ensembles revealed a strong consensus across the model ensembles on the direction of change as well as the strength of the forced response in relation to internal variability (Figure 3.7). The direction of change over these regions may therefore be considered robust with a high degree of confidence regardless of the observation that the rate of change varies to some extent across models.
While a comprehensive investigation is beyond the scope of the study, it should be noted that our results could be sensitive to our choice of comparing decadal epoch differences. The effect of internal variability will likely be more pronounced and consequently ensemble size requirements will be greater for detecting forced changes at the interannual timescale. Conversely, choosing a longer averaging period, for example twenty years, would lead to a reduction in temporal variance and consequently, detection would require less ensemble members. Additionally, we note that fitting a linear trend is a more robust approach than comparing epoch differences, however we chose to examine decadal averages so that we did not need to assume linearity in time (Barnes and Barnes 2015). Our choice of decadal averaging was motivated by our goal to investigate changes over a range of future time periods (near-, medium- and far- future).

Likewise, averaging across spatial domains, in general, results in a reduction of variability which may help to discern a signal. Qian and Zhang (2015) are able to attribute a reduction in the seasonal cycle amplitude over the observational period to increased anthropogenic emissions, most clearly when averaged over all NH land. Averaging over larger scales, however, can also mask the climate change signal; we have identified competing responses in gain in Siberia and Europe which would counteract each other. The regions we have chosen to investigate further are identified because they contain strong uniform signals. Additionally, we also note that spatial resolution could also play an important role. For example, it is likely that the biases which are found over mountainous regions (e.g: Figures 3.2b and 3.2c) arise because the resolution of the models smooth out the effect of the topographic features notwithstanding possible defects in surface parameterization (Rhoades et al. 2016). An alternative approach to that pursued in this study which could address the concerns about model biases and resolution is to estimate internal variability from the observational record on temporal and spatial scales of interest (e.g: Thompson et al. 2015, McKinnon et al. 2017).

We finally list two limitations of this study. First, we found large and persistent CMIP5 model biases in the physical parameters controlling the historical annual cycle. As mentioned earlier, how these biases imprint upon future projections is not clear to us and is worthy of further investigation. Second, it is important to note that the time of emergence of climate change signals in a climate model ensemble is a
function of the variability simulated by the ensemble (e.g. McKinnon et al. 2017). Specifically, variability in the ensemble that is higher than that present in the real climate system would lead to a later detection while variability that is lower would lead to an earlier detection. An assessment of how representative variability in the annual cycle simulated by the CESM-LE is of the variability in the observed annual cycle is therefore warranted but is beyond the scope of this study. Regardless, this paper underscores the importance of internal variability for future projections of the annual cycle. Further, our study alerts policymakers and stakeholders in the three regions to the remarkable robustness of changes in the annual cycle, and suggests that observational studies aimed at detecting forced changes in the annual cycle are best served by focusing on these regions.
Appendix I: Supplementary figures and tables

Figure 3.12. 46-year (1960-2005) mean (a) gain and (b) lag as a function of effective heat capacity for area averaged NH land in 22 CMIP5 models (black; see Table 3.1 for list of models), member 1 of the CESM-LE (green) and BEST observations (blue).
Table 3.2. CMIP5 multimodel mean contributions to future changes in the annual cycle of surface temperature. Contributions to changes in gain ($G_T$) in °C/(kW/m$^2$) and lag ($\lambda_T$) in days. Standard deviation given in parentheses. Individual member values can be seen in Figure 3.10.

<table>
<thead>
<tr>
<th></th>
<th>$C_{eff}$</th>
<th>$\beta$</th>
<th>$Q$</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G_T$</td>
<td>0.14</td>
<td>2.75</td>
<td>2.63</td>
<td>5.53</td>
</tr>
<tr>
<td></td>
<td>(0.62)</td>
<td>(1.88)</td>
<td>(1.04)</td>
<td>(2.64)</td>
</tr>
<tr>
<td>$\lambda_T$</td>
<td>-0.38</td>
<td>1.62</td>
<td>0.19</td>
<td>1.42</td>
</tr>
<tr>
<td></td>
<td>(1.30)</td>
<td>(1.04)</td>
<td>(0.96)</td>
<td>(1.79)</td>
</tr>
<tr>
<td>$G_T$</td>
<td>0.93</td>
<td>8.56</td>
<td>-2.20</td>
<td>7.30</td>
</tr>
<tr>
<td></td>
<td>(1.13)</td>
<td>(3.49)</td>
<td>(2.53)</td>
<td>(2.34)</td>
</tr>
<tr>
<td>$\lambda_T$</td>
<td>-1.21</td>
<td>2.18</td>
<td>0.83</td>
<td>1.81</td>
</tr>
<tr>
<td></td>
<td>(1.46)</td>
<td>(0.85)</td>
<td>(1.02)</td>
<td>(1.20)</td>
</tr>
<tr>
<td></td>
<td>(2.14)</td>
<td>(5.79)</td>
<td>(7.60)</td>
<td>(5.28)</td>
</tr>
<tr>
<td>$\lambda_T$</td>
<td>8.13</td>
<td>-3.11</td>
<td>-1.81</td>
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<tr>
<td></td>
<td>(3.31)</td>
<td>(1.61)</td>
<td>(2.77)</td>
<td>(2.57)</td>
</tr>
</tbody>
</table>

Table 3.3. CESM-LE ensemble mean contributions to future changes in the annual cycle of surface temperature. Contributions to changes in gain ($G_T$) in °C/(kW/m$^2$) and lag ($\lambda_T$) in days. Standard deviation given in parentheses. Individual member values can be seen in Figure 3.11.

<table>
<thead>
<tr>
<th></th>
<th>$C_{eff}$</th>
<th>$\beta$</th>
<th>$Q$</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Europe</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$G_T$</td>
<td>-0.16</td>
<td>3.01</td>
<td>5.08</td>
<td>7.93</td>
</tr>
<tr>
<td></td>
<td>(0.45)</td>
<td>(0.94)</td>
<td>(0.86)</td>
<td>(1.11)</td>
</tr>
<tr>
<td>$\lambda_T$</td>
<td>0.37</td>
<td>1.64</td>
<td>-0.69</td>
<td>1.32</td>
</tr>
<tr>
<td></td>
<td>(1.01)</td>
<td>(0.51)</td>
<td>(0.60)</td>
<td>(1.24)</td>
</tr>
</tbody>
</table>
| North Africa
| $G_T$ | 0.59      | 7.02     | -3.50 | 4.11    |
|       | (0.65)    | (1.87)   | (2.05)| (1.45)  |
| $\lambda_T$ | -0.75    | 1.41     | 1.36  | 2.02    |
|       | (0.82)    | (0.37)   | (0.70)| (0.62)  |
| Siberia |           |          |       |         |
| $G_T$ | -3.14     | -13.79   | 6.48  | -10.45  |
|       | (0.38)    | (3.02)   | (1.66)| (2.32)  |
| $\lambda_T$ | 5.62     | -1.93    | -0.89 | 2.80    |
|       | (0.81)    | (0.45)   | (0.58)| (1.05)  |
Chapter 4

An ensemble covariance framework for quantifying forced climate variability and its time of emergence

4.1 Abstract

Climate variability and its response to increasing greenhouse gases are important considerations for impacts and adaptation. Modeling studies commonly assess projected changes in variability in terms of changes in the variance of climate variables. Despite the distant and impactful covariations that climate variables can exhibit, the covariance response has received much less attention. Here, a novel ensemble framework is developed that facilitates a unified assessment of the response of the regional variances and covariances of a climate variable to imposed external forcings and their time of emergence from an unforced climate state.

Illustrating the framework, the response of variability and covariability of land and ocean temperatures is assessed in the Community Earth System Model Large Ensemble under historical and RCP 8.5 forcing. The results reveal that land temperature variance emerges from its preindustrial state in the 1950s and, by the end of the 21st century, grows to 1.5 times its preindustrial level. Demonstrating the importance of covariances for variability projections, the covariance between land and ocean temperature is considerably enhanced by 2100, reaching 1.4 times its preindustrial estimate. The framework is also applied to assess changes in monthly temperature variability associated with the Arctic region and the Northern Hemisphere midlatitudes. Consistent with previous studies and coinciding with sea ice loss, Arctic temperature variance decreases in most months, emerging from its preindustrial state in the late 20th century. Overall, these results demonstrate the utility of the framework in enabling a comprehensive assessment of variability and its response to external climate forcings.
4.2 Introduction

The Earth’s climate is changing rapidly in response to anthropogenic radiative forcing (IPCC 2013). The response manifests as changes in not only the mean state of the climate but also in the variability about the mean state. While the potential consequences of mean state changes have long been recognized (Houghton et al. 1990), variability changes are also important (e.g: Katz and Brown 1992, Addo-Bediako et al. 2000, Wheeler et al. 2000, Schar et al. 2004, Porter and Semenov 2005). Changes in interannual (and longer time-scale) variability are of particular interest because of the protracted nature of the associated climate anomalies (Rajagopalan and Lall 1998; Meehl 2004). The occurrence of an extreme anomaly that is of an extended duration (a month, a season or longer) can translate into catastrophic outcomes. For example, the 2003 extreme European summer, which was attributed to an increased temperature variability regime in combination with mean climate warming (Schar et al. 2004), claimed more than 52000 lives (Larsen 2006). The low rainfall and unprecedented heat further resulted in crop failures, reduced plant respiration and growth, and consequently a large positive flux of CO$_2$ into the atmosphere (Ciais et al. 2005).

Recognizing such severe societal and ecological effects of extended climate anomalies, a natural question to ask is: how will interannual variability change in a warmer climate? Using climate models, previous work has addressed this question for various climate variables at global (e.g.: Räisänen 2001, Stouffer and Wetherald 2007; Boer 2009; Wetherald 2009) and regional (e.g.: Schar et al. 2004; Scherrer et al. 2008; Fischer et al. 2012) scales under different anthropogenic forcing scenarios. While these studies have uncovered robust variability changes that can be expected with a high degree of confidence in a warmer climate (e.g: Huntingford et al. 2013; Holmes et al. 2016; Yettella and England 2018) and have improved our understanding of the climate system, they leave two key areas unexplored that are of specific interest to this paper.

First, existing model studies on interannual variability have largely focused on the influence of external climate forcing on the variance. On interannual (and longer) timescales, climate variables can exhibit covariances across distant locations through numerous well-known circulation patterns (e.g.:...
Bjerknes 1969; Wallace and Gutzler 1981; Simmons et al. 1983; Trenberth and Shea 1987; Thompson and Wallace 1998) as well as potentially undiscovered patterns in the coupled climate system. These covariations often are associated with enormous impacts on a global scale (IPCC 2013). Therefore, interannual variability is in general a problem of not only the variances but also the covariances associated with interacting regions. While the joint variability associated with a system of interacting regions has alternatively been investigated in terms of empirical orthogonal functions or variants thereof (Jolliffe 2002), these techniques are not designed for the goal of physical interpretation (Hannachi et al. 2001). The variances and covariances on the other hand are directly physically interpretable. Despite its obvious physical relevance and importance, only a few studies have considered the covariance response (e.g: Leeds et al. 2015; LaJoie and DelSole 2016; Poppick et al. 2016) to anthropogenic forcing.

Recognizing the importance of covariance to interannual variability naturally leads us to the second area of our study: the time of emergence of forced covariance signals from an unforced climate. Changes in variability that are of considerable magnitude relative to the variability that might naturally occur in an unforced climate can translate into major impacts (e.g.: Kunkel et al. 1999; Fischer et al. 2007; Robine et al. 2008). As such, assessing the time of emergence of forced variability is important for adaptation and mitigation planning. It is also an important step in the attribution of variability changes to a specific cause, for example, anthropogenic forcing (Bindoff et al. 2013). While the emergence of forced mean state and variance signals has received a lot of attention (e.g.: Giorgi and Bi 2009; Deser et al. 2012; Hawkins and Sutton 2012; Mora et al. 2013; although also see Hawkins et al. (2014); Thompson et al. 2015; Yettella and Kay 2016; LaJoie and DelSole 2016), fewer studies have looked at the time of emergence of covariance signals (e.g.: Poppick et al. 2016).

Estimating forced variability statistics using a single model simulation is challenging. Variability statistics under rapidly changing forcing can evolve in time periods shorter than those that are required for their accurate estimation with a single model realization. That is, the conventional idea of computing variability statistics from a long model simulation (Leith 1978) is of limited use in a transient climate change setting and one necessarily has to resort to using ensembles of model simulations. Initial condition climate
model ensembles are particularly useful here (Collins and Allen 2002; Kay et al. 2015). The members of such an ensemble are simulated under the same external forcing with small perturbations introduced at the start of their integrations. After the memory of the initial conditions is lost, each member evolves independently (Lorenz 1963; Deser et al. 2012). As such, the members of such an ensemble serve as independent samples for the computation of forced statistics.

In this paper, we develop a framework for analyzing an initial condition ensemble under transient forcing that facilitates a unified assessment of the regional variances and covariances and their contributions to global variance. We accomplish three specific goals with the framework. First, we decompose global variance into subjectively chosen regional variance and covariance components. Such a decomposition is useful in understanding the contributions of the regional variances and covariances to global variance. Second, we offer a simple method for calculating the evolving regional variances and covariances along with their sampling uncertainties in climates undergoing transient forcing using initial condition climate model ensembles. Third, we address the time of emergence of forced variability statistics. Specifically, we derive the estimates of the regional variances and covariances along with their sampling uncertainties in long unforced control simulations. By comparing the forced variability statistics with their unforced estimates in the presence of sampling uncertainties, the time of emergence can be quantified.

After developing the framework, we demonstrate its application in a state-of-the-art initial condition ensemble: the Community Earth System Model Large Ensemble (CESM-LE, Kay et al. 2015). The CESM-LE consists of multiple realizations of a single model (CESM-CAM5, Hurrell et al. 2013b) under historical and RCP 8.5 (Meinshausen et al. 2011) forcing scenarios while a companion multcentury preindustrial control run provides a stationary climate for the derivation of baseline statistics. Leveraging the CESM-LE and the preindustrial run, we explore the forced evolution and emergence of the surface temperature variability statistics associated with two distinct regional decompositions. The first decomposition consists of two regions: the land and the ocean. The second decomposition consists of three regions: the Arctic (70° N - 90° N), the Northern Hemisphere midlatitudes (30° N - 70° N, midlatitudes hereafter) and the rest-of-the-globe (all regions on the globe except the Arctic and Northern midlatitudes).
We organize the paper as follows: In Sect. 4.3, we detail our methods and describe the model. In Sect. 4.4, we utilize the framework to explore the variability statistics in the two decompositions of simulated global interannual variance. As we will show, our results highlight the importance of regional covariances to global interannual variance. Finally, in Sect. 4.5, we offer a summary and concluding remarks.

4.3 Methods and data

4.3.1 Decomposition of global variance into regional variance and covariance components

A key goal of the framework is identifying the contributions of regional variances and covariances to global variance. We achieve this by a simple diagnostic relationship between global variance and regional variances and covariances, which we develop in this section. While the decomposition is applicable to any climate variable of interest and any timescale, we apply the framework to interannual surface temperature variability.

Let $S = \{r_1, r_2, r_3, \ldots, r_n\}$ be a system of $n$ non-overlapping regions, with the $i^{th}$ region denoted by $r_i$, which together cover the entire surface of the globe. Let $T_r$ represent the surface temperature averaged over a region $r$ and over a period of interest, e.g.: season, month, year. The globally averaged temperature $T_g$ can be expressed as an area-weighted sum of temperatures averaged over the $n$ regions:

$$T_g = \sum_{i=1}^{n} f_i T_{r_i} \quad \text{Eq. (4.1)}$$

where $f_i = \frac{A_{r_i}}{A_g}, A_{r_i}$ denotes the area of region $r_i$, and $A_g$ is the area of the globe. The variance of $T_g$ can be expressed in terms of the covariance matrix $C$:

$$\sigma_{T_g}^2 = \bar{f}^T C \bar{f}, \quad \text{Eq. (4.2)}$$

$$C = \begin{bmatrix}
\sigma_{T_{r_1}}^2 & \text{cov}(T_{r_2}, T_{r_1}) & \ldots & \text{cov}(T_{r_n}, T_{r_1}) \\
\text{cov}(T_{r_1}, T_{r_2}) & \sigma_{T_{r_2}}^2 & \ldots & \text{cov}(T_{r_n}, T_{r_2}) \\
\vdots & \vdots & \ddots & \vdots \\
\text{cov}(T_{r_1}, T_{r_n}) & \text{cov}(T_{r_2}, T_{r_n}) & \ldots & \sigma_{T_{r_n}}^2
\end{bmatrix}, \quad \text{Eq. (4.3)}$$
\[ \vec{f} = \begin{bmatrix} f_1 \\ \vdots \\ f_n \end{bmatrix} \]

Eq. (4.4)

where \( T \) denotes transpose and \( \text{cov} \) denotes covariance. Grouping terms arising from the variances and covariances separately, Eq. (4.2) can be written as the following “decomposition”:

\[
\sigma^2_{\tau_g} = \sum_{i=1}^{n} f_i^2 \sigma^2_{\tau_{r_i}} + \sum_{i=2}^{n} \sum_{j=1}^{i-1} 2f_i f_j \text{cov} \left( \tau_{r_i}, \tau_{r_j} \right).
\]

Eq. (4.5)

We note from Eq. (4.5) that the decomposition of \( \sigma^2_{\tau_g} \) yields a total of \( n(n+1)/2 \) independent area-weighted components: \( n \) variance components of the form \( f_i^2 \sigma^2_{\tau_{r_i}} \), and \( n(n-1)/2 \) covariance components of the form \( 2f_i f_j \text{cov} \left( \tau_{r_i}, \tau_{r_j} \right) \). By expressing the regional variance and covariance components as fractions of \( \sigma^2_{\tau_g} \), the contribution of regional variances and covariances to global variance can be assessed in a straightforward manner.

4.3.2 Forced evolution and time of emergence of variability statistics

4.3.2.1 Estimation of forced variability components in initial condition ensembles

To estimate the forced components in an \( M \)-member initial condition ensemble undergoing transient forcing, we begin with the ensemble estimates of the variances and covariances at each year \( t \). Let \( \tau^t_r \) represent the temperature averaged over region \( r \) and over a period of interest during year \( t \). Some examples of potential periods of interest are monthly means, seasonal means, and annual means. Unbiased ensemble estimates of the mean \( \tilde{\tau}^t_r \) and ensemble variance \( \hat{\sigma}^t_{\tau_r} \) of \( \tau^t_r \) are:

\[
\tau^t_r = \frac{1}{M} \sum_{\alpha=1}^{M} \tau^{t,\alpha}_r \\
\hat{\sigma}^t_{\tau_r} = \frac{1}{M-1} \sum_{\alpha=1}^{M} (\tau^{t,\alpha}_r - \tilde{\tau}^t_r)^2 
\]

Eq. (4.6)

Eq. (4.7)

where \( \tau^{t,\alpha}_r \) denotes the \( \alpha \)th ensemble realization, and \( \tau^{t,\alpha}_r - \tilde{\tau}^t_r \) is the residual obtained by subtracting the ensemble mean from the \( \alpha \)th ensemble realization. Note that the residuals represent a slightly damped realization of internal variability (LaJoie and DelSole 2016). Both the overbar (e.g: \( \tilde{\tau}^t_r \)) and the hat symbols
(e.g: $\hat{\sigma}^2_{T_r}$) denote unbiased estimates. The unbiased ensemble covariance associated with regions $r$ and $s$ is:

$$c\overline{\nu}(T_r^t, T_s^t) = \frac{1}{M-1} \sum_{\alpha=1}^{M} (\bar{T}_r^t - T_r^t)(\bar{T}_s^t - T_s^t). \tag{4.8}$$

Theoretically, in the limit of an infinite number of ensemble members, the unbiased estimates presented above converge to the population variances and covariances. In practice however, the number of ensemble members that can be generated is limited by computational expense and therefore is finite. Our results from the CESM-LE suggest that, even with large climate model ensembles consisting of as many as 40 ensemble members, the ensemble estimates of the second moments (Eq. (4.7), Eq. (4.8)) and as a consequence, of the components, are in general very noisy. That is, the estimates in practice are associated with large sampling uncertainty.

The sampling uncertainty in the noisy ensemble estimates can be reduced and more precise estimates of the components can be obtained by fitting a statistical model in time. In the case of a linear time dependence, a simple linear fit across the time period under investigation can serve as a reasonable statistical model. However, as will be clear from the results, the time dependence of climate variability under transient climate forcing can be very non-linear. Therefore, to obtain more precise estimates in the general setting of non-linear time dependence, we use a smoothing approach. For each year, we apply a thirty-one-year window centered on that year. Our choice of the window length is motivated by the World Meteorological Organization (WMO) approach of calculating climatic normals over a thirty-year period. As expected, in the case of a linear time dependence of climate variability, the smoothing approach yields results that are very close to the estimates from ordinary linear regression.

Sensitivity tests (not shown) revealed that the results were virtually identical for window lengths ranging from 25 to 45 years. We estimate the value of the forced components at year $t$ by averaging across the window. This results in smoothed estimates of the forced components:

$$< f_i^2 \hat{\sigma}^2_{T_{r_i}} > = \frac{1}{31} \sum_{k=t-15}^{k=t+15} 2 f_i f_j c\overline{\nu} \left( T_{r_i}^t, T_{r_j}^t \right), \tag{4.9}$$

$$< 2 f_i f_j c\overline{\nu} \left( T_{r_i}^t, T_{r_j}^t \right) > = \frac{1}{31} \sum_{k=t-15}^{k=t+15} 2 f_i f_j c\overline{\nu} \left( T_{r_i}^k, T_{r_j}^k \right). \tag{4.10}$$

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and a smoothed version of the decomposition:

\[
\langle \sigma^2_{T_g} \rangle = \sum_{i=1}^{n} f_i^2 < \sigma^2_{T_{ri}} > + \sum_{i=2}^{n} \Sigma_{j=1}^{i-1} 2f_i f_j < c \bar{\sigma}v(T_{ri}, T_{si}) >.
\]

Eq. (4.11)

where the angle brackets \(< >\) denote smoothing over time. The forced evolution of the variances and covariances is assessed in terms of the smoothed estimates of the components presented above. Likewise, the contribution of the variances and covariances to global variability is assessed as ratios of the smoothed components relative to global variability \(< \sigma^2_{T_g} \rangle\).

### 4.3.2.2 Estimation of variability components in unforced simulations

Assessing time of emergence entails detecting significant differences between forced and unforced variability. Having developed a simple method for estimating forced variability statistics in transient climate simulations, we here present the estimation of variability statistics in unforced control simulations.

Following Schneider and Griffies (1999), the unforced components can be estimated from a single \(N\) year control simulation:

\[
f_i^2 \sigma^2_{T_{ri}}^{clim} = \frac{1}{N-1} \Sigma_{l=1}^{N} (T_{ri}^l - \bar{T}_{ri}^{clim})^2,
\]

Eq. (4.12)

\[
2f_i f_j c \bar{\sigma}v^{clim}(T_{ri}, T_{rj}) = \frac{2f_i f_j}{N-1} \Sigma_{l=1}^{N} (T_{ri}^l - \bar{T}_{ri}^{clim})(T_{rj}^l - \bar{T}_{rj}^{clim}),
\]

Eq. (4.13)

and

\[
\bar{T}_{r}^{clim} = \frac{1}{N} \Sigma_{l=1}^{N} T_{r}^l
\]

Eq. (4.14)

where the superscript \(clim\) refers to climatological statistics of an unforced climate.

### 4.3.2.3 Time of emergence of forced variability components

Due to the finite number of ensemble members and the finite length of control simulations, estimates of the forced variability necessarily contain sampling uncertainties. Quantifying time of emergence is a problem of the detection of significant differences between the forced and unforced variability statistics in the presence of sampling uncertainty.
Two difficulties arise when attempting to estimate the sampling uncertainties in unforced variability statistics. First, the underlying probability distributions of climatic variables are not always known which precludes analytical estimation of the uncertainties. Second, climatic time series, in general, exhibit auto-correlation. Auto-correlation complicates the estimation of sampling uncertainties in the second moments even when the underlying distributions are known.

A statistical resampling technique that facilitates the estimation of sampling uncertainties in the presence of serial dependence, without requiring the knowledge of the underlying distributions, is the moving block bootstrap (Wilks 2011). In this technique, multiple realizations of the control time series are generated by randomly selecting with replacement and splicing contiguous blocks of data in time such that the resulting realizations are of the same length as the original time series. Sample bootstrap estimates of the unforced variability statistics are calculated for each realization and the sampling uncertainty is quantified as the spread across the distribution of the bootstrap estimates.

Application of the moving block bootstrap relies on a few critical assumptions: (1) the climate statistics are stationary in time, (2) the temporal dependence of climatic variables is preserved within blocks, (3) there is relatively weak dependence between blocks and, (4) the spread across the bootstrap estimates sufficiently captures the variability associated with the stochastic process that generated the data. The assumption of stationarity is generally well satisfied in control simulations that have equilibrated under constant forcing. The other assumptions are satisfied by choosing an appropriate block length. As noted by Wilks (2011) and originally conceived by Politis et al. (1999), a straightforward, data-driven choice of the block length is a value from a range of lengths to which the spread across the bootstrap estimates is insensitive (the so-called “minimum volatility method”). We note that there is no universal optimal block length and the optimal block length based on the minimum volatility method will, in general, vary for different time series. See Efron (1981) for a formal treatment of the bootstrap technique.

For the present analysis, we derive the sampling distributions of the unforced variability statistics from 10,000 random time series realizations generated by the moving block bootstrap. Sensitivity tests (not shown) for the spread across the sampling uncertainties in the unforced estimates with blocks lengths
varying from 6 to 12 years yielded essentially the same results. Following the minimum volatility method, we thus arbitrarily choose a block length of 10 years for bootstrapping.

Estimating the sampling uncertainties associated with the forced variability statistics in initial condition ensembles is relatively straightforward via bootstrapping. We outline the steps below:

1. Create multiple (for the present analysis, 10,000) bootstrapped ensembles consisting of \( M \)-members each by uniformly sampling with replacement the entire time series of the members in the original \( M \)-member ensemble. Sampling the entire time series of the ensemble members completely preserves the temporal structure in the time series.

2. For each bootstrapped ensemble, compute smoothed estimates of the forced components (Eq. (4.9) and (4.10)). This results in a distribution of bootstrap estimates at each time point. The spread across the distribution is then used to compute sampling uncertainty.

Time of emergence is assessed in terms of the spread across the distributions of the forced and unforced bootstrap estimates. For the investigations in this paper, we use 95% confidence intervals as the metric for the spread. When there is no overlap between the bootstrapped 95% confidence intervals of the forced and unforced estimates, the forced estimates are considered to be significantly different from an unforced climate at that time point and are considered to have emerged.

### 4.3.3 Data Ellipses

Central to the variability assessment framework is the covariance matrix of regional variances and covariances. The data ellipse (Friendly et al. 2013) serves as a useful tool to visualize the covariance matrix and forced changes in the covariance matrix.

We present its construction and interpretation for a system of two regions. For systems with a larger number of regions, pairwise ellipses can be utilized. For a system \( S = \{r_x, r_y\} \) and its covariance matrix \( \mathbf{C} \) as defined in section 4.3, the standard data ellipse centered at zero is constructed from (Friendly et al. 2013):

\[
\bar{z}^T \mathbf{C}^{-1} \bar{z} = k^2
\]

Eq. (4.15)
where $\vec{z} = \begin{bmatrix} T'_x \\ T'_y \end{bmatrix}$ is a point in the coordinate system defined by $T'_x$ on the x-axis and $T'_y$ on the y-axis, $k$ is a constant and $T'_x = T_x - T_{\bar{x}}$ denotes ensemble-mean removed temperature anomaly. The geometrical properties of the ellipse serve as a sufficient visual summary of the second moments:

1) The projections of the ellipse onto the coordinate axes are directly related to the standard deviations of the respective variables (Figure 4.1). That is to say, the relative magnitudes of the variances of $T_{r_x}$ and $T_{r_y}$, $\sigma^2_{T_{r_x}}$ and $\sigma^2_{T_{r_y}}$ can be quickly approximated from the ellipse.

2) The correlation between $T_{r_x}$ and $T_{r_y}$, $\rho$ can be visually approximated as the ratio of the length of the vertical tangent line to the height of the horizontal tangent line above the x-axis (Figure 4.1). As such, changes in correlations can be visually approximated by the changes in this ratio.

3) The variances and covariances can be retrieved from the ellipse geometry in a straightforward manner:

$$\theta = \frac{1}{2} \cdot \text{atan} \left( \frac{2 \cdot \text{cov}(T_{r_x}, T_{r_y})}{\sigma^2_{T_{r_x}} - \sigma^2_{T_{r_y}}} \right)$$  \hspace{1cm} \text{Eq. (4.16)}$$

$$l^2_{\text{major}} = 2k^2 \left( \sigma^2_{T_{r_x}} + \sigma^2_{T_{r_y}} + \sqrt{\left( \sigma^2_{T_{r_x}} - \sigma^2_{T_{r_y}} \right)^2 + 4 \left[ \text{cov}(T_{r_x}, T_{r_y}) \right]^2} \right)$$  \hspace{1cm} \text{Eq. (4.17)}$$

$$l^2_{\text{minor}} = 2k^2 \left( \sigma^2_{T_{r_x}} + \sigma^2_{T_{r_y}} - \sqrt{\left( \sigma^2_{T_{r_x}} - \sigma^2_{T_{r_y}} \right)^2 + 4 \left[ \text{cov}(T_{r_x}, T_{r_y}) \right]^2} \right)$$  \hspace{1cm} \text{Eq. (4.18)}$$

where $\theta$ is the angle made by the major axis with the x-axis and $l_{\text{major}}$ and $l_{\text{minor}}$ are the lengths of the major and minor axes.

The geometrical relationships presented above hold regardless of the joint probability distribution of $T_{r_x}$ and $T_{r_y}$. But if the distribution is Gaussian, the data ellipse has an important probabilistic interpretation. In this case, $\vec{z}^T \mathbf{C}^{-1} \vec{z}$ is chi-square distributed with 2 degrees of freedom (Wilks 2011). Thus, on setting $k^2 = \chi^2_2(\alpha)$, the ellipse constructed from Eq. (4.15) represents an approximate $1 - \alpha$ probability surface. That is, the ellipse bounds 100(1 - $\alpha$)% of the joint realizations of $T_{r_x}$ and $T_{r_y}$. As such, changes in the shape of the ellipse under forcing for a given $\alpha$ allows one to readily gauge changes in the joint probabilities.
The variability of space and/or time averaged climate variables often follows a Gaussian distribution (Toth 1991). Indeed, on application of a multivariate test for normality (Henze and Zirkler 1990) all pairs of the model $T_r$'s associated with the systems in our study were indistinguishable from a Gaussian at a significance level of 0.01 at all times under consideration. For these reasons, the ellipses in our study are constructed by setting $k^2 = \chi^2_2 (0.05)$, and may be interpreted as contours of 95% probability.

For convenience, we drop the hat, overbar and angle bracket notations in the rest of the paper and the variability statistics where they appear hereafter are to be understood as estimates of the population statistics.

4.3.4 Applications to climate model simulations: the CESM large ensemble

We make use of the CESM-LE: an initial condition ensemble consisting of 40 CESM1-CAM5 simulations at $1^\circ \times 1^\circ$ resolution. A detailed description of the CESM-LE experimental design can be found in Kay et al. (2015). The CESM-LE includes a 2200-year pre-industrial control run under constant 1850 forcing. The ocean component of this control run was initialized with modern day ocean observations while the atmosphere, land and sea ice components were initialized with results from previous CESM1-CAM5 simulations. The initial states of the atmosphere, land and sea ice components lose their influence on the climate system within a few years of integration while the upper ocean adjusted to a preindustrial state after several decades. With the exception of a small climate drift present in the deep ocean, the control run was in quasi-equilibrium with preindustrial forcing by year 400. The first ensemble member was initialized using January 1 conditions of a randomly selected year (year 402) of the preindustrial control run and then integrated forward from 1850 to 2100 under historical (Lamarque et al. 2010) and Representative Concentration Pathway 8.5 (RCP 8.5, Meinshausen et al. 2011) forcing. The rest of the ensemble members were integrated from states that only differed by small perturbations to the air temperature field of the first ensemble member on Jan 1, 1920 and integrated forward to 2100. Chaos leads to a growth in these perturbations, eventually creating spread among the ensemble members.
Figure 4.1. Schematic of a standard data ellipse constructed from Eq. (4.13) for variables $T_{rx}$ and $T_{ry}$. The projections of the ellipse on the coordinate axes (blue solid lines) give the standard deviations of the variables. The ratio of the vertical tangent length ($l$) to the height of the horizontal tangent line above the horizontal axis ($L$) gives the correlation $\rho$. $k$ is a constant that defines the ellipse surface (see Eq. (4.13)). If $T_{rx}$ and $T_{ry}$ are jointly Gaussian, the data ellipse represents contours of constant probability and the area bounded by the ellipse represents the probability of the joint occurrence of the variables.

Using the spread across the independent CESM-LE members, we assess the effect of forcing on the interannual variability statistics of annual surface temperature associated with the land/ocean system and monthly surface temperatures associated with the Arctic/midlatitude/rest-of-the-globe system. We further assess time of emergence by comparing transiently forced statistics against those estimated from the unforced stationary climate provided by 1800 years (year 400 – 2200) of the preindustrial control simulation.
4.4 Results

4.4.1 Forced interannual temperature variability in a land/ocean decomposition

Because it offers a simple and interesting application of our framework, we begin by presenting results for the coupled land/ocean system (Figures 4.2-4.4). We start with Figure 4.2, which shows the decomposition of the variance in global annual temperature (Figure 4.2a) into land (Figure 4.2b) and ocean (Figure 4.2c) variance components, and a land/ocean covariance component (Figure 4.2d) under historical and future business as usual (RCP8.5) forcing in the CESM-LE. Figure 4.2b shows that greenhouse gas forcing strongly enhances land variance. Under historical forcing, the land variance emerges from its preindustrial state rapidly in just three decades after the start of the ensemble integration in 1920 and under RCP 8.5 forcing, rapidly increases to 1.5 times its preindustrial estimate by the end of the 21st century. Greenhouse gas forcing, however, has little effect on ocean variance. The ocean variance remains constant at its preindustrial value for most of the integration period, with a small decrease towards the end of the 21st century. A critically increasing land variability with constant ocean variability suggests that, under increased greenhouse gases, ocean temperatures exert a stronger influence on land temperature variability. Accordingly, we find that the land/ocean temperature covariance is enhanced substantially. By the end of the integration, the covariance grows to 1.4 times of its preindustrial estimate, emerging from its preindustrial state in the first quarter of the twenty first century. Driven by the increases in the land variance and land/ocean covariance, global annual variance grows steadily, emerging in approximately 2040.

We next assess the contributions of the regional variances and covariance to global annual variance. We calculate the contributions as ratios of the variance and covariance components to global annual variance in the CESM-LE and present the ratios in Figure 4.3. We find that the land/ocean covariance has the greatest contribution (~40% of global annual variance), that is almost twice that of the land variance, throughout the integration, demonstrating the importance of the covariance between land- and ocean-annual temperature to global annual temperature variance. The contribution of the ocean variance is similar to that of the land-ocean covariance in the 20th century. The land variance has the smallest contribution to the global variance (~20% of global annual variance) throughout the integration, despite the larger variance
Figure 4.2. Decomposition of (a) global (σ²₆₉) annual temperature variance into (b) land (f₁σ²₆₁) and (c) ocean (fₒσ²ₒ) variance components and (d) the land/ocean (2f₁fₒcov(T₁,Tₒ)) covariance component in the CESM-LE. Preindustrial estimates are shown by the horizontal red dashed lines in each panel. The noisy time series are the ensemble estimates of the variance and covariance components (see Eqs. (4.7) and (4.8) in text). Forced estimates derived from smoothing the noisy ensemble time series are shown by the black dashed lines. 95% bootstrap confidence intervals for the preindustrial and forced estimates are shown by horizontal red and black solid lines respectively. f₁, fₒ represent the fractions of global area occupied by land and ocean. Note the different scales on the y-axes.

of temperature over land (see data ellipse in Figure 4.4), reflecting the smaller fractional area of land (29% of global area). Coinciding with the transition from historical to RCP 8.5 forcing in the early 21st century, the contribution of the covariance increases at a nearly constant rate until the end of the integration by 5% while the contribution of the ocean variance decreases by ~10% with the decrease being more rapid after 2020. Compensating for this more rapid decrease, the contribution of the land variance rises after 2020.
Figure 4.3. Contributions of land (green), ocean (blue) variance components and land/ocean (cyan) covariance component to global annual temperature variance. The contributions are computed as ratios of the components in relation to global annual temperature variance and can range from 0 to 1.

In Figure 4.4, we show the 95% data ellipse of land- and ocean-temperatures constructed from the 30-year smoothed estimates of the forced variances and covariance at 1935 (blue) and at 2085 (red). The changes in the ellipse reveal two important characteristics of the forced variability response that are both interesting and not obvious from the decomposition in Figure 4.2. First, the ellipse in the 21st century is stretched along the major axis and is more tilted towards the land axis (x-axis in the figure) than in the early 20th century (see Eqs. (4.16)-(4.18)). These changes in the shape and orientation of the ellipse indicate that land- and ocean-temperatures become more correlated (see Figure 4.1 and Section 4.3.3), that is, they vary more coherently in a warmer climate. Second, the ellipse encloses a wider range of land temperatures in a warmer climate. That is, there is a greater probability of extreme fluctuations in land temperature relative to the late 21st century mean state.
Figure 4.4. 95% data ellipses for land and ocean temperature anomalies at 1935 (blue) and 2085 (red). The ellipses were constructed from forced estimates of the variances and covariances associated with the land/ocean system in the CESM-LE using methods in Sections 4.3.3. Anomalies are calculated as deviations from the ensemble mean.

In summary, the framework reveals (1) a large contribution (>20%) of the land- and ocean-temperature covariance to global annual temperature variance, (2) greater 21st century global- and land-temperature variance that are significantly different from their preindustrial estimates, (3) ocean temperature variance that is not significantly different from its preindustrial estimate throughout the 20th and 21st centuries and (4) greater 21st century covariance and correlation between land- and ocean temperature with an increased risk of extreme fluctuations in land temperature.
4.4.2 Forced interannual variability of monthly-mean temperature: Arctic/midlatitude/rest-of-the-globe decomposition

The loss of Arctic sea ice under increased greenhouse gas forcing is one of the largest and most visible manifestations of climate change (IPCC 2013). Arctic sea ice extent loss has a pronounced impact not only on mean surface warming but also on temperature variability (Screen and Simmonds 2010; Serreze and Barry 2011). In the CESM-LE, as in other climate models, Arctic sea ice extent loss is particularly large at the end of the summer melt season in September (Jahn et al. 2016). For these reasons, we begin our assessment of the forced interannual monthly temperature variability with a focus on the month of September. Specifically, we decompose the interannual variance in global September temperature into variance and covariance components associated with the Arctic (70° N - 90° N), the Northern midlatitudes (30° N - 70° N), and the rest-of-the-globe regions in the CESM-LE.

Figure 4.5 shows the forced evolution of the variance components arising from the September decomposition. The Arctic variance (Figure 4.5b) stays relatively constant from the start of the integration until 2020, after which it decreases in a striking non-linear fashion, coinciding with the loss of September sea ice in the CESM-LE (see Appendix Figure 4.15b). As most of the September sea ice is lost by 2060, the Arctic variance asymptotes to a level that is smaller than its early 20th century level by a remarkable 75%. In contrast with the strongly decreasing Arctic variance, the midlatitude variance (Figure 4.5c) remains largely constant throughout the integration with a small increase towards the end of the integration. The rest-of-the-globe variance (Figure 4.5d), on the other hand, grows steadily until the end of the integration emerging from its preindustrial state in the mid-20th century. Interestingly, the changes in the smoothed covariance estimates associated with this three-region system were found to be negligible and therefore are not shown.
Figure 4.5. Decomposition of (a) global ($\sigma_{T_g}^2$) September temperature variance into (b) Arctic ($f_a\sigma_{T_a}^2$), (c) Midlatitude ($f_m\sigma_{T_m}^2$), and (d) Rest-of-the-globe ($f_r\sigma_{T_r}^2$) variance components in the CESM-LE. Preindustrial estimates are shown by the horizontal red dashed lines in each panel. The noisy time series are the ensemble estimates of the variance and covariance components (see Eqs. (4.7) and (4.8) in text). Forced estimates derived from smoothing the noisy ensemble time series are shown by the black dashed lines. 95% bootstrap confidence intervals for the preindustrial and forced estimates are shown by horizontal red and black solid lines respectively. $f_a$, $f_m$, $f_r$ represent the fractions of global area occupied by the Arctic, Midlatitudes and Rest-of-the-globe. Note the different scales on the y-axes.

We next assess the contributions of the regional variances and covariances to global September variance in Figure 4.6, as ratios compared to global September variance. We find that the rest-of-the-globe variance has the greatest contribution to global September variance throughout the integration (>90%). The Arctic and midlatitude variances have much smaller contributions, which is not surprising considering the smaller fractions of global area occupied by the Arctic (3%) and the midlatitudes (22%) compared to rest-of-the-globe (75%). Unlike the land/ocean system where the covariance has a large and positive contribution (Section 4.4.1), the covariances here have a small and negative total contribution.
How does the large September Arctic sea ice extent loss affect the temperature probabilities in the Arctic/midlatitude/rest-of-the-globe system? We address this question using data ellipses. Assuming the pairwise distributions of the Arctic-, midlatitude- and rest-of-the-globe- temperatures to be Gaussian, we visualize the changes in probabilities using 95% data ellipses (Figure 4.7). We find that the large decrease in the Arctic variance results in a large shrinkage of the Arctic/midlatitude (Figure 4.7a, see Eqs. (4.16)-(4.18)) and the Arctic/rest-of-the-globe (Figure 4.7b) September temperature ellipses along their major axes. Simply put, the ellipses show the probability of extreme fluctuations of September Arctic temperature about the 21st century mean state is greatly reduced.

Fascinated by the large reduction in the September Arctic variance, we next ask: How do the variances and covariances associated with the other months respond to historical and RCP8.5 forcing? Is there a seasonal character to the response? Are the covariance changes negligible in all months, or just in September? To address these questions, we perform a month-by-month decomposition of interannual variance in global monthly temperature into variance and covariance components arising from the

Figure 4.6. Contributions of Arctic (blue), Midlatitude (brown), Rest-of-the-globe (green) variance components, and Arctic/Midlatitude (purple), Arctic/Rest-of-the-globe (cyan) and Midlatitude/rest-of-the-globe (yellow) covariance components to global September temperature variance. The contributions are computed as ratios of the components and teleconnections relative to global September temperature variance. The sum of the covariance contributions is shown by the black dashed line.
Arctic/midlatitude/rest-of-the-globe system. The forced variances varied by more than an order of magnitude from month to month. Therefore, for ease of comparing across different months, we normalize by taking the ratios of the forced variances to their unforced estimates. We present the ratios in Figure 4.8. We find that the forced response of the Arctic variance (Figure 4.8b) has a strong seasonal character: it displays large decreases in the fall, minor decreases in the spring, and negligible decreases in the summer and winter. The forced response of the midlatitude variance (Figure 4.8c) is weak, except in October and November during which it displays significant decreases and in July during which it displays a striking increase (~120%). The forced response of the rest-of-the-globe variance (Figure 4.8d) is more uniform: it increases in most months. As in September, the changes in the covariances in all months were found to be negligible and therefore are not presented.

Intrigued by the large increase in the July midlatitude variance, we more fully explore in Figure 4.9, the variance components arising from the decomposition of global July variance. We find that the Arctic variance (Figure 4.9b) remains constant until 1980 after which, coinciding with the commencement of July sea ice loss in the CESM-LE (See Appendix Figure 4.15a), it decreases until 2040. After 2040, despite continued sea ice loss in the CESM-LE and coinciding with the increase in the midlatitude variance (Figure 4.9c), the Arctic variance remarkably grows back to its preindustrial value.
Figure 4.7. 95% data ellipses for September (a) Arctic and Midlatitude (b) Arctic and Rest-of-the-globe and (c) Midlatitude and Rest-of-the-globe temperature anomalies at the 1935 (blue) and 2085 (red). The ellipses were constructed from forced estimates of the variances and covariances associated with the Arctic/Midlatitude/Rest-of-the-globe system in the CESM-LE. Anomalies are calculated as deviations from the ensemble mean.

The contributions of the regional variances and covariances to global July variance are assessed in Figure 4.10 as ratios. We find that the rest-of-the-globe variance has the greatest contribution (>80%) to
Figure 4.8. Ratios of (a) interannual global monthly temperature variance, (b) Arctic variance component, (c) midlatitude variance component, and (d) rest-of-the-globe variance components estimated in the CESM-LE to their preindustrial estimates. Ratios where the forced estimates do not differ significantly from their preindustrial estimates are shown in white. Note the different color scales.

global July variance (Figure 4.10) as in Figure 4.6. Further as in Figure 4.6, we find that the contributions of the Arctic and midlatitude variances, and the covariances are much smaller than the contributions of the rest-of-the-globe variance to global July temperature variance.

Finally, we assess changes in the temperature probability distributions induced by the substantial increases in the July midlatitude variance. Again, assuming the pairwise distributions of the Arctic-, midlatitude- and rest-of-the-globe- temperatures to be Gaussian, we visualize the changes in probabilities using 95% data ellipses (Figure 4.11). We find that the increase in the midlatitude variance results in only a marginal stretch of the midlatitude/rest-of-the-globe (Figure 4.11c, see Eqs. (4.16)-(4.18)) July temperature ellipse along its major axes. We further find that the changes in the geometrical properties of the Arctic/midlatitude (Figure 4.11a) and the Arctic/rest-of-the-globe ellipse (Figure 4.11b) are negligible. That is, the probabilities of the fluctuations about the Arctic-, midlatitude- and, rest-of-the-globe- July temperatures remain more or less unchanged in a warmer climate.
In summary, our investigations of the forced interannual monthly temperature variability associated with the Arctic/midlatitude/rest-of-the-globe system revealed (1) large 21st century Arctic temperature variance decreases in the fall months, (2) large 21st century midlatitude temperature variance increases in the summer months, (3) negligible changes in temperature covariances in most months and (4) large 21st century increases in the rest-of-the-globe temperature variance in most months.

4.5 Summary and discussion

Broadening the scope of variability studies, we have here developed a simple framework that facilitates a unified assessment of the interannual variances and covariances associated with a system of interacting regions in climate model ensembles. The three central constituents of the framework are 1) a decomposition of global variability into regional variance and covariance components, 2) the computation of the evolving components in an ensemble of climate model simulations under transient forcing and, 3)
Figure 4.10. As in Figure 4.6 but for July

the application of a statistical resampling method to quantify the time of emergence of forced variability signals. As our investigations have demonstrated, the three constituents combine to provide a simple yet comprehensive assessment of the forced response of regional interannual variability.

Our investigations have revealed interannual variability changes in the CESM-LE that are consistent with results from literature. For example, we found large decreases in fall Arctic temperature variance (Figure 4.8b). These decreases occurring due to the loss of sea ice cover and the moderating influence of the exposed waters, are a consistent feature across a host of variability studies (e.g: Räisänen 2001; Stouffer and Wetherald 2007; Boer 2009; LaJoie and DelSole 2016). The increases in the summer midlatitude temperature variance (Figure 4.8c) are also a robust result of variability studies and have been linked to a drying of continental land due to depletion of soil moisture (e.g: Räisänen 2001; Stouffer and Wetherald 2007; Scherrer et al. 2008; Fischer et al. 2012).
While our investigations have uncovered variability changes that are robust across existing twenty-first century model simulations, have a known physical basis and perhaps therefore are not surprising, there are three important findings that are shown here for the first time. First, the land temperature variance (Figure 4.2b) increases to almost 1.5 times its preindustrial level. This increase will manifest as an enhanced likelihood of extreme land temperatures (see Figure 4.4). These extreme heat events will be superimposed upon a mean state that is almost 5°C warmer than the present day in the CESM-LE (analysis not shown).
and will have important implications for the society and ecology (e.g: Ciais et al. 2005; Larsen 2006; Liu et al. 2010). We also find that the land and ocean temperature covariance increases in a warmer climate, suggesting that land and ocean temperatures will vary more coherently in a warmer climate and as a result the knowledge of Sea Surface Temperatures (SST) may contribute to increased predictability of land temperatures (e.g: Årthun et al. 2017). Third, we find that July temperature variance in the Arctic grows towards the end of the 21st century. While the physical mechanisms underlying this growth are unknown to us at present, the fact that the growth occurs despite continued sea ice loss in the CESM-LE suggests the influence of processes non-local to the Arctic and warrants further investigation. Finally, the land temperature variance (Figure 4.2b), the September Arctic (Figure 4.5b) and midlatitude (Figure 4.5c) temperature variances emerge from their preindustrial states in the first few decades of the 20th century. If the CESM-LE accurately captures the variability of these regions, an assumption we have not tested, the signals of forced historical variability would be expected to be embedded in the observed record. These results therefore motivate future studies to perform a formal detection and attribution analysis leveraging observations and climate model simulations to identify these signals in observations and attribute them to external forcings (e.g: Hegerl and Zwiers 2011).

An important and perhaps fundamental insight that has emerged from our investigations is the importance of regional covariances to global variance on interannual timescales as demonstrated by the major contribution of the land- and ocean- temperature covariance to global variance (Figure 4.3). Our finding that regional covariances can have an enormous influence on global interannual variance suggests that studies seeking to understand the relationship between global variance and regional variability (e.g: Sutton et al. 2015) may benefit by taking into account regional covariances.

The investigations in this paper are limited to the variability associated with systems consisting of two and three regions in a single climate model ensemble. The applications of the framework, however, are more general. The framework, through the decomposition that can admit an arbitrary number of regions, can be adapted to the assessment of the variance and covariance components arising from as many number of regions as desired on the globe. This flexibility can enable an integrated study of the modes of climate
variability that often couple numerous regions on the planet. For example, the ENSO phenomenon, a prominent mode of interannual variability, is concentrated in the Tropical Pacific but has teleconnections to remote regions of the globe and therefore is of great interest for climate projections (Collins et al. 2010). How will the year-to-year ENSO variability change in a warmer climate? How will the numerous ENSO teleconnections change under mean warming? When will these changes emerge? These are the kinds of questions that can be addressed with the framework in a comprehensive manner.

While the flexibility of the decomposition is a key strength of the framework, we note that it can also be a limitation. The number of components to be assessed grows approximately as a square of the number of regions under consideration (see Eq. (4.5) in Section 4.3.1). For systems consisting of a very large number of regions therefore, it can be impractical to apply the framework. In such high dimensional settings, several multivariate measures from the predictability literature (e.g.: Schneider and Griffies 1999, Kleeman 2002, DelSole and Tippett 2009) can be adapted to assess future variability changes. However, such measures have shortcomings of their own. For example, the measures proposed by Schneider and Griffies (1999) and Kleeman (2002) mix signals from changes in variability statistics with those from changes in other moments, while the measure proposed by DelSole and Tippett (2009) mixes signals from changes in the variances with those from changes in the covariances. The individual contributions of the signals can be difficult if not impossible to separate.

Finally, we list three opportunities for future research. Given the potentially broad implications of our findings, future work could assess their robustness across existing model ensembles, for example, those from the Coupled Model Intercomparison Project Phase 5 (CMIP5)). The ensemble framework presented in this paper provides a natural means for this purpose. In this context, the production of large ensemble simulations by individual modeling groups participating in the ongoing CMIP6 experiments (Eyring et al. 2016) will be particularly useful. Another obvious next step would be to extend the framework to the assessment of covariances between variables. The methods in this paper are limited to the covariance of one variable between different regions. It would be straightforward and useful to extend these methods to quantify the forced evolution and time of emergence of covariance between variables, for example, the
covariance between tropical Pacific SSTs and rainfall patterns in various ENSO affected regions around the world (e.g. Perry et al. 2017). Finally, it is useful to note that the decomposition framework developed in this paper can be easily adapted to decompose global predictability into regional components which could prove useful in uncovering relationships between global predictability and regional variability (see Appendix I for a discussion of the application of the framework to predictability studies).
Appendix I: Application of variability decomposition framework to problems of the predictability of the first kind

In chapter 4, we developed a mathematical framework for quantifying forced changes in climate variability and its time of emergence from an unforced climate state using initial condition climate model ensembles. Variability was measured in terms of the regional variances and covariances of climate variables and the time evolution and emergence of the variances and covariances in response to changing greenhouse gases were studied. That is, we were interested in the problem of evolving second moments of “forecast” probability distributions under changing external forcings or “boundary conditions”. When the second moments of the forecast distributions differed significantly in a statistical sense from their climatological values, variability was considered to have emerged. Such problems, wherein one is interested in predictable changes to the statistics of climatic distributions forced by changes in boundary conditions, are considered problems of forced predictability or predictability of the second kind (Lorenz 1975). While forced predictability arising from changes in the second moments was the focus of chapter 4, forced predictability can also arise from changes in other moments, and more generally, in any property of climatic distributions (DelSole 2004).

Measuring predictability amounts, in one way or another, to quantifying the predictive information that can be gained from the forecast distribution of a climate variable in relation to its climatological distribution (Schneider and Griffies 1999, DelSole 2004, Branstator and Teng 2010). While changes in boundary conditions can give rise to predictability, as is clear from the results presented in chapter 4, predictability can also arise from knowledge of the initial state of a climate variable. Consider, for the purpose of illustration, the evolution of global averaged daily surface temperature ($T_g$) in the CESM-LE (Figure 4.12). On Jan 1, 1920, all realizations of $T_g$ are virtually identical except for very small differences of the order of $10^{-14}$ K that were introduced by construction (see description of the CESM-LE in section 4.3.4). That is, there is almost no uncertainty in our knowledge of $T_g$ on Jan 1, 1920 and predictability is
considered near-perfect. As the ensemble integration progresses forward, internal modes of variability grow leading to divergence among the ensemble members and as a result uncertainty as to which ensemble member may actually be realized. This uncertainty may be characterized by measuring the similarity of the forecast distribution, which in Figure 4.12 is the distribution of ensemble realizations, to the background climatological distribution. The uncertainty grows until the forecast distribution asymptotes to and becomes indistinguishable from the climatological distribution, which in Figure 4.12 occurs in about 40 days. All predictability arising from the near-perfect initial state, also known as *Initial Value Predictability* (IVP) or the *predictability of the first kind* (Lorenz 1975), is then said to be lost. In other words, specifying a prediction from the forecast distribution is only as good as specifying a random draw from the climatological distribution. This inherent limit on IVP (40 days in Figure 4.12), arising due to the chaotic nature of the climate system, is of fundamental importance for forecasts on the daily to decadal timescales (see Figure 2 of Meehl 2009).

As mentioned above, measuring predictability, be it forced or initial value, amounts to quantifying the divergence between a forecast and a climatological distribution. A number of metrics exist in the literature for measuring predictability, all of which satisfy a common condition: they vanish when the forecast distribution equals the climatological distribution and predictability is non-existent. The key difference between metrics pertains to the specific property of the climatic distributions that the metrics measure. Some metrics measure deviations in specific moments of climatic distributions. Most commonly, such metrics measure deviations in the second moments between the forecast and climatological distributions (e.g: Lorenz 1965, Shukla 1981, Pohlmann et al. 2004, DelSole and Tippett 2009). Obviously, it is possible that the predictability measured by metrics that focus on a specific moment vanish despite predictability arising from deviations in other moments or properties of the distributions being present. Addressing this inadequacy requires metrics that vanish if and only if the forecast distribution is exactly equal to the climatological distribution. Several metrics (e.g: relative entropy, Kleeman (2002)) inspired by principles from information theory serve this purpose. However, a drawback of such metrics is that they are not always easy to interpret except under some restrictive assumptions. For example, under the
assumption of

Figure 4.12. Globally averaged daily surface temperature ($T_g$) in the CESM-LE. Black lines represent ensemble members. Red line represents ensemble mean.

Gaussianity, relative entropy between a forecast and climatological distribution can be decomposed into two parts – one part that depends solely on the means of the climatic distributions and another part that depends solely on the covariance matrix of the distributions, thus facilitating a straightforward interpretation of initial value predictability (see Eq. (4) in Branstator and Teng (2010)).

Of specific relevance to the variability decomposition framework developed in chapter 4, a simple variance based metric Prognostic Potential Predictability ($PPP$) of Pohlmann et al. (2004) measures the fractional difference between the variances of forecast and climatological distributions. Consider for example the $PPP$ of global surface temperature:

$$PPP_{T_g} = \frac{\sigma_{T_g}^2_{clim} - \sigma_{T_g}^2_t}{\sigma_{T_g}^2_{clim}}$$  \hspace{1cm} \text{Eq. (4.19)}$$

where the notation developed in chapter 4 has been adopted. This metric has two intuitive properties: 1) it decreases to zero as the forecast spread $\sigma_{T_g}^2_t$ increases and asymptotes to the climatological spread $\sigma_{T_g}^2_{clim}$, and 2) it is close to unity when the forecast spread is small and predictability is near perfect. The variability
decomposition framework can be easily applied to Eq. (4.19) to decompose PPP into regional components. On substituting the decomposition in Eq. (4.5) into Eq. (4.19), $PPP^T_g$ decomposes into area-weighted regional components:

$$PPP^T_g = \sum_{\ell=1}^{n} f_i^2 \frac{\sigma^2_{TR}^{\text{clim}} - \sigma^2_{TR}^{t}}{\sigma^2_{TG}^{\text{clim}}} + 2 \sum_{\ell=2}^{n} \sum_{j=1}^{\ell-1} \frac{f_i f_j [\text{cov}^{\text{clim}}(TR_i,TR_j) - \text{cov}^{t}(TR_i,TR_j)]}{\sigma^2_{TR}^{\text{clim}}}$$

Eq. (4.20)

The decomposition yields a total of $n(n + 1)/2$ independent components: $n$ variance components of the form $f_i^2 \frac{\sigma^2_{TR}^{\text{clim}} - \sigma^2_{TR}^{t}}{\sigma^2_{TG}^{\text{clim}}}$, and $n(n - 1)/2$ covariance components of the form $2f_i f_j \frac{\text{cov}^{\text{clim}}(TR_i,TR_j) - \text{cov}^{t}(TR_i,TR_j)}{\sigma^2_{TR}^{\text{clim}}}$. Forced quantities, denoted by the $t$ subscript may be estimated using resampling methods in initial condition ensembles as described in sections 4.3.2.1 and climatological quantities, denoted by the $\text{clim}$ subscript, using resampling methods in control simulations as described in section 4.3.2.2.

Decomposing predictability into components often leads to useful insights. A commonly used strategy in the literature is to decompose predictability into components that maximize it (Schneider and Griffies 1999; DelSole 2004; DelSole and Tippett 2009). Such decompositions are useful because climate predictability and variability often organize into a few coherent structures and therefore identifying such structures by maximizing predictability allows investigators to focus on the most significant structures and ignore the insignificant ones (analogous to decomposing variability into maximizing components using principal component analysis). A drawback of such decompositions however is that the constraints imposed by the optimizing criteria used to maximize the components often renders the physical interpretation of the components difficult. For example, principal component analysis of a system’s variability yields variability components that are strictly orthogonal to each other and therefore may not coincide with the actual physical modes of variability present in the system (Navarra and Simoncini 2010). The decomposition derived in Eq. (4.20) is useful in this context because the components are based on regional variances and covariances and therefore are more straightforward to interpret and physically relatable. Furthermore, the decomposition
elucidates regional contributions to global predictability. Note however that the decomposition has a limitation of its own. The number of components grows approximately as a square of the number of regions included in the decomposition. It can therefore be impractical to apply the framework to systems consisting of a very large number of regions.

To illustrate the utility of the decomposition in the study of initial value predictability, we apply it to decompose the predictability of global averaged daily temperature into components arising from land and ocean in Figure 4.13. Global predictability is perfect at the start of the integration (Figure 4.13a), consistent with the negligible spread across the ensemble realizations (see Figure 4.12). The chaotic growth of the initial condition perturbations eventually creates spread among the ensemble members leading to global predictability decay to zero in about 3 months. The three components (Figures 4.13b–d), the sum of which is global predictability, start at values less than 1 with the land variance component (Figure 4.13b) contributing more than the others initially. The land variance component decays rapidly to zero in about a month, faster than the other components. The ocean variance component (Figure 4.13c) on the other hand, decays much more slowly due to the long initial-condition memory of ocean surface temperatures. In fact, it displays a significant upward trend after two months. In contrast to the other components, the land-ocean covariance component (Figure 4.13d) initially increases for about a month after which it decays to zero in approximately the same time as global predictability. Until its decay to zero, its contribution to overall predictability is comparable to the ocean’s.

Some interesting features emerge when we extend the decomposition to 10 years (Figure 4.14). Gains in the ocean variance component (Figure 4.14c) drive statistically significant rebounds in global predictability for almost 2 years (Figure 4.14a). The ocean variance component decays to zero over the course of 2 years and remains indistinguishable from the zero level for the rest of the 10-year time period. The land variance component and land-ocean covariance component remain at zero for most of the 10-year period. The notable high frequency fluctuations in the time series of all components reflect the high sampling variability arising from the use of a finite-sized ensemble to estimate the second moments.
Figure 4.13. (a) Potential Prognostic Predictability (PPP) of global average daily surface temperature in the CESM-LE and its components associated with (b) land variance, (c) ocean variance, and (d) land-ocean covariance. In each panel, the thick line represents ensemble estimates of the second moments. Shading represents 95% confidence intervals based on 10,000 bootstrap resamples. See section 4.3.2 for methods. Units in all panels are $K^2/K^2$.

In summary, application of the decomposition framework to the land-ocean system in the initial value predictability setting revealed characteristics, perhaps expected, of the land-ocean system: the land variance component loses its influence on global predictability faster than the ocean variance component. Interestingly, the decomposition also showed that land-ocean interactions as captured by the land-ocean covariance component have a non-negligible contribution to global initial value predictability suggesting that studies seeking to understand the relationship between global predictability and regional climate may benefit by taking into account regional covariances.
Figure 4.14. As in Figure 4.13 but plots extended to 10 years.
Appendix II: July and September Sea Ice Extent (SIE) in the CESM-LE

Arctic Sea Ice Extent (SIE) is a strong control on temperature variability in the high latitudes. Sea ice shuts off radiative and turbulent heat exchanges between the atmosphere and the underlying waters. The only mode of energy exchange between the atmosphere and ocean is heat conduction through sea ice. Not surprisingly therefore, the effective heat capacity of sea ice is lower than that of the oceans and is close to that of land (Dwyer et al. 2012). As a consequence, temperature variability over sea ice resembles that over land. As the Arctic loses sea ice in response to anthropogenic warming, the underlying ocean is exposed and the large thermal inertia of the ocean has a strong damping effect on temperature variability.

In Figure 4.15, we document the loss of Arctic SIE in the CESM-LE for the months of July (Figure 4.15a) and September (Figure 4.15b). Note that while September temperature variability greatly decreases monotonically in response to sea ice loss (Figure 4.5b), July temperature variability decreases until mid-21st century and despite continued sea ice loss, increases in the second half of the 21st century (Figure 4.9b). The reasons underlying this increase are unclear and need further investigation.

Figure 4.15. Arctic Sea Ice Extent (SIE) in the CESM-LE for (a) July and (b) September. Black lines represent different ensemble members. Red line represents ensemble mean SIE. Units are million sq. km. SIE is calculated by averaging over grid cells with sea ice concentration greater than a threshold of 15%.
Chapter 5

Conclusions and Future Work

In this thesis, we investigated the role of internal variability in twenty-first century projections of two climate features - precipitation within extratropical cyclones (Chapter 2; Yettella and Kay 2016) and the annual cycle of Northern Hemispheric surface temperature (Chapter 3; Yettella and England 2018). To separate human-induced changes from fluctuations due to unforced internal variability, we leveraged a large initial condition climate model ensemble (CESM-LE) forced with a plausible greenhouse gas emissions scenario. We further investigated the physical mechanisms underlying the forced changes in the two climate features. Leveraging the CESM-LE, we also developed a statistical framework to enable the identification of forced changes in climate variability (Chapter 4; Yettella et al. 2018b). In this concluding chapter, we document the salient findings from these works and provide directions for future research.

In Chapter 2, we used cyclone detection and compositing techniques within the CESM-LE to compare cyclonic precipitation in a warmer world with the present day in the presence of internal variability. We also applied a simple statistical procedure to elucidate the roles of cyclone moisture and cyclone wind speeds on changes in cyclone precipitation. The main findings of this chapter are listed below:

- Cyclone composites for the near-future (2016 - 2035) and the far-future (2081 - 2100) in two seasons (DJF, JJA) and hemispheres (NH, SH) showed increased cyclone precipitation in all cyclone sectors, with the greatest increases occurring near the composite centers. Further, these changes were found rise above the noise of internal variability, that is, were detectable with the CESM-LE in both future time periods.

- We used the ‘Bonygram’ technique to partition increases in cyclone precipitation aggregated over the entire Northern and Southern hemispheres into contributions from changes in cyclone moisture and wind speeds. This analysis revealed that more than 90% of the increases in cyclone
precipitation, in both future time periods, arise from increases in cyclone moisture across all ensemble members.

- The application of the cyclone detection procedure to thirty members of the CESM-LE yielded, at every grid point, nearly thirty times the number of cyclones that occur in a single realization of the climate system. The availability of such a large number of cyclones at every grid point facilitated the application of the Bonygram technique not only to cyclones aggregated over the hemispheres but also to cyclones occurring at the grid point level. This regional analysis revealed that, with some local exceptions, cyclone precipitation increases throughout both hemispheres are chiefly driven by increases in cyclone moisture with changes in wind speed and cyclone occurrence frequency playing only a secondary role.

- There were important regional exceptions to the main conclusion of Chapter 2 that increases in cyclone moisture drive increases in cyclone precipitation. For example, we found that cyclone precipitation decreased in the Mediterranean region despite increased cyclone moisture and unchanged cyclone wind speeds in that area. This suggests that the WCB model used in Chapter 3 is inadequate to explain changes in cyclone precipitation over such regions. The formulation and application of a model complex enough to capture the dependency of cyclone precipitation and its controlling factors will be therefore useful in understanding precipitation changes over those regions.

In chapter 3, we focused on the uncertainty in future projections of the annual cycle of surface temperature arising from internal variability. Using the CESM-LE, we quantified forced changes in the amplitude and phase of the annual cycle over the Northern Hemispheric land regions in relation to internal variability. We also leveraged a simple one dimensional energy balance model (Eq. (3.4)) and the CMIP5 mutli-model ensemble to quantify the relative contributions of changes in three physical parameters that
control the annual cycle (effective heat capacity of the surface ($C_{eff}$), net shortwave radiation at the surface ($Q$) and surface heat fluxes parameterized as a damping factor ($\beta$). The main findings were:

- Internal variability exerts a strong influence on the detection of forced changes in the annual cycle - medium to large ensembles will be required to detect forced changes over many land areas of the Northern Hemisphere by mid 21st century.

- Despite the confounding influence of internal variability over much of the Northern Hemisphere, large and easily detectable forced changes are found in the annual cycle over three regions - Europe, North Africa and Siberia. The amplitude of the annual cycle increases over Europe, North Africa by almost 2.5 °C whereas it decreases over Siberia by 3 °C by the end of the twenty first century. The phase of the annual cycle, on the other hand, advances by almost 5 days over all three regions. These changes are detectable with as few as three ensemble members in the coming decade. We also note that these large changes are present not only in the CESM-LE but also across multiple CMIP5 ensembles.

- The large changes over the three regions are not only detectable in small ensembles but were also found to be detectable within a single realization of the climate system as soon as the coming decade. Future observational studies of the annual cycle over these regions will therefore be well-positioned to test the validity of these findings.

- Decomposing the changes in the annual cycle over the three regions using the energy balance model showed that these changes are chiefly driven by changes in $\beta$ with only secondary contributions from changes in $Q$ and $C_{eff}$.

- The energy balance model was also applied to decompose biases in the historical annual cycle into contributions from biases in the three controlling parameters. While the biases in the simulation of the historical annual cycle are small, it was found that this was a result of compensation between large and opposing biases in the controlling parameters.
In Chapter 5, we leveraged a time-series resampling method (the moving block bootstrap) in the CESM-LE to devise a statistical framework that facilities (i) the decomposition of the global variance of a climate variable into regional variance and covariance components, (ii) the computation of evolving the regional variance and covariance components of climate variables under rapidly changing external forcings and, (iii) the assessment of the time of emergence of these statistics from a control climatology. We also introduced ‘data ellipses’ from the statistics literature to facilitate a visual and probabilistic interpretation of changes in variability. The framework was illustrated by applying it to understand the response of the variability and covariability of land and ocean temperatures, and that of Arctic and Midlatitude temperatures. The main findings were:

- Greenhouse gas forcing has a notable amplifying effect on land temperature variance. This effect becomes particularly pronounced after RCP 8.5 forcing is introduced in the CESM-LE. By the end of the twenty first century, the land temperature variance increases to a remarkable 1.4 times its preindustrial control value. The ocean variance on the other hand is found to be robust to greenhouse gas forcing and remains constant at its preindustrial value throughout much of the twenty first century. The framework also revealed that land/ocean temperature covariance increases and has the greatest contribution to global temperature variance throughout the period of the ensemble integration.

- The data ellipse for land and ocean temperature variability showed that the increases in land variance and land/ocean covariance translate into a great probability of extreme land temperatures relative to the climatology of the late 21st century.

- A decomposition of the variability and covariability of monthly Arctic and midlatitude temperatures revealed a pronounced reduction of Arctic temperature variance in the fall months, coinciding with sea ice loss towards the end of the 21st century. Midlatitude temperature variance was observed to decrease in the winter months and, surprisingly, increase in the summer months.
Data ellipses for Arctic and midlatitude temperature variability showed that the large decrease in Arctic temperature variance during the fall months translates into a large reduction of the probability of extreme Arctic fall temperatures relative to the climatology of the late 21st century.

The research work presented in this thesis clearly highlighted the utility of initial condition climate model ensembles for studying a variety of climate problems in the presence of internal variability. Not only are large ensembles useful for studying changes in the mean state of the climate but, as demonstrated in Chapter 4, are indispensable for investigating the response of the higher-order moments of climate variables to external forcings. As computational power increases, modeling centers around the world are shifting their focus from single climate simulations to large and even “grand” (e.g. Stevens 2015) ensembles in appreciation of internal variability. This presents the opportunity to test our results and conclusions across other ensembles and leverage the ensemble-specific methods developed in this thesis to aid in the understanding of climate variability.
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