AN EXAMINATION OF ATMOSPHERIC RIVER MOISTURE TRANSPORT AND HYDROLOGY USING ISOTOPE-ENABLED CAM5

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An Examination of Atmospheric River Moisture Transport and Hydrology Using Isotope-enabled CAM5.

Thesis directed by Associate Professor David C. Noone.

Atmospheric rivers are a feature of the atmospheric circulation that play a major role in terms of precipitation, flooding, drought, and even the global climate system itself. Thus understanding what the main controls on these weather systems are is critical if one wants to be able to determine the impact they could eventually impose on society. Also too, almost all climate projections are performed by global climate or earth system models. Thus there is a need to ensure that these sorts of models can accurately simulate atmospheric rivers, and the global hydrologic cycle in general, if one is to have confidence in the projections generated by these programs.

These concerns are examined in this thesis. In particular, the CAM5 model is used to generate a climatology of extreme moisture transport from transient eddies and atmospheric rivers, which is compared to a reanalysis. It is found that although the average climatological results are similar, the average moisture flux per event was too weak, indicating that the model may not adequately simulate the more extreme flux and/or precipitation events, which can have the largest impact on society.

To further investigate what might be causing this bias, water tracer and isotope physics were added to CAM5, where the biases present in the isotope-enabled simulations show that CAM5 generates too much precipitation. A sensitivity analysis is performed to try and determine the specific cause of the bias, and it is found that CAM5 generates deep convection
too frequently, particularly in the winter midlatitudes over the ocean. This could also help explain the weakened moisture fluxes in atmospheric rivers, as too much moisture is lost in the model due to overly active convection.

Finally, water tracers are used to examine the moisture sources for the West Coast of the United States, including in atmospheric rivers. It is found that atmospheric rivers pull more moisture from the tropics than average. It is also found that in the future, the fraction of locally-sourced moisture decreases, compensated for by an increase in long-distance moisture transport. This new information provides a new way to examine the atmospheric hydrologic cycle, and eventually, create better climate projections.
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CHAPTER I

Introduction

1. Statement of the problem

At the moment of this writing, the US state of California is currently experiencing an “exceptional” drought, with over $2.7 billion worth of losses in the State’s agricultural sector alone [Howitt et al., 2015]. One of the major sources of precipitation and needed water resources in California is the weather system known as an “Atmospheric River”, which is a long, thin plume of elevated, vertically-integrated water vapor flux [Newell et al., 1992, Ralph et al., 2004]. These Atmospheric Rivers (ARs) are usually associated with moisture fluxes in the warm sector of extratropical cyclones that move in from the Pacific Ocean, and tend to occupy the lower troposphere in terms of vertical extent [Ralph et al., 2005]. Once they make landfall, mountain ranges such as the Sierra Nevada can generate orographic uplift, and thus heavy precipitation [Ralph et al., 2006]. Studies have estimated that 20-50% of all the precipitation that falls in the West Coast of the United States, including California, comes from these AR systems [Dettinger et al., 2011]. It has also been found that 33-74% of all US West Coast droughts were at least partially brought to an end by an atmospheric river precipitation event [Dettinger, 2013].

Besides being related to drought, Atmospheric Rivers are also known to produce flooding events [e.g. Ralph et al., 2006, Neiman et al., 2011]. The connection between flooding and ARs is just not for the West Coast of the United States, as ARs have been found to produce flooding events in Tennessee [Moore et al.,2012], Norway [Stohl et al., 2008], and the United Kingdom [Lavers et al., 2011]. Atmospheric rivers have also been shown to at least produce heavy
precipitation events in the Central Andes [Viale and Nuñez, 2011], Western Europe [Lavers and Villarini, 2013], and East Antarctica [Gorodetskaya, 2014]. Thus understanding atmospheric rivers is vital if one wants to understand and predict hydrologic extremes, including both floods and droughts.

It is unclear how hydrologic extremes will change with global warming. In general, it’s expected that regions with higher average precipitation will receive more precipitation in the future, while below average regions will get even dryer, commonly thought of as a “wet-gets-wetter, dry-gets-dryer” change [Held and Soden, 2006]. This is expected to result in a global precipitation increase of 2-3% per °C of warming [Held and Soden, 2006]. However, these changes refer to the global average precipitation amount, and may not be representative of extreme events. In fact, at least one study suggested that extreme precipitation will increase at a rate of almost 7.5% per °C of warming, which is close to rate of increase in atmospheric water vapor [Pall et al., 2007]. It should also be noted that a global change does not necessarily imply that the same change will occur locally or regionally. For example, changes in certain weather systems, including Atmospheric Rivers, may produce large hydrologic changes in the West Coast of the United States that may not clearly manifest itself when quantifying changes in the global average. Therefore it is vital to examine ARs, including their hydrology, using more focused and sophisticated analysis tools, including numerical water tracers, water isotope ratios, and advanced observational platforms that can observe water isotope ratios in the atmosphere.

2. Atmospheric Rivers in general circulation models

Several studies have attempted to examine how atmospheric rivers might change due to global warming. Dettinger et al., [2011] examined integrated water vapor and 925 mb upslope wind speeds from seven different IPCC-class Global Climate Models (GCMs) for a single grid
cell off the Central Californian coast, and found that although the average number of AR events doesn’t significantly change, the number of extreme AR events increases substantially. A larger analysis done by Warner et al., [2015] for the entire United States West Coast found that the amount of vertically integrated water vapor transport during AR events increased by 25-30%, which due to their threshold definition of atmospheric rivers resulted in a 230-390% increase in the frequency of events. They also found a 4-6% per °C increase in winter average precipitation and a 5-19% per °C increase in extreme precipitation, which is over twice the global average rate of 2-3% per °C. Finally, Lavers et al., [2013] used vertically-integrated water vapor transport to identify and predict changes in ARs striking Britain in the end of the 21st century, and also found an increase in the total amount of transported water vapor, as well as an increase in AR frequency. These studies imply that changes in ARs will indeed occur in certain locales, and could ultimately result in an increased risk for extreme precipitation and flooding.

Although these studies represent a good start, there is still much more that can be done to better understand ARs and their future changes. To begin with, all of these studies examine only changes in certain locations. Although it is expected that AR changes will only have a regional (as opposed to global) effect on precipitation, more and more regions are being found to be impacted by these weather systems, and thus could be influenced by future changes in their characteristics [e.g. Moore et al., 2012; Viale and Nuñez, 2011; Gorodetskaya et al., 2014]. Also, changes in circulation patterns, including a shift in the storm tracks [e.g. Chang et al., 2012], could cause locations that don’t currently experience ARs to become vulnerable to their impacts later this century. Thus by devising methods that can detect ARs globally in gridded meteorological data, such as the one described by Newman et al., [2012], how ARs vary in
frequency and intensity can be determined for any geographic location, and regions may be identified where the influence of ARs changes in the future.

To date there has been a scarcity of work to understand the potential biases in GCMs that could result in AR characteristics that do not have the correct magnitude or frequency, thus biasing future projections. Lavers et al., [2013] described that most models had too few ARs, and attempted to adjust for it by creating a model-dependent vapor transport threshold for each model. Although this corrects for a bias in frequency, it does not change the fact that the total amount of advected moisture is too low, and thus would result in weaker moisture convergence (and thus lower precipitation rates). Warner et al., [2015] also shows a negative vapor transport bias (Figure 2a in their paper) in the models compared to the NCEP-NCAR reanalysis, although a positive precipitation bias (their Figure 2g), which, assuming that vapor transport should lead directly to precipitation during landfall, could indicate a compensating bias in the models or the reanalysis, which could also bias future projections. Ideally, model parameterizations, specifically those related to sub-grid atmospheric transport or hydrology, should be examined to determine if missing or improperly simulated physical mechanisms in the models could be resulting in atmospheric moisture flux biases, and thus biases in simulated amounts of precipitation, flooding, and drought in both modern and future climate.

A further need for improved understanding is in regard to how accurately the hydrology of ARs is simulated, even before possible changes in the hydrology are considered. For example, it is still unclear the degree to which atmospheric rivers are associated with long ranged transport: specifically if ARs export tropical moisture into the midlatitudes, or simply involve the convergence of local moisture sources. Numerous studies using weather-scale models have attempted to estimate moisture sources in AR storms [e.g. Bao et al., 2006; Stohl et al. 2008].
However, both studies used Lagrangian parcel tracking to estimate the moisture sources, which limits the timescales over which one can perform the analysis [Sodemann et al., 2008]. Also, many of these studies only examine individual events (and typically those which are extreme in some way), which may not be representative of most AR storms. Thus there is still a large amount of uncertainty on the climatological moisture sources, and sinks, of atmospheric rivers, as well as essentially no knowledge on if and how those sources and sinks might change due to global climate change. Having an understanding of the hydrology can help with the forecasting of ARs and the generation of accurate future AR projections. Also, the same processes that influence atmospheric hydrology also can influence the chemical or isotopic composition of the water vapor [e.g. Bailey et al., 2013], including in Atmospheric Rivers. Thus better understanding these influence can help in the re-construction of past climates based on chemical or isotopic proxies [Dee et al., 2015b], particularly in regions that can be impacted by ARs, including Greenland [Neff et al., 2014] and Antarctica [Gorodetskaya et al., 2014].

The final issue that needs to be better understood is not just how ARs change with global climate change, but how the changes in ARs could modify the global climate itself. It has been found that atmospheric rivers are the main contributors to poleward moisture transport in the extratropics [Newman et al., 2012], with some estimates indicating that over 90% of all extratropical poleward moisture transport occurs in ARs [Zhu and Newell, 1998]. Water vapor is a greenhouse gas whose warming influence is dependent on the change in water vapor relative to the total amount of water vapor in the region [Held and Soden, 2000]. Thus changes in moisture transport, particularly into regions of relatively low water vapor, such as the poles, could amplify local warming.
The same physical processes that control water vapor also control, or at least influence, clouds and cloud properties. Since clouds impact the atmospheric radiative budget it is important to understand how clouds might change as the global climate changes [Gettelman et al., 2012]. This is because a change in clouds due to a change in climate could alter the radiative budget, resulting in an increase or decrease in the radiative flux, and thus another change in the climate itself, resulting in a potential feedback. However, this “cloud feedback” is poorly constrained, and is believed to be one of the major causes of uncertainty in climate sensitivity estimations, and thus future global climate projections [Gettelman et al., 2012]. Thus by understanding Atmospheric River changes, as well as changes in global meridional moisture transport, one may be able to better constrain the cloud feedback, and thus future projections of global and regional warming.

Although these questions and issues are important to resolve, doing so using only standard meteorological observations as a constraint could be extremely difficult. For one, there is no established method to determine where moisture in the atmosphere originated from using conventional measurements of numerical means. Although one can use the chemical or aerosol concentration and composition to determine the air’s potential origin [e.g. Creamean et al., 2013], that does not necessarily correspond to the origin of the water vapor. Another method is to apply Lagrangian tracers to wind and humidity model output [Bao et al., 2006; Stohl et al., 2008]. However, there are numerous problems with this method. One issue is that it is computationally expensive, as one first needs to run a model, and then run the parcel tracking afterward. Air parcel trajectories also need to be reset after a certain period of time, or else the trajectories will begin to diverge and all useable information will be lost [Sodemann et al., 2008]. This means that very long-distance transport of moisture cannot be captured, and thus some
potential sources and sinks will not be detected. Finally, it is important to note that these types of tracers track air, not water. Although one can attempt to deduce the moisture changes by examining the change in humidity along the trajectory, these changes may not necessarily be due to precipitation or surface evaporation, and could instead be caused by cloud formation, condensate advection, or sub-grid scale diffusion.

3. Importance of model parameterizations

Other issues that limited the capacity to estimate moisture origins are that the physical processes that could influence or be influenced by ARs, such as clouds and precipitation, tend to be parameterized in GCMs, and often-times contain a large number of poorly constrained free parameters [e.g. Yang et al., 2013]. This uncertainty can not only cause uncertainties for atmospheric river simulations, but for the climate as a whole [e.g. Gettelman et al., 2012, Yang et al., 2013]. The problem is that many of the quantities that are needed to accurately simulate cloud processes, such as the super-saturation, are extremely difficult to observe [Bolot et al., 2013], which results in poorly known parameters being used to close the parameterization system and potentially resulting in aspects of the model responding in physically un-realistic ways.

A secondary aspect to poorly constrained model parameters is that they can occasionally be used to have the model simulate the “correct” results, but for the wrong reasons. In other words, climate and earth system models are usually tuned in such a way that they simulate the modern climate as accurately as possible [Washington and Parkinson, 2005]. However, if the model parameters are not physically or observationally constrained well enough, they can be adjusted to an unrealistic value in order to compensate for other physical errors in the model. This means that even if the model appears to get the modern climate correct, it may not necessarily capture the change in the climate accurately, nor the climate in a state that is
substantially different from the current one (such as an ice age or hot house climate). This is true not just for the mean global climate, but for the system’s variability as well, including Atmospheric Rivers.

One way to try and resolve the issue of model “over-tuning” is to use one’s model to simulate past climates. This provides an opportunity to simulate a climate state, such as an ice age, that is substantially different from our modern climate. Also, un-like idealized or future climates, one has observational data that can be used to constrain the response one expects, and thus it allows one to see if a certain feature of the model doesn’t respond correctly when the model is placed in a significantly different climate.

However, even paleoclimate simulations have limited usefulness. This limitation is mostly due to the fact that the observations are sparse, and the observations that do exist aren’t actually true observations at all, but are instead measurements of a proxy that one believes is correlated with the true quantity of interest. In the past it was assumed that a direct linear relationship between the proxy and the observation was adequate. However, recently it has been found that many proxy systems can be influenced by multiple processes, and thus a robust linear relationship may not always be valid [e.g. Dee et al., 2015b]. This uncertainty in proxy-climate relationships can confound the expected results, and thus make it difficult to determine the accuracy of the model simulation.

4. Methods for hydrological evaluation

Is there any way a model can overcome these limitations, and at the same time reveal a better understanding of atmospheric rivers, or at least atmospheric moisture transport? One advantage of climate and earth system models is that one can add variables and preform experiments that simply wouldn’t be feasible in physical space. This includes the addition of
“water tracers”, which are tracers in the model that experience all of the same physical processes as regular water, such as advection, condensation, and precipitation, but have no impact on any other aspect of the climate, such as radiation, or latent heat release. This allows one to modify the water tracers’ hydrologic cycle while leaving the actual simulated climate unaffected, including constraining the locations of surface evaporation. This provides a direct way to measure moisture sources, sinks, and transport in the model, including individual simulated weather systems.

There are also several advantages in using water tracers to understand the hydrology of weather and climate phenomena, including atmospheric rivers. One is that the water tracers are calculated internally in the model. This allows one to run them at the same time as the model simulation itself, saving computer time. They also go through all of the same model processes that regular water does, and in fact can be setup to quantify each of those processes (like convective detrainment or rain re-evaporation). This allows for a much less ambiguous quantification of moisture transport and sinks, and removes the need to make certain assumptions (like a parcel re-moistening as soon as it enters the boundary layer). Finally, given that one is tracking moisture, and not the actual atmospheric flow, the water tracers never need to be reset, thus allowing for an examination of atmospheric hydrology over a longer time-scale, including very long-distance moisture transport. These advantages allow one to generate a true climatology of moisture sources and sinks for ARs, at least as simulated by the model. They also allow for one to determine how that hydrology might change due to climate forcings or very low-frequency inter-annual variability, which is one of the missing pieces of knowledge needed to better predict and prepare for changes in ARs as the global climate warms.
Another advantage of water tracers is that they lay the groundwork for the simulation of water isotopes. Water isotopes, technically referred to as water isotopologues, are molecules of water that contain a heavier oxygen or hydrogen isotope, usually either oxygen-18 or deuterium. This change in the mass and structure of the molecules means that water isotopes have a different saturation vapor pressure and molecular diffusivity compared to regular water [Bigeleisen, 1961, Merlivat, 1978]. These differences cause a change in the amount of water isotopes relative to bulk water whenever a phase change occurs, known as “fractionation” [e.g. Craig and Gordon, 1965]. Fractionation is sensitive to the environmental conditions during phase changes, including temperature and humidity [e.g. Merlivat and Jouzel, 1979; Jouzel and Merlivat, 1984]. Thus if one can measure changes in the ratio of water isotope mass relative to regular water, one can, in theory at least, back out the temperature or humidity. Given that water isotope ratios can be measured in numerous different glaciological or biogeochemical systems [Dee et al., 2015b], they are frequently used as paleoclimate proxies. As stated previously, simple assumptions about the correlation between water isotope proxy records may not always be valid [e.g. Sime et al., 2009]. However, by adding water isotopes and the related physical parameterizations directly into climate models, one can by-pass the need to invert the proxy into a different variable, and thus eliminate much of the uncertainty that comes with comparing paleoclimate model simulations to the proxy records.

Recently, new observational platforms have been developed to observe water isotope ratios in water vapor from satellite [Worden et al., 2006; Frankenberg et al., 2009; Randel et al., 2012], and thus for the first time truly global measurements of water isotope ratios can be made. Along with satellites, new in-situ water isotope spectrometers allow for the measurements of water isotope ratios in the field at extremely high temporal resolution [e.g. Noone et al. 2013;
Bailey et al., 2015b], which allows for one to investigate water isotope processes at scales that were not observable previously. Combined, these new observations provide a way to use water isotopes as an additional constraint on the modern hydrologic cycle. This is especially useful because water isotope ratios are strongly sensitive to convective, cloud, and precipitation processes [Bolot et al., 2013; Field et al., 2014; Dee et al., 2015a], which are always parameterized, sometimes with uncertain parameter choices, in GCMs [e.g. Yang et al., 2013]. Also, water isotope ratios can be used to derive certain quantities, such as super-saturation, that are extremely difficult to measure otherwise [Jouzel and Merlivat, 1984; Bolot et al., 2013]. This means that if a GCM or earth system model simulates water isotopes, these new observations can be used to more accurately tune model parameters, or expose biases that would be difficult to detect otherwise. Given that these parameters and biases would be most strongly associated with cloud and convective processes that also influence Atmospheric Rivers (and in-turn the global hydrologic cycle), isotope ratios of water vapor could be used to better diagnose biases and errors in AR simulations, and ultimately be used to account for or correct those biases, allowing for more accurate forecasts and future projections of these socially and economically important weather systems.

5. **Outline**

This dissertation describes a combination of studies that try and alleviate many of the uncertainties regarding atmospheric rivers, and the ability to simulate the climate system as a whole. In the following chapter, an examination of how well atmospheric rivers are simulated in the Community Atmosphere Model version 5 (CAM5) [Neale et al., 2010] is presented, including the testing of different AR detection methods as well as how the simulated ARs change in response to different dynamical cores and model resolutions. In Chapter 4, a description of a
newly developed water isotope scheme for CAM5 is presented, including a tuning experiment that exposes a bias in deep convection in the model, and how that impacts poleward moisture transport (which includes atmospheric rivers). Making use of this numerical tool, Chapter 5 describes a water tagging experiment that is used to determine the average moisture sources in atmospheric rivers that impact the West Coast of the United States, and how these sources might change due to global warming. The changes in the water isotope values are also examined, and implications for monitoring and paleoclimate proxy records are discussed. Finally, conclusions are presented, including what the results mean in terms of flooding, drought, and atmospheric hydrology as a whole. Lastly, future work is discussed, including multiple new opportunities for research that expand beyond understanding atmospheric rivers, and which become available following the development of the water isotope and water tracer-enabled earth system model described here.
CHAPTER II

The ability of the NCAR Community Atmosphere Model version 5 (CAM5) to simulate extreme moisture transport by transient eddies, including atmospheric rivers.

1. Introduction

Understanding precipitation, floods, and water resources is important for supporting and protecting lives, property, and industry. In particular, precipitation in many regions could change as the global climate warms [Held and Soden, 2006; Sun et al., 2007], thus potentially requiring changes in flood and water resource management. It has been found that as the climate warms, the dry regions become dryer while the wet regions become wetter [Sun et al., 2007]. However, these changes in average intensity and frequency may not necessarily represent changes in “extreme” precipitation events, or precipitation events occurring at the tail ends of the distribution, which are important for flooding events.

The main method for evaluating future climate change is through numerical climate and earth system models. However, it is unclear how well climate models can simulate extreme precipitation events. This is compounded by the fact that much of the uncertainty in these models lies in the ability to simulate subgrid-scale convection and cloud microphysics, which directly influences precipitation [Neale et al., 2010]. Thus it can be difficult to have confidence in a climate model’s precipitation projections, particularly for extreme events, or regional and local changes.

An alternative way to study extreme precipitation events is to analyze the mechanisms that produce them. Outside of the tropics, much of the precipitation is produced by extratropical cyclones, or transient eddies that occur on a 2-7 day timescale [e.g. Chang et al., 2002]. It is also
known that extreme precipitation events can be strongly related to atmospheric moisture fluxes and transport, at least in the midlatitudes [Lavers et al., 2015]. Thus as an alternative to examining precipitation directly, one can examine extreme moisture transport by transient eddies. This could allow one to better understand not only changes in the atmospheric hydrologic cycle, but also help constrain precipitation projections, and potentially identify areas of improvement for the models themselves.

One particular type of synoptic system that is associated with extreme transient moisture transport that has received much attention recently is the Atmospheric River (AR), also known as a tropospheric river or moist conveyor belt, which is a long, thin, horizontal plume of elevated moisture transport [Newell et al., 1992; Ralph et al., 2004; Bao et al., 2006]. Atmospheric rivers have been found to produce major precipitation and flooding events in California [Ralph et al., 2006; Dettinger and Ralph, 2011], Washington State [Neiman et al., 2011], Norway [Stohl et al., 2008], the United Kingdom [Lavers et al., 2011], and South America [Viale and Nunez, 2011]. Understanding how atmospheric rivers might change as the climate changes could help one predict changes in extreme precipitation and flooding events caused by ARs, as well as determine more clearly what the AR’s role in the atmospheric hydrologic cycle is. However, first one needs to determine how well they are simulated in climate models, and what sort of information they provide over an examination of the transient eddy flux alone.

This study will examine both extreme transient eddy moisture fluxes and atmospheric rivers in simulations of the modern era using the NCAR Community Atmosphere Model Version 5 (CAM5), which is the atmospheric component of the Community Earth System Model (CESM), an IPCC-class earth system model. Multiple simulations are performed to determine the sensitivity of moisture transport and AR results to the model’s horizontal resolution and
dynamical core. The model results themselves will be compared against reanalyses, which will be used to quantify any errors or biases, and how they differ between the model runs. This should verify whether or not CAM5, and potentially other climate models, can accurately simulate tail-end moisture transport by transient eddies and ARs, and thus the precipitation events that result from those atmospheric processes.

2. Data and Methods

2.1 CAM5:

The free-running IPCC-class Global Climate Model (GCM) used in this study is the NCAR Community Atmosphere Model Version 5 (CAM5) which is the atmospheric component of the Community Earth System Model Version 1 (CESM1) [Neale et al., 2010; Hurrell et al., 2013]. The model is configured to be forced with prescribed ocean state and land surface data exchange is modeled with the normal land component of CESM (i.e., CLM4) [Lawrence et al., 2011]. Three different model experiments were performed, all with year 2000 boundary conditions. The first, or “control” simulation, is a 1.9° N x 2.5°E finite-volume run, which ran for 35 years (with the first five years ignored for spin-up). The second, or “spectral” run, is a T42 Eulerian run, which also ran for 35 years. This simulation will have a similar resolution (~ 2.8° N x 2.8° E) to the control run, but will be using a completely different dynamical core (Spectral/Eulerian vs. Finite-volume). Another CAM5 run, or the “high-res” run, is a 0.9° N x 1.25°E Finite-volume run, which ran for only 25 years due to the computational cost. Results are based on six-hourly output intervals. These different simulations allow one to constrain the influence of resolution and dynamical core on CAM5's ability to simulate transient eddies fluxes, and ARs.
2.2 Reanalysis:

The reanalysis data chosen for this study is the Modern-Era Retrospective Analysis for Research and Applications (MERRA), which will be considered the “truth” for this study, even though much of the data is still generated by a model [Reinecker et al., 2011]. The reanalysis runs from 1979 to 2009, providing 30 years of data at a six-hourly interval. The MERRA data used in this study has been interpolated to a 1.25° N x 1.25° E grid, with 21 vertical pressure levels (from 1000 hPa to 300 hPa). Although pressure is not the model's native grid, we suspect that the interpolation will have a minimal effect. Any vertical integration was done using a method similar to Trenberth and Solomon, [1994], which should minimize errors in the calculation.

2.3 Transient eddy fluxes:

In order to verify that CAM5 can simulate tail-end moisture transport by transient eddies, a climatology was created by separating moisture fluxes into mean, stationary, and transient eddy components via Reynold's averaging, with a month being the timescale separating a stationary eddy from a transient one. Those fluxes were then vertically integrated from 1000 hPa to 300 hPa, and the 99th percentile value of moisture flux magnitude was calculated for each latitude, and was used as a cutoff value. Thus any vertically-integrated moisture flux due to a transient eddy present at a particular point at a particular time that was greater than or equal to this cut off value was marked as an extreme eddy flux. This was then compiled together to produce a climatology of tail-end transient moisture fluxes for both MERRA and CAM5, which can then be compared to each other.

2.4 Atmospheric rivers:

The AR detection method used to generate the AR climatology in this study will be the
algorithm developed by Zhu and Newell, [1998]. This method has been used in previous AR climatology studies [Zhu and Newell, 1998; Newman et al., 2012], along with similar methods which used integrated water vapor instead of integrated moisture flux [Newman et al., 2012] and zonal and meridional averages [Jiang and Deng, 2011]. In this method, one first calculates the vertically-integrated moisture flux:

\[
\vec{Q} = \mathbf{i} \left( \frac{1}{g} \int_{ps}^{300 \text{ hPa}} q \, \bar{u} \, dp \right) + \mathbf{j} \left( \frac{1}{g} \int_{ps}^{300 \text{ hPa}} q \, \bar{v} \, dp \right)
\]

(1)

where \( \vec{Q} \) is the total moisture flux vector, \( g \) is the acceleration due to gravity, \( q \) is the specific humidity, \( u \) is the zonal wind velocity, \( v \) is the meridional wind velocity, \( p \) is the air pressure, \( ps \) is the air pressure at the surface, and \( i \) and \( j \) are unit vectors. A grid point is flagged as an AR when \( \vec{Q} \) exceeds a value related to the deviation from the zonal mean at a given instant:

\[
AR \, \text{present if: } Q \geq Q_{\text{mean}} + 0.3(Q_{\text{max}} - Q_{\text{mean}})
\]

(2)

where \( Q \) is the vertically integrated moisture flux magnitude, \( Q_{\text{mean}} \) is the zonal mean of the moisture flux magnitude, and \( Q_{\text{max}} \) is the maximum value for the moisture flux magnitude at that particular latitude. Any grid point that has a vertically-integrated moisture flux greater than the term on the right-hand side contains an AR, and the moisture flux present at that grid point is defined to be the AR moisture flux.

It has been noted that the Zhu and Newell definition of atmospheric rivers is rather ad-hoc [Newman et al., 2012], and while in common use may not be ideal. Specifically, there are no clear dynamical restrictions in this algorithm. That means that many of the features defined
as ARs may in fact be other types of weather systems. There is also no indication that the fluxes represent extreme transport, as no temporal averaging is involved (so the flux simply has to be the largest for that day). Still, it appears to be an acceptable operational definition for atmospheric rivers, and considered a metric that is capable of exposing any biases or errors in CAM5’s simulations.

3. Results

3.1 Transient eddy fluxes:

The 99th percentile of moisture fluxes was calculated for transient eddies at each latitude, and that value was then used to indicate every place and time one of these tail-end transport events was occurring. Figure 1 shows the average tail-end transient moisture fluxes in boreal Winter (DJF) and Summer (JJA) in the MERRA data set. The first row (Figure 1 a and b) shows the probability of an extreme transient moisture flux event being present every six hours. The probability is proportional to the frequency, so that the higher the probability is, the higher the frequency of eddy occurrence. The actual probability values, and thus the actual frequency of occurrence, is quite small. This makes sense given that the very definition used for these transient eddies specifies that they should occur relatively infrequently, since the 99th percentile of moisture flux should only occur about 1% of the time at a particular latitude. Outside of the tropics, transient eddy “tracks” can be seen in most ocean basins. The presence of these tracks is mostly likely due to the actual midlatitude storm-tracks [Chang et al., 2002], and the fact that extratropical cyclones themselves are large-scale transient eddies, and thus their influence shows up in the analysis performed here.
Figure 1: This figure shows the average 99\textsuperscript{th} percentile transient eddy moisture flux probability (a, b), Average moisture flux due to extreme transient eddies (c, d), and average moisture flux per extreme eddy event (e, f) for MERRA for both Boreal winter (DJF – a, c, e) and Boreal summer (JJA – b, d, f).

The second row (c, d) shows the average moisture flux due to extreme transient eddy events. Again, the focus should be outside of the tropics, where many tropical weather systems produce false-positives in the detection algorithm. It can be seen that this flux is quite small. This indicates that the tail-end moisture fluxes by transient eddies occur too infrequently to have a large impact on the average poleward moisture flux. However, another key feature is the fact that the fluxes are almost always westward and poleward. A calculation of the zonal average poleward flux, and the average zonal poleward flux due just to transient eddies, shows that transient flux events produce almost all of the poleward moisture flux in the subtopics and mid-
latitudes, as shown in figure 2a and 2b. This indicates that transient eddy moisture fluxes, at least as defined here, are important for global poleward moisture transport.

Figure 2: This figure shows the zonally-averaged total poleward moisture flux (blue solid line), the poleward moisture flux due to all eddies (red dashed line), stationary eddies (green dot-dash line), and transient eddies (orange dotted line) for both MERRA (a, b) and the CAM5 1.9° N x 2.5° N finite-volume control run (c, d) for both DJF (a, c) and JJA (b, d).
The final row (e, f) shows average transient eddy moisture flux divided by the average extreme eddy flux probability. This is approximately equal to the average moisture flux per event. It should be noted that any probability less than 0.001 was set to 1.0 to avoid erroneously creating huge fluxes in low probability regions. In general, the average moisture flux per eddy event is largest in the midlatitudes, and is generally constant across the midlatitude ocean basins. It can also be seen that many of these fluxes are directed inland. Thus accurately capturing the average flux per extreme eddy event is important since it is this moisture flux that, when exposed to an uplifting mechanism such as orography, produces extreme precipitation events [Ralph et al., 2006; Viale and Nunez, 2011]. This indicates that extreme transient eddy fluxes should be properly modeled by a climate model if one hopes to simulate extreme events properly.

Figure 3 shows the tail-end transient eddy moisture fluxes as simulated in the CAM5 control run. The probability (Figure 3a and 3b) of these transient eddy events in the Northern Hemisphere is noticeably higher in boreal winter for CAM5 than it is for MERRA, while in the summer the frequency is noticeably less. This difference in Northern Hemisphere summer could be due to the fact that the CAM5 run has much stronger stationary eddy moisture fluxes than MERRA (not shown), and thus less moisture is transported by transient eddies, decreasing the frequency of these tail-end transient events. The average fluxes due to these transient eddies follows a similar pattern, with the CAM5 run having more moisture transported in winter and less moisture transported in summer in the Northern Hemisphere when compared to MERRA. Finally, the magnitude of moisture fluxes per transient eddy event (Figure 3e and 3f), is much smaller than it is in MERRA. This is true for both the Northern and Southern Hemispheres. The difference in transient eddy probability, along with the difference in average moisture flux per transient eddy event, indicates that CAM5 might have difficulty simulating these tail-end
moisture transport events, and thus could have trouble simulating extreme precipitation events caused by these transports.

**Figure 3:** Same as Figure 1, except the data is from the CAM5 control simulation.

To evaluate how model resolution and dynamical core impact CAM5's ability to simulate these tail-end transient eddy moisture transport events, figure 4 shows the difference in probability for all three CAM5 runs compared to MERRA. All the areas outlined in black are statistically significant at 99% confidence according to a Mann-Whitney U test. The most noticeable features include a positive frequency bias in the North Atlantic and Pacific during boreal winter and a negative frequency bias in the South Pacific during boreal winter and in the North Pacific during boreal summer. Although much of this bias is tropical in location, some of
the bias does extend up into the midlatitudes. As can been seen in the mean absolute error values shown in Table 1, the high-resolution CAM5 run performs the best compared to MERRA, while the control run and spectral run appear to be equal, at least on an annual basis.

**Figure 4:** This figure shows the difference in probability between MERRA and the CAM5 control run (a, b), the CAM5 T42 Eulerian/Spectral run (c, d) and the CAM5 0.9° N x 1.25° N high-resolution run (e, f) for both DJF (a, c, e) and JJA (b, d, f). The areas outlined in black are statistically significant at the 99% confidence level according to a Mann-Whitney U test.
Table 1: This table shows the Mean Absolute Error values for each CAM5 simulation as compared to MERRA for the tail-end (99th percentile) transient eddy moisture flux probability, average fluxes due to tail-end transient eddies, and the average flux per tail-end transient eddy event for both Boreal winter (DJF) and Boreal summer (JJA).

<table>
<thead>
<tr>
<th></th>
<th>CAM5 Control</th>
<th>CAM5 Spectral</th>
<th>CAM5 high-res</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eddy prob – DJF</td>
<td>0.006</td>
<td>0.005</td>
<td>0.005</td>
</tr>
<tr>
<td>Eddy prob – JJA</td>
<td>0.005</td>
<td>0.006</td>
<td>0.005</td>
</tr>
<tr>
<td>Eddy flux – DJF</td>
<td>1.42 kg/m/s</td>
<td>1.46 kg/m/s</td>
<td>1.35 kg/m/s</td>
</tr>
<tr>
<td>Eddy flux – JJA</td>
<td>1.20 kg/m/s</td>
<td>1.32 kg/m/s</td>
<td>1.10 kg/m/s</td>
</tr>
<tr>
<td>Flux per Eddy – DJF</td>
<td>106.85 kg/m/s</td>
<td>106.84 kg/m/s</td>
<td>94.32 kg/m/s</td>
</tr>
<tr>
<td>Flux per Eddy – JJA</td>
<td>109.57 kg/m/s</td>
<td>112.55 kg/m/s</td>
<td>95.29 kg/m/s</td>
</tr>
</tbody>
</table>

Figure 5 shows the difference in average moisture flux due to tail-end transient eddy transport. In general, the average flux difference matches the probability difference, with regions that have a low (high) probability bias also having a smaller (larger) flux bias. However, there are exceptions, particularly in the tropics. These differences, though, are probably not associated with the strong extratropical cyclone-induced moisture fluxes in which we are interested, and thus will be left for future work. Again, the high-resolution CAM5 run has the best Mean Absolute Error (MAE) out of the three runs, while the spectral CAM5 run has the worst, as shown in Table 1.
Figure 5: Same as figure 4, except for average moisture flux due to transient eddies.

Figure 6 shows the difference in average moisture flux per transient eddy event. Here almost all of the ocean basins show large, statistically-significant negative biases in the CAM5 simulations, with the two exceptions being the southwestern edge of the North Pacific, and in the Southern Ocean Southeast of Australia. Although a similar result was found for atmospheric rivers (as can be seen in figure 6), the area of statistical significance is much larger. Table 1 shows that the high-resolution CAM5 run performed the best, while the spectral CAM5 run
performed slightly worse than the control run. Still, the fact is that all of the models generally under-predict the flux magnitude globally, indicating that CAM5 may not simulate the magnitude of these tail-end eddy transport events, and the extreme precipitation they might produce, properly. It should also be stated that MERRA most likely has errors as well, and thus the improvement in the higher-resolution CAM5 run may just be due to the model approaching the MERRA resolution, and not necessarily due to an improvement relative to the actual earth system.

**Figure 6:** Same as figure 4, except for average moisture flux per AR event.
### 3.2 Atmospheric rivers:

Figure 7 shows the average state of atmospheric rivers, as defined by Zhu and Newell, 1998, in boreal winter (DJF) and summer (JJA) in the MERRA data set. The first row (a, b) shows the probability of an AR being present every six hours. The most dominant features occur in the tropics. However, it is likely that those features are actually the ITCZ and the Indian Monsoon, and not atmospheric rivers in the traditional sense. Instead, attention should be paid to the subtropics and midlatitudes, where, again, “tracks” can be seen in most ocean basins. The presence of these tracks is mostly likely due to the fact that many ARs are frontally-forced [Ralph et al., 2004; Ralph et al., 2005; Bao et al., 2006], and thus occur where extratropical cyclone also occur. It also points to the connection between ARs and transient eddy moisture fluxes.
Figure 7: Same as Figure 1, except for ARs as defined by Zhu and Newell, 1998.

The second row (Figure 7 c and d) shows the average moisture flux due to atmospheric rivers. Again, the focus should be outside of the tropics, where many tropical weather systems produce false-positives in the detection algorithm. The key feature to notice is the fact that the fluxes are almost always westward and poleward. If one calculates the zonal average poleward flux, and the average zonal poleward flux due just to ARs, one will find that ARs produce almost all of the poleward moisture flux in the subtopics and mid-latitudes, as shown in figure 8. This indicates that atmospheric rivers, at least as defined by Zhu and Newell, are important for global poleward moisture transport, and appear to capture much more of the meridional moisture flux than tail-end transient eddies do, at least at the 99th percentile.
Figure 8: Zonally-averaged total poleward moisture flux (orange dotted line), the poleward moisture flux due to ARs (blue solid line) and the difference between the two (red dashed line) for both MERRA (a, b) and the CAM5 1.9° N x 2.5° N finite-volume control run (c, d) for both DJF (a, c) and JJA (b, d).

The final row (e, f) shows the average AR moisture flux divided by the average AR moisture probability. This is approximately equal to the average moisture flux per AR event. It
should be noted again that any probability less than 0.001 was set to 1.0 to avoid erroneously creating huge fluxes in low probability regions. In general, the average moisture flux per AR is largest in the midlatitudes, and is generally constant across the midlatitude ocean basins. It also appears to have a larger moisture flux than the flux from extreme transient eddies. However, ARs include not only the moisture flux from transient eddies, but also from stationary eddies and the mean flow. Thus one cannot do a direct comparison between the two, although it does provide evidence that both could be used to predict the chances of extreme precipitation events, at least in the extratropics.

The average state of ARs in the CAM5 control run are shown in figure 9. In general, the CAM5 simulation shows the same centers of high AR activity compared to MERRA, but with a higher AR probability (and thus a higher frequency). The average AR flux in CAM5 is qualitatively similar to MERRA, and the CAM5 control run accurately captures the total amount of poleward flux due to ARs, as can be seen in figure 8c and 8d. In fact, all of the CAM5 runs show that ARs are responsible for the majority of poleward moisture transport in the subtropics and midlatitudes, indicating that this result is robust against changes in the configuration of the model, and that CAM5 can adequately simulate this feature of global atmospheric moisture transport.
Figure 9: Same as Figure 3, except for ARs as defined by Zhu and Newell, 1998.

The bottom row (e, d) in figure 9 shows the average moisture flux per AR event in the CAM5 control simulation. Again, the pattern is qualitatively similar to MERRA, except that the distribution of max flux per AR is not as zonally homogeneous in CAM5 as it is in MERRA, indicating that CAM5 might have a negative moisture flux bias for atmospheric rivers in certain midlatitude regions, at least when compared to MERRA. This also matches up with the under-prediction of moisture fluxes by transient eddies, which implies that the same bias might be affecting both types of weather systems. This also indicates, again, that CAM5 may not accurately simulate the magnitude of extreme moisture flux events in certain regions, and thus may not be able to accurately simulate the magnitude of the extreme precipitation caused by
those flux events.

In order to more accurately determine how model resolution and dynamical core impact the simulation of atmospheric rivers, global differences for each quantity shown in figures 7 and 9 were calculated between MERRA and the three different CAM5 simulations. Figure 10 shows the difference in AR probability between the CAM5 runs and MERRA. All the areas outlined in black are statistically significant at 99% confidence according to a Mann-Whitney U test. The first key thing to notice is that the biggest differences are in tropics, while the smallest differences tend to occur in the midlatitudes. Since atmospheric rivers are generally thought of as extratropical phenomenon, this indicates that much of the error seen may be due to weather systems that aren't actually atmospheric rivers. It is also important to note that the high-resolution CAM5 run has the least amount of significant differences compared to MERRA. Table 2 contains the mean absolute error for each quantity and season of interest for each model run. The high-resolution model run has the lowest MAE for every quantity and every season, demonstrating that model resolution may be important for accurately generating an AR climatology. There is also more statistically significant differences in the midlatitudes for the spectral CAM5 run compared to the control run, which possibly provides evidence that the spectral dynamical core does worse at simulating AR frequency. This can also be seen in the slightly higher MAE values.
Figure 10: Same as Figure 4, except for ARs as defined by Zhu and Newell, 1998.

Table 2: This table shows the Mean Absolute Error values for each CAM5 simulation as
compared to MERRA for AR probability, Average fluxes due to ARs, and the average flux per AR event for both Boreal winter (DJF) and Boreal summer (JJA).

Figure 11 is the same as figure 10, except the difference is in the average moisture flux produced by ARs. The same pattern holds for the average AR moisture flux as it does for the AR probability, with the smallest differences occurring in the midlatitude ocean basins, and the high-resolution CAM5 run having the smallest difference, as can be seen in the MAE values. There are also some distinct regional differences, including a poleward shift in AR moisture flux magnitude in the Northern Hemisphere during boreal summer. There also appears to be no real difference between the CAM5 control run and spectral run, indicating that the dynamical core chosen may not have a large influence on the average moisture flux due to atmospheric rivers.
Figure 11: Same as Figure 5, except for ARs as defined by Zhu and Newell, 1998.

Figure 12 is similar to figure 11 and 10, except measuring the difference in the average moisture flux per atmospheric river. In other words, this quantity indicates how accurately CAM5 simulates individual AR events, or at least the moisture fluxes associated with them. Again, as with the previous quantities, the smallest differences are in the extratropics, while the largest differences tend to be in the tropics. In particular, large differences appear to occur over North Africa and the Mediterranean. Given the low average AR probability in those regions, it is possible that these differences are due to a few (or lack of a few) random events in the MERRA.
data set. However, it is also possible that this indicates a real difference between CAM5 and MERRA in the simulation of weather systems in that region. It should be noted that although the differences are smaller in the extratropics than the tropics, differences still exist. In particular, there appears to be a negative bias for both the Pacific and Atlantic basins for all CAM5 runs. This indicates that CAM5 may not be able to accurately capture the large moisture fluxes associated with ARs, which in-turn indicates that CAM5 may not be able to capture the magnitude of the extreme events caused by these ARs. Again, as before, the high-resolution model run preformed the best, as can be seen in the MAE values in table 2. There also appears to be no real difference between the spectral and control model runs, although the spectral run does slightly better in Boreal winter, and slightly worse in Boreal summer. Still, it does appear that the dynamical core chosen is not as important as the horizontal resolution, at least when compared to reanalysis.
3.3 The relationship between atmospheric rivers and extreme transient eddy moisture transport

Although atmospheric rivers are important in their own right, the major question here is how closely they are related to extreme transient eddy moisture fluxes, at least in the midlatitudes. In particular, determining the relationship between the two is important for connecting large-scale dynamics, particularly those simulated by global climate models, to the meteorological impacts that are known to be caused by ARs, such as extreme precipitation and

Figure 12: Same as Figure 6, except for ARs as defined by Zhu and Newell, 1998.
flooding. One of the defining characteristics of ARs is their geometry, in the sense that they are often described as long, thin filaments. For example, Neiman et al., [2008] defined integrated water vapor plumes as ARs if they were more than 2000 km long, and less than a 1000 km wide. In order to determine if the Zhu and Newell, [1998] defined ARs and the tail-end transient eddy moisture transports have a similar shape, the direction of the moisture flux was determined for every grid box that contained an AR or a transient eddy. Then, the number of grid boxes perpendicular to this flux direction that also contained an AR or transient eddy was counted. Once a grid box was reached that did not contain an AR or transient eddy, the counting was stopped. The number of counted grid boxes is then converted into an actual distance, and that distance is considered the “width” of the AR or transient eddy.

Figure 13 shows the average width of both ARs and the transient eddies as a function of latitude. It should be noted that the data has been smoothed by a 5 grid point moving average in order to make the data more legible. It can be seen that the minimum in width for all quantities is in the midlatitudes. Since this is the latitude location examined by most of the observational studies [e.g. Neiman et al., 2008; Ralph et al., 2004], this indicates that the ARs and transient eddies in this study satisfy the width requirements set by these previous studies. One can also see that MERRA and the high resolution CAM5 run have the thinnest ARs and transient eddies, demonstrating that a higher model resolution might be key in accurately simulating the correct size of these moist atmospheric plumes. Finally, it can be seen that the transient eddies are thinner than the ARs, indicating that the Zhu and Newell, [1998] definition might be capturing features other than ARs as seen in observational studies, which means that it may not actually be ideal in detecting these locations of enhanced moisture flux.
Figure 13: This plot shows the average width of ARs (a) and 99th percentile transient eddy moisture fluxes (b) for MERRA (blue solid line), the CAM5 control run (red dashed line), the CAM5 Eulerian/Spectral run (orange dotted line), and the CAM5 high-resolution run (green dot-dash line). The lines have been smoothed by a five-grid box moving average to make the lines easier to read.

The vertical structure of wind speed within an AR is a critical attribute of the systems. Ralph et al., [2005] used dropsondes to measure the wind speed in an AR, and found a strong low-level jet around 900 mb, which is also where the majority of the moisture transport occurs (since specific humidity decreases with height above the boundary layer). Figure 14 shows the average vertical profile of wind speed for both ARs and transient eddies for both MERRA and the CAM5 control run. The profiles were taken from the location that had the highest probability between 35° N and 45° N for the December-January-February season. This was done in order to guarantee that the ARs or transient eddies used to calculate the profile come from winter-time extratropical cyclones, and not other phenomenon like tropical cyclones.
Figure 14: Average vertical profile of wind speed for MERRA (a and b) and the CAM5 control run (c and d) for both ARs (a and c) and 99th percentile transient eddy moisture flux events (b and d). The blue line is the mean, while the black dotted line is ± one standard deviation. The profiles were calculated for the grid box between 35° N and 45° N that had the highest probability of AR or transient eddy occurrence.

It can be seen that both the ARs and the transient eddies for both MERRA and CAM5 have a small maximum in wind speed below 900 mb. This is likely the low-level jet as seen in observations [Ralph et al., 2005]. However, the wind speed in the modeled jet is much smaller than what is seen in the dropsonde analysis, indicating that both MERRA and CAM5 have
difficulty in simulating this feature of ARs. It could also indicate that neither data set accurately match the magnitude of moisture fluxes associated with atmospheric rivers, or low-level jets in general. One can also see that vertical wind shear is present in all of the profiles, which, assuming that the thermal wind balance is accurate, indicates a strong temperature gradient near the grid point where the profile is taken. This indicates that both may be associated with the warm conveyor belt [Carlson, 1980], and supports the idea that both of these fluxes are associated with fronts and extratropical cyclones. Finally, the fact that both have similar profiles supports the fact that ARs might in fact be tail-end transient eddy moisture fluxes, and that both are representing the same dynamical process.

4. Discussion and Conclusions

One of the questions concerning global warming is how the global hydrologic cycle will change. In particular, it has been found that the hydrologic cycle intensifies, with wet areas becoming wetter, and dry areas becoming dryer [Held and Soden, 2006; Sun et al., 2007]. However, this is more representative of averages, even though it is the changes in extreme events that are more likely to cause changes in flooding and other natural disasters. Thus by examining the meteorological phenomenon that can produce extreme precipitation, particularly in global climate models, one could try to project how hydrologic extremes might be modified due to global climate change.

In the extratropics, one of the major drivers of meridional moisture flux, as well as precipitation, are transient eddies, often-times associated with baroclinic cyclones. By examining extreme transient eddy moisture fluxes, i.e. those that are greater than the 99th percentile, one can determine how capable a climate model would be in accurately simulating the
extreme precipitation generated by those extreme flux events.

Another type of weather feature that could have a strong impact in the extratropics are atmospheric rivers, defined as long, thin filaments of elevated moisture flux [Newell et al., 1992; Ralph et al., 2004]. ARs have been associated with extreme precipitation events and flooding in numerous locations around the world [Ralph et al., 2006; Dettinger and Ralph, 2011; Neiman et al., 2011; Stohl et al., 2008; Lavers et al., 2011; Viale and Nunez, 2011]. Although there have been multiple attempts at generating a climatology of ARs [Zhu and Newell, 1998; Neiman et al., 2008; Jiang and Deng, 2011; Newman et al., 2012], none of them have determined whether or not an IPCC-class global climate model can simulate that climatology, which is necessary to create future climate projections. There has also been a concern that the way atmospheric rivers are defined and described may be inaccurate [Bao et al., 2006; Knippertz and Martin, 2007; Knippertz and Wernli, 2010; Newman et al., 2012], particularly since many ARs are associated with local moisture convergence, and the warm conveyor belt [Carlson, 1980]. By examining both extreme transient eddy moisture fluxes and atmospheric rivers, one can ensure that the results of the simulation are robust, and not just a product of the detection method. The analysis also helps reveal similarities between the two phenomena, and thus allows for a deeper understanding of both.

This study has made progress on these overarching concerns, by first analyzing a global climatology of the 99th percentile of moisture fluxes due to transient eddies, and by examining a global climatology of ARs in one of the ways defined in the literature [Zhu and Newell, 1998]. The climatology was generated for both MERRA, which is a reanalysis, and for three different CAM5 simulations, one with a different dynamical core, and one with a higher resolution, to determine how those choices impact the climatologies.
It was found that, qualitatively, all of the CAM5 runs match the eddy and AR climatologies. However, there were some large quantitative differences. In particular, the CAM5 simulations under-predicted the moisture flux magnitude for both ARs and tail-end transient eddy fluxes, which provides evidence that CAM5, at least when compared to MERRA, might not be able to accurately predict the magnitude of extreme precipitation events caused by these moisture fluxes. The reason for this underestimation is unknown, but it could be due to the inadequate representation of subgrid scale processes that are more accurately simulated in MERRA for one reason or another. For example, there is evidence that CAM5 produces too much deep convection in the winter midlatitudes [Nusbaumer et al., in prep], which could cause too much rainout along the transport path, and thus horizontal moisture fluxes that are too weak. There is also the possibility that the winds themselves may be biased low, meaning that even if the atmospheric humidity was simulated perfectly, the flux of moisture would still be too weak.

It was found that the high resolution CAM5 simulation did the best in simulating tail-end transient eddy fluxes and ARs, at least when compared to the MERRA climatology. This perhaps unsurprising result could simply be due to the fact that the high resolution CAM5 run most closely matches the MERRA resolution, or it could be due to the high-resolution model more accurately capturing the smaller-scale flows and processes associated with these moisture fluxes. More comparisons, particularly with direct observations, will be needed to more accurately answer this question. However, at higher resolution climate model will performs better in simulating ARs and tail-end transient eddy moisture fluxes than a low resolution model. There also appeared to be only a slight difference between the finite-volume control run, and the Eulerian/spectral run, demonstrating that horizontal resolution, and not the dynamical core used, is more important in simulating these midlatitude moisture fluxes.
Finally, it was shown that both the extreme transient eddy moisture fluxes (associated with the tail end of the distribution) and the Zhu and Newell, [1998] defined ARs have similar horizontal widths, and similar vertical profiles of wind speed. This indicates that both methods are probably detecting the same thing, which is likely to be moisture that is transported by the warm conveyor belt that exists in the warm sector of extratropical cyclones [Carlson, 1980]. This supports the claim that” moist conveyor belt” may be a more accurate term than “atmospheric river”, as described previously [Bao et al., 2006; Knippertz and Martin, 2007]. It was also found that the transient eddy fluxes were actually thinner (had a smaller width) than the ARs identified from typical definitions, which indicates that using the tail-end moisture transport by transient eddies might more accurately detect the filamentary moisture transports seen in observations than the methods that use slightly more ad-hoc definitions. This is similar to the results found in Newman et al., [2012], who found that using anomalous low-level meridional wind speed, which would usually be associated with transient eddies, was the most effective at defining ARs.

Transient eddies and atmospheric rivers might change as the global climate changes, as indicated by studies of the West Coast of the United States [Dettinger, 2011; Warner et al., 2015]. By demonstrating that an IPCC-class climate model can simulate these moisture fluxes globally, at least in terms of general location and frequency, then it should be possible to project how they might change due to global warming anywhere on the planet. It also provides an opportunity to perform water tracer studies, and determine what the sources and sinks of water are in these filamentary structures. Finally, the fact that CAM5 under-predicts the magnitude of these fluxes provides an opportunity to better understand what processes the model is having troubles with, such as moist convection [Nusbaumer et al., in prep], and to hopefully improve the modeling of
those processes so that not only the simulation of extratropical cyclones is improved, but also the modeling of the climate system as a whole. This would ultimately result in better climate projections, particularly in regards to extreme precipitation events, and thus provide the information needed to produce well-designed adaption and mitigation strategies.
CHAPTER III


1. Introduction

Isotopes of hydrogen and oxygen in water have been found to provide unique information on the environmental conditions experienced by a given mass of water. Since the 1950s, researchers have examined the potential benefits of water isotopologues (water molecules that contain an isotope of hydrogen or oxygen) and water isotope ratios to better understand the oceans [Craig and Gordon, 1965], precipitation [Dansgaard, 1964], land surface water masses, such as rivers [IAEA, 2012], and the fluxes between all the major reservoirs in the earth system [e.g. Merlivat and Jouzel, 1979]. One of the major strengths of water isotopologues is that their signal can be recorded over a long period of time in certain environmental systems, allowing for the use of water isotope ratios as a paleoclimate record. These water isotope ratio-based proxy records can be found in ice cores, sediment cores via biogenic carbonates and leaf waxes, speleothems, corals, and tree cellulose [e.g. Dee et al., 2015]. Thus improving our knowledge of water isotope ratios and leveraging that knowledge can help increase our understanding of the earth system, both in the past and the present, which could then be used to improve our predictions of the future.
However, water isotope ratios are sensitive to many physical processes, including the history of phase changes experienced by the water mass of interest, the type of phase changes that occur, and the temperature and relative humidity during the phase changes. This problem can be confounded even more by the fact that atmospheric or oceanic circulations can result in moisture source and sink changes, which can be difficult to disentangle if one only has a single point measurement, or an overly-simple model. These processes also influence the distribution of water vapor and moist convection in the atmosphere, so thus by better understanding how they influence water isotope ratios one could also better understand climate changes and feedbacks, such as the water vapor feedback [Sherwood et al., 2010].

One way to alleviate these issues is to use the additional information provided by the stable isotope chemistry of water, and to make use of an isotope-enabled Global Climate Model (GCM) or earth system model, which has the capability to simulate all the relevant physical processes, including the impact of circulation changes. The development and use of isotope-enabled GCMs has been progressing since the 1980s [Joussaume, 1984], and now many different GCMs can simulate water isotopologues, at least in the atmosphere [e.g., Noone and Sturm, 2010; Risi et al., 2012; Conroy et al., 2013]. Much of the focus of these models has been to try and understand paleoclimate proxy records, including possible uncertainties in their use as paleothermometers or hydrologic indicators [e.g. Sime et al., 2009].

GCMs have substantial errors, however, particularly when it comes to simulating unresolved, or sub-grid scale, processes. Many of these processes have a direct influence on water isotope ratios, specifically cloud physical and convective processes [e.g. Bolot, et al., 2013]. Thus one can use water isotope ratios to help constrain model process and diagnose model errors or biases. This approach has been illustrated succinctly in studies using several different GCMs.
For example, Risi et al., [2012], used a wide set of different isotopic observations along with the isotope-enabled LMDZ4 model to determine that the vertical diffusion in the model was too high. Similarly, Field et al., [2014], showed a high sensitivity for water isotope ratios in vapor to parameters used to generate an MJO in the isotope-enabled GISS model. Although these studies show much promise, they have been somewhat preliminary, and have left many opportunities open for further research. Understanding these processes is vital, particularly when using the models to project future climate conditions, given the potentially strong role convection and clouds have on climate feedbacks and sensitivity [Sherwood et al., 2010, Sherwood et al., 2014].

The opportunities for exploiting the advantages of isotope-enabled GCMs has been greatly increased given new isotopic observational platforms. Specifically, two new technologies have greatly expanded the spatial and temporal coverage of water isotope ratio measurements over the past decade. The first is the development of satellite instruments and retrieval algorithms that can deduce deuterium to hydrogen isotope ratios in atmospheric water vapor at scientifically relevant precision, allowing for near global coverage [Worden et al., 2006; Frankenberg et al., 2009; Randel et al., 2012]. The other development has been of in-situ spectrometers that can provide isotopic vapor measurement in a continuous fashion [e.g. Bailey et al., 2015a], allowing for very detailed time series data at key locations around the globe, including deployments on mobile platforms (e.g., Bailey et al., 2013; Kurita et al., 2011). These data create an additional observational constraint on water isotope ratios in the atmosphere, allowing for new isotope-enabled model experiments that can more closely examine cloud and transport processes, using the additional information provided by the observed isotopic ratios.

This paper examines the simulation of atmospheric water isotopologues by the newly developed isotope-enabled Community Atmosphere Model, Version 5 (iCAM5), which will be
the atmospheric component of the isotope-enabled version of the National Center for Atmospheric Research’s Community Earth System Model Version 1 (iCESM1). First, a description of the physics of water isotopologues and their implementation in iCAM5 is presented in section 2. Next, a comparison between an iCAM5 simulation of the modern climate and a suite of observations, including isotopic spectrometer and satellite data, is presented in section 3. This demonstrates the model’s ability to simulate water isotope ratios correctly, but will also quantify the errors and biases present in the model itself. Then, in section 4, results from a parameter sensitivity analysis are described, with the key objective being to determine which model parameters have values that can be changed to minimize the mismatch between simulated water isotope ratios and observations. The sensitivity analysis demonstrates which processes water isotope ratios are most sensitive to in the model, and what iCAM5 may not be simulating properly. It is important to note that iCAM5 has been developed within an era where satellite and in-situ observations of water vapor isotope ratios are widely available. Therefore, while there is a need from the model to provide a credible simulation of the isotope ratios in precipitation, it will have to be balanced by a need to accurately simulate isotope ratios in water vapor as well. Finally, conclusions and future work are presented in section 5.

2. Isotopic fractionation physics in CAM5

The Community Atmosphere Model Version 5 (CAM5) [Neale et al., 2010] is the atmospheric component of the NCAR Community Earth System Model (CESM) [Hurrell et al., 2013]. The broad strategy for implementing water isotopic tracers follows previous modeling work [e.g., Joussaume, 1984; Jouzel et al., 1987; Jouzel et al., 1991; Hoffman et al., 1998; Noone and Simmonds, 2002; Yoshimura et al., 2008; Bony et al., 2008] and in the description which
follows, we give the manner in which fractionation has been added to the advanced parameterization schemes in CESM. Water isotopologues, HDO and H$_2^{18}$O, were added and are tracked in all aspects of the model’s hydrological cycle, including surface fluxes, condensation processes, and atmospheric transport. The advected tracer quantity used for each water isotopologue is the ratio of the total water isotopologue mass to the mass of the air. For water vapor only, this would be equivalent to the specific humidity of the water isotopologue, although cloud liquid and cloud ice is advected as well. Transport by boundary layer turbulence and large-scale advection occurs without fractionation, and thus the water isotopologues are treated as conservative tracers.

Fractionation processes differentiate the abundance of heavy isotopologues from the more abundant species. Both equilibrium and kinetic fractionation is included, although the present version of the model omits mass-independent fractionation effects, which are considered to have limited influence on water in the troposphere [Winkler et al., 2013]. Equilibrium fractionation is theoretically very well understood [Bigeleisen, 1961] and is temperature dependent. The equilibrium fractionation factor, $\alpha_e$, is the ratio of the saturation vapor pressure of the heavy isotopologue to normal water and in CAM5 we use values from empirical fits from the laboratory determinations of Horita and Wesolowski, [1994] for liquid/vapor equilibration of H$_2^{18}$O/H$_2^{16}$O and HD$_2^{18}$O/H$_2^{16}$O, Majoube, [1971] for ice/vapor equilibration of H$_2^{18}$O/H$_2^{16}$O, and Merlivat and Nief, [1967] for ice/vapor equilibration of HD$_2^{18}$O/H$_2^{16}$O.

Kinetic fractionation emerges from the fact that the diffusivity for water molecules with heavy isotopes is lower than regular water and thus there is an isotopic separation when diffusion limits mobility. This results in a fractionation that occurs whenever the phase change occurring is not in thermodynamic equilibrium (i.e., relative humidity is not equal to 100%). In CESM,
kinetic fractionation occurs during oceanic evaporation, evaporation and transpiration from land, the deposition of vapor onto ice, and during the evaporation of rain into a sub-saturated environment. The details of the fractionation will be described in the respective sub-section.

2.1 Surface evaporation and condensation

Ocean evaporation is calculated using the bulk aerodynamic formula [Neale et al., 2010]:

\[ E = \rho_a C_E \Delta q \]  

Where \( \rho_a \) is the atmospheric surface density, \( C_E \) is the exchange coefficient, and \( \Delta q \) is the difference between the specific humidity at the lowest model layer, and the specific humidity in a thin surface layer that is in equilibrium with the ocean surface. The same formulation is used for water isotopologues, except that the equation for water isotopologues follows the Craig and Gordon, [1965] hypothesis that the near surface vapor is in isotopic equilibrium with sea water, and is written as:

\[ \Delta q_i = q_i - \frac{R_{ocn}}{\alpha_e} q_s \]  

\[ E_i = \alpha_k \rho_a C_e \Delta q_i \]  

Where \( q_i \) is the bottom atmospheric layer isotopic specific humidity, \( R_{ocn} \) is the isotopic ratio for the ocean surface, \( \alpha_e \) is the equilibrium fractionation factor at the ocean surface temperature, \( q_s \) is the bulk water saturated layer humidity, and \( \alpha_k \) is a kinetic fractionation factor. Kinetic fractionation is parametrized following Merlivat and Jouzel, [1979], and is calculated as:

\[ \alpha_k = 1 - \frac{\left( \frac{D}{D_i} \right)^n - 1}{\left( \frac{D}{D_i} \right)^n + M} \]
\[ M = \frac{1}{k} \ln \left( \frac{\bar{u} z_b}{30 \nu} \right) \frac{13.6 S c^{2/3}}{7.3 R e^{1/4} S c^{1/2}} \]
\text{If } Re < 1
\hspace{1cm} (5)

\[ M = \frac{1}{k} \ln \left( \frac{z_b}{z_0} - 5 \right) \frac{7.3 R e^{1/4} S c^{1/2}}{7.3 R e^{1/4} S c^{1/2}} \]
\text{If } Re \geq 1
\hspace{1cm} (6)

\[ z_0 = \frac{u_*^2}{81.1 g}, \quad \nu = \frac{1.7^{-5}}{\rho_a} \]
\hspace{1cm} (7,8)

\[ Re = \frac{u_* z_0}{\nu}, \quad Sc = \frac{\nu}{D_a} \]
\hspace{1cm} (9,10)

Where D is the bi-molecular diffusivity of regular water in air, D_i is the diffusivity of isotopic water in air, n is a scaling constant [Merlivat, 1978], k is the Von Karman constant, equal to 0.4 in CESM, z_b is the height of the lowest atmospheric layer in the model, u_* is the friction velocity, Sc is the Schmidt number, Re is the Reynolds number, z_0 is the roughness length, g is gravity, \( \nu \) is the kinematic viscosity of air, and D_a is the diffusivity of air. The quantity M describes the relative importance of turbulent versus molecular transport within the surface layer, and comes from the work of Brutsaert [1975a and 1975b].

The isotopic evapotranspiration fluxes from land are computed in a similar manner, but also accounting for evaporation from soils, intercepted canopy water, and snow pack, as well as transpiration, and is described in detail in a separate study [Wong et al., in prep.]. Isotopic evaporative fluxes associated with sea ice, on the other hand, are assumed to be non-fractionating.

2.2 Moist convection
In CAM5, moist convection is split into deep convection [Zhang and Macfarlane, 1995] and shallow convection [Park and Bretherton, 2009]. The convective schemes are quite different from each other in terms of their physical processes and assumptions, and the water isotopologues are designed such that they experience the same convective transport that standard water vapor and condensate experience in each of these separate parameterizations. However, the phase changes that occur in these convective schemes are similar enough that the impact of these changes on water isotope ratios can be parameterized consistently.

The water vapor isotopic tendency for the deep convection [Zhang and Macfarlane, 1995] inside the cloud is:

\[
\frac{\partial q_i}{\partial t} = E_i - C_i - \frac{1}{\rho} \frac{\partial}{\partial z} \left( M_u q_{iu} + M_d q_{id} - M_c q_i \right) 
\] (11)

Where \( q_i \) is the isotopic specific humidity, \( E_i \) is the evaporation of isotopic cloud condensate (including precipitation), \( C_i \) is the isotopic condensation rate, \( q_{iu} \) is the isotopic vapor in the updraft, \( q_{id} \) is the isotopic vapor in the downdraft, \( M_u \) is the updraft mass flux, \( M_d \) is the downdraft mass flux, \( M_c \) is the net convective mass flux, and \( \rho \) is the density of air. Below cloud base, the water vapor isotopic tendency is:

\[
\frac{\partial q_i}{\partial t} = - \frac{1}{z_b - z_s} \left( M_b (q(z_b) - q_{iu}(z_b)) + M_d (q(z_b) - q_{id}(z_b)) \right) 
\] (12)

Where \( z_b \) is the height of the cloud base, \( z_s \) is the surface height, and \( M_b \) is the cloud base mass flux. The water vapor isotopic tendency for the shallow convection [Park and Bretherton, 2009] is:

\[
\frac{\partial q_i}{\partial t} = - g \frac{\partial}{\partial p} \left( M(q t_i - q t_{ie}) + M_{pen} (q t_{pen} - q t_{ie}) \right) - P_i + E_{pi} - \frac{\partial L_l}{\partial t} - \frac{\partial I_i}{\partial t} 
\] (13)

Where \( M \) is the convective mass flux, \( M_{pen} \) is the penetrative entrainment mass flux, \( L_l \) is the isotopic cloud liquid, \( I_i \) is the isotopic cloud ice, \( q_i \) is the total isotopic water mass in the cloud
\(q_i\) is the total environmental isotopic water mass, \(P_i\) is the production of isotopic precipitation, and \(E_{pi}\) is the re-evaporation of isotopic precipitation. The cloud liquid and ice tendencies include both advection and detrainment, which are non-fractionating, as well as phase changes to and from water vapor, which produce an isotopic fractionation.

Below the freezing level, for both schemes, cloud liquid is formed via condensation, and it is assumed that all cloud liquid is in isotopic equilibrium with the remaining water vapor. The new equilibrated isotopic masses are calculated during the formation of the condensate using the method:

\[
q_i = (q_{i0} + L_{i0}) \left\{ \frac{1}{\Gamma - 1} \right\} + 1, \quad \Gamma = \frac{q}{q + L}
\]  

\[L_i = L_{i0} - (q_i - q_{i0}) \]  

Where \(q_i\) is the equilibrated isotopic water vapor, \(L_i\) is the equilibrated isotopic cloud liquid in specific humidity units, \(q_{i0}\) is the isotopic water vapor pre-equilibration, \(L_{i0}\) is the isotopic cloud liquid pre-equilibration, \(q\) is the standard model water vapor, \(L\) is the standard model cloud liquid, and \(\alpha_e\) is the equilibrium fractionation factor.

Whenever cloud ice is formed, either when the updraft is fully glaciated or in the case of mix-phased clouds, it is assumed to deposit directly from vapor. During this process the isotopic water is assumed to undergo Rayleigh distillation, such that the final isotopic vapor and ice masses are solved for using these equations:

\[
q_i = q_{i0} \left( \frac{q}{q_0} \right)^{\alpha_{ki}} \]  

\[l_i = l_{i0} - (q_i - q_{i0}) \]
Where $q_i$ is the distilled isotopic vapor, $I_{i0}$ is the distilled isotopic ice, $q_{i0}$ is the isotopic vapor pre-distillation, $I_{i0}$ is the isotopic ice pre-distillation, $q$ is the standard model water vapor, $q_0$ is the standard model water before ice formation, and $\alpha_{ki}$ is the special kinetic fractionation factor for vapor depositing onto ice:

$$\alpha_{ki} = \frac{\alpha_e S}{\alpha_e \frac{D}{D_i} (S - 1) + 1}$$  \hspace{1cm} (18)$$

Where $\alpha_e$ is the equilibrium fractionation factor, $D$ is the molecular diffusivity of regular water, $D_i$ is the molecular diffusivity of isotopic water, and $S$ is the supersaturation (i.e., relative humidity greater than one, or 100%) [Jouzel and Merlivat, 1984]. In the model, the supersaturation is parameterized using the equation:

$$S = A_s + B_s \times (T - T_{zero})$$  \hspace{1cm} (19)$$

Where $S$ is the supersaturation, $T$ is the temperature in Kelvin, $T_{zero}$ is the triple point for fresh water, which in the model is equal to 273.16 K, and $A_s$ and $B_s$ are parameters which must be selected [Jouzel and Merlivat, 1984]. Here we use values of $A_s = 1.0$ and $B_s = -0.002$, which were tuned in order to match the observed precipitation d-excess over Antarctica.

While the shallow convection scheme manages cloud liquid and ice independently, the deep convective scheme uses a bulk condensate instead. In order to separate liquid and ice in deep convection, a liquid/ice fraction variable is calculated based on temperature:

$$\nu = \frac{268.15 - T}{30}$$  \hspace{1cm} (20)$$

Where $\nu$ is the liquid/ice fraction of condensate, and $T$ is the temperature in Kelvin. If the temperature is above 268.15 K then all of the condensate is assumed to be liquid, while if the temperature is below 238.15 K then all of the condensate is assumed to be ice. This liquid/ice fraction formulation is the same one used in the CAM5 macrophysics [Park et al., 2014] for
determining the fraction of ice and liquid in detrained convective condensate. This formulation assumes that all new liquid or ice is formed directly from vapor condensation/deposition, and currently does not allow for other microphysical processes, such as the Wagner-Bergeron-Findeison process.

There is also one phase change, the evaporation of precipitation in near-saturated in-cloud downdrafts produced by the deep convection, where it is assumed that no fractionation occurs. This is equivalent to assuming that the vapor starts off in isotopic equilibration with the rain drops, and that all evaporative fluxes come from the complete evaporation of small raindrops. This assumptions was also used in model developed by Kurita et al., [2011].

Finally, any phase change also causes latent heating or cooling, which changes the air temperature and in-turn the fractionation factor. Therefore, the temperature of fractionation is chosen to be the arithmetic mean temperature during the time step, including the air temperature before and after latent energy changes.

2.3 Stratiform cloud physics

Stratiform cloud physics is split into two parameterizations to separately handle the macrophysics [Park et al., 2014], which calculates the grid-scale condensation and cloud fraction, and the microphysics [Gettelman et al., 2008], which calculates all of the subgrid scale processes occurring internally in the cloud. Both of these parameterizations have similar-enough aspects that they can be grouped together for the purposes of discussing their impact on water isotope ratios.

All cloud liquid condensate that is formed is kept in isotopic equilibrium with the vapor under the assumption that the equilibration timescale for cloud-size droplets is shorter than the typical model time step of 15-30 minutes, and ice formed from vapor experiences a Rayleigh
distillation with an accompanying kinetic fractionation. All processes that generate rain or snow from existing condensate (autoconversion, accretion, collection, and sedimentation) occur with no fractionation. Similarly there is no fractionation during the freezing or melting of condensate. Figure 1 shows all of the reservoirs of water in the cloud physics routines, and the processes that move mass between them. All of the processes that produce a fractionation in the water isotope ratios are shown in red.

Figure 1: The blue boxes represent all of the physical states of water and water isotopologues allowed in the cloud physics schemes. The arrows indicate physical processes that convert between the different states of water, with the red arrows being processes that produce isotopic fractionation.

The Wagner-Bergeron-Findevson (WBF) process is treated explicitly within the isotopic scheme despite the underlying formulation in CAM5 that treats the process as a direct transfer of
liquid to cloud ice or snow. This is because the WBF processes involve phase changes from liquid to vapor, and then from vapor to ice, which generates isotopic fractionation. Thus the WBF process for water isotopologues is modeled as an evaporation of cloud liquid, an equilibration of cloud liquid and water vapor, and then a deposition, and isotopic distillation, of the isotopologue vapor onto cloud ice.

Each time step condensate sedimentation is modeled as an advective processes, with a subsequent adjustment to account for evaporation or sublimation of condensate that falls into a clear sky region. Since the evaporation is assumed to involve the complete removal of cloud droplets, there is no accompanying fractionation. The remaining isotopic cloud liquid and vapor are then isotopically equilibrated to account for the addition of new liquid or vapor at each vertical level.

The temperature used to calculate the fractionation factors is an average between the temperatures before and after phase changes occur.

2.4 Isotopic exchange during rain evaporation

Rain evaporation produces a fractionation for both the rain mass itself and the vapor receiving the evaporated moisture [Stewart, 1975], which can have a substantial impact on the global distribution of water isotope ratios [Risi et al., 2008]. In CAM5 rain evaporation occurs in both the deep and shallow convective schemes, and in the large-scale microphysics. The scheme developed for CAM5 follows Stewart [1975] and is formulated similarly to the scheme described by Lee et al., [2007] and Lee and Fung, [2008].

Precipitation from convective and large-scale clouds is tracked downward as it falls, and evaporates if it encounters a sub-saturated layer. The isotope ratio of a drop tends toward a fully-equilibrated state relative to the ambient water vapor. However, this isotopic equilibration may
not be complete if the drop is large and the atmospheric layer the drop is falling through is shallow. Thus often-times a “partial” equilibration occurs, with only a fraction of the raindrop’s mass experiencing full equilibration. The magnitude of this partial fractionation is calculated as the ratio between the time it takes for the raindrop to equilibrate, and the time it takes for the rain-drop to fall through the atmospheric layer of interest. The isotopologue-specific e-folding equilibration time given by Stewart [1975] and Lee and Fung, [2008] is

$$\tau_e = \frac{\alpha_e r^2 \rho_{H_2O} R_{H_2O} T}{3 f_v D_{ia} e_s}$$

(21)

here $\alpha_e$ is the equilibrium fractionation factor, $r$ is the raindrop radius in m, $\rho_{H_2O}$ is the density of liquid water in kg m$^{-3}$, $R_{H_2O}$ is the gas constant for water vapor in J K$^{-1}$ kg$^{-1}$, $T$ is the air temperature in K, $D_{ia}$ is the diffusivity of isotopic water vapor through air in units of m$^2$ s$^{-1}$, $e_s$ is the saturation vapor pressure at temperature $T$ in Pa, and $f_v$ is a ventilation factor calculated as:

$$x = Re^{1/2} Sc^{1/3}$$

(22)

$$f_v = \begin{cases} 
0.78 + 0.308 \times x, & x \geq 1.4 \\
1 + 0.108 \times x^2, & x < 1.4 
\end{cases}$$

(23)

Where $Re$ is the Reynold’s number and $Sc$ is the Schmidt number, with the formula itself from Pruppacher and Klett, [1997]. The Reynolds and Schmidt numbers themselves are calculated as:

$$Re = \frac{2r \rho V_{rain}}{\mu}$$

(24)

$$Sc = \frac{\mu}{\rho D_{ia}}$$

(25)

Where $\rho$ is the density of air, $V_{rain}$ is the vertical fall velocity of the rain drop (described below), and $\mu$ is the viscosity of air in kg m$^{-1}$ s$^{-1}$, calculated as:
\[ \mu = (1.72 \times 10^{-5}) \left( \frac{T}{273} \right)^{1.5} \left( \frac{393}{T + 120} \right) \]  

(26)

Which comes from Rodgers and Yau, [1989]. The equations for the Reynolds and Schmidt numbers come from Pruppacher and Klett, [1997]. Finally, the diffusion of isotopic water vapor through air is calculated as:

\[ D_{ia} = (2.11 \times 10^{-5}) \left( \frac{D}{D_i} \right) \left( \frac{T}{273.15} \right)^{1.94} \left( \frac{101325}{P} \right) \]  

(27)

Where P is the air pressure in Pa, as shown in Pruppacher and Klett, 1997.

The time scale for the drop to fall through a vertical layer is calculated as:

\[ \Delta z = z_{\text{top}} - z_{\text{bottom}} \]  

(28)

\[ \tau_f = \frac{\Delta z}{V_{\text{rain}}} \]  

(29)

Where \( z_{\text{top}} \) is the altitude for the top of the atmospheric layer in m, \( z_{\text{bottom}} \) is the altitude for the bottom of the atmospheric layer in m, and \( V_{\text{rain}} \) is the raindrop fall velocity in m/s. The fall velocity is assumed to equal the terminal velocity, resulting from the balance of gravitational acceleration and non-linear drag [e.g. Straka, 2009], which is:

\[ V_{\text{rain}} = V_{\text{terminal}} = \sqrt{\frac{4gr\rho_{H_2O}}{3C_d\rho}} \]  

(30)

Where \( g \) is gravity, \( r \) is the raindrop radius, \( \rho_{H_2O} \) is the density of liquid water, \( \rho \) is density of air, and \( C_d \) is the drag coefficient, set to be 0.6 [Straka, 2009]. The raindrop radius itself is assumed to be the mass-weighted average based off the rain rate, along with the assumption that the raindrop size distribution follows a Marshall-Palmer distribution [Marshall and Palmer, 1948]. It can be derived following the equation of Williams and Gage, [2009] and is found to be:

\[ r = \frac{2}{4.1\beta^{-0.21}} \]  

(31)
Where $\beta$ is the rain rate in units of mm/hr. Finally, the fraction equilibrated is calculated to be an exponential approach to complete equilibration using the ratio of the two timescales:

$$f_e = 1 - e^{-\frac{t_f}{\tau_e}}$$  \hspace{1cm} (32)

This results in the final equilibrated values being equal to:

$$q_i = (1 - f_e)q_{i0} + f_e q_{ie}$$  \hspace{1cm} (33)

Where $q_i$ is the final isotopologue mass value (for either water vapor or rain), $q_{i0}$ is the mass value pre-equilibration, and $q_{ie}$ is the mass value if the system was completely equilibrated. This formulation is consistent with the formulation given by Stewart [1975] in delta notation. The kinetic effect that Stewart [1975] exposed is also captured in our formulation through the difference in $\tau_e$ and thus $f_e$ for the different isotopologues. What makes this formulation unique is that the strength of the fractionation is directly dependent on the rain rate, and thus the influence of drop size, which is allowed to be different for each rain event, can now be captured.

### 2.5 Model configuration

An isotope-enabled CAM5 control simulation was run for the years 1975-2014, with only data since 1979/1980 being examined in this paper in order to avoid spin-up issues. The model uses a finite-volume dynamical core with a horizontal resolution of 1.9 °N x 2.5 °E, and a hybrid sigma-pressure vertical coordinate system with thirty vertical levels that increase in depth with height up to 3 hPa. The model is coupled to an isotope-enabled land model (iCLM4) for land-surface processes, an isotope-enabled sea ice model (iCICE4) for sea-ice processes (although with prescribed sea ice coverage), and prescribed sea surface temperatures for the ocean. Ocean isotope ratios are assumed to be constant in time but vary in space, with a d-excess of zero, based off the ocean oxygen isotope data set of LeGrande and Schmidt, [2006]. All other boundary conditions are based off historical data, and vary through time.
3. Model results

Figure 2 shows the zonally-averaged model results for specific humidity and temperature for the years 1979-2013, and their differences when compared to ERA-Interim [Dee et al., 2011]. It can be seen that compared to the reanalysis, the model has higher specific humidities (+0.23 g/kg) and lower temperatures (-1.59 K). Figure 3 shows the average precipitation and surface evaporation fluxes over that same time period, along with the differences compared to ERA-Interim. The global bias in precipitation is +0.13 mm/day, although most of the positive bias occurs over the ocean, with large negative biases in some tropical land regions, including the Amazon and Congo. There is also a large positive evaporative flux bias, particularly over the subtropical oceans. The bias when averaged over the globe is +0.16 mm/day.
Figure 2: The temporally and zonally-averaged specific humidity in g/kg (a) and temperature in K (c) as simulated by CAM5 for 1979-2013, and the difference between the model and ERA-Interim in terms of specific humidity in g/kg (b) and temperature in K (d).
A physical consistency between these fields would suggest that some of these biases are simply a response to others. For example, if there is an error in the surface evaporative flux such that it adds too much moisture to the atmosphere, then the precipitation increase could simply be a response to the additional mass and higher relative humidity. On the other hand, if the convection and cloud parameterizations generate too much precipitation, then the surface moisture flux bias may simply be a response to the drying of the atmosphere. Water isotopologues can help distinguish between these possibilities, but first, the biases in simulated water isotopologue values must be examined.

Figure 4 shows the annual, December-January-February (DJF), and June-July-August (JJA) average $\delta^{18}O$ and d-excess of precipitation from iCAM5 averaged over the years 1980-2014, compared against stations from the Global Network of Isotopes in Precipitation (GNIP) [IAEA, 1994]. Only stations with at least two full years of data were used, which resulted in a
total of 276 stations available for comparison. An additional seven stations were added from studies in the Maritime Continent region as well, in order to improve the spatial coverage of isotopic precipitation stations globally [Kurita et al., 2009; Moerman et al., 2013]. The model is generally depleted everywhere in terms of $\delta^{18}$O, with a global average bias of -2.57 ‰, while the bias for $\delta$D is -20.03 ‰ (not shown). This bias is similar to the results from Lee et al., [2007], which found a depleted bias for certain regions in the older CAM2. The model also has $d$-excess values that are too high (global average bias = +3.25 ‰), although the sign of the local bias varies by region. It is important to note that GNIP has the majority of its stations in Europe, and thus weights any results towards Northern Hemisphere midlatitude land. However, these isotopic biases have similar values even if the European stations are ignored (not shown). Thus these biases do in fact represent a global signal, and not just an issue for the European continent.

Figure 4: The long-term average $\delta^{18}$O of precipitation in permil for DJF (a) and JJA (b), and the long-term average $d$-excess of precipitation in permil for DJF (c) and JJA (d), as simulated by isotope-enabled CAM5 for the years 1980-2014. The circles indicate GNIP stations, with the colors of the circles indicating the respective long-term average $\delta^{18}$O or $d$-excess of precipitation measured at that site using the same color scale as the contours. It should be noted that for $\delta^{18}$O, the contours increase by 10 ‰ up to -20.0 ‰, then jumps to -17.5 ‰ and increases by 1.25 ‰.
afterwards. For the d-excess, it increases by 2 ‰ up to +4 ‰, then increases by 1 ‰ up to +10 ‰, after which it again increases by 2 ‰.

One concern when using climate or earth system models is whether the horizontal resolution is high enough to capture the features one is interested in. In order to evaluate the impact of resolution, two extra runs were generated for the years 1995-2009, with the first five years ignored for spin-up. The first run, labeled “1x1” had a 0.9°N x 1.25°E resolution, which is double the control run’s resolution. The second run, labeled “0.5x0.5”, had a 0.47°N x 0.63°E resolution, which is double that of the 1x1 run. The annual average $\delta^{18}$O of precipitation for each of these runs, along with difference between the higher resolution runs and the control (“2x2”) run, is shown in Figure 5. It can be seen that although some regional areas, particularly in the high-latitudes, improve, most likely due to better-simulated topography, the overall global bias remains the same. In fact, the annual average $\delta^{18}$O bias is the same for all three simulations, at a value of -2.45 ‰. Thus the global bias seen in precipitation is not just a result of low resolution, but must instead be related to the physics of the model itself.
Figure 5: Maps of the long-term annual average $\delta^{18}O$ of precipitation for a simulation at: a. 0.9°N x 1.25°E (“1x1”) resolution, and c. 0.47°N x 0.67°E (“0.5x0.5”) resolution, along with the annual average from the GNIP stations (colored circles). The contours are the same as Figure 4 for $\delta^{18}O$. Also shown is the difference in the annual average $\delta^{18}O$ of precipitation between the 1x1 simulation and the control simulation (b), and the difference between the 0.5x0.5 simulation and the control simulation (d). The higher-resolution simulations were re-gridded to the control run grid in order to allow for a direct comparison. The units are in permil (‰).

Figure 6 shows the vertical column-integrated $\delta D$ of vapor as simulated by iCAM5 for the years 2003-2007, and the average difference between the model and column-integrated $\delta D$ as measured by SCIAMACHY [Frankenberg et al., 2009; Scheepmaker et al., 2013]. The model is depleted throughout the tropics, but enriched in the extratropics. The global average bias is -9.76 ‰. Thus, at least for the tropics, the low bias of the $\delta D$ in precipitation is consistent with the column mean water vapor $\delta D$, and demonstrates the reliability of isotopic fractionation schemes in clouds.
Figure 6: The vertically-integrated average δD of water vapor as simulated by iCAM5 for the years 2003-2007 (a), and the difference between the model and SCIAMACHY, averaged over the same time-frame (b). The units are in permil (‰).

To more closely examine the vapor, figure 7 shows the average simulated surface vapor δ¹⁸O and d-excess for each month at four point locations for each model resolution, along with monthly average measurements as provided by in situ laser spectrometers. The four locations are Niwot Ridge, CO [Berkelhammer et al. submitted], Erie, CO [Kaushik et al., in prep], Mauna Loa, HI [Bailey et al., 2015b], and Summit, Greenland [Bailey et al., 2015b]. The vertical solid lines indicate ± one standard error for the measurements. For the different climate zones sampled by these sites, CAM5 shows general agreement in the shape of the seasonal cycle, but
the magnitude is too small, particularly for Niwot Ridge. This result does not seem to be significantly improved by model resolution, at least for the resolutions examined here. The model is also, on average, enriched in δD compared to observations, which is opposite of what one would expect given the precipitation bias. However, most of these locations are in the extratropics, where SCIAMACHY also showed an enriched vapor bias. Finally, it is important to note that both Mauna Loa and Niwot Ridge are elevated in height, and thus do not necessarily represent the actual atmospheric surface layer. It should also be noted that Niwot Ridge, CO and Erie, CO are only separated by ~60 km. Thus they may potentially represent the same grid box, especially at the lower resolution control (2x2) run.
Figure 7: The monthly average surface vapor δD as simulated by CAM5 at three different resolutions (2x2 – red dashed line, 1x1 – green dashed line, and 0.5x0.5 – purple dashed line), and as measured by a Picarro spectrometer (blue solid line) for: a. Niwot Ridge, CO, c. Erie, CO, e. Mauna Loa, HI, and g. Summit, Greenland, along with the average surface vapor d-excess for: b. Niwot Ridge, CO, d. Erie, CO, f. Mauna Loa, HI, and h. Niwot Ridge, CO. The vertical black lines represent ± one standard error for the in situ measurements. All units are in permil (‰).

From mass balance, the negative precipitation δD bias must be associated with a negative bias in the amount of isotopologue mass in the atmosphere. However, which side of the balance is the ultimate cause has yet to be determined: there either must be too little isotopologue mass being evaporated or transpired into the atmosphere, or too much isotopologue mass must rain out, particularly over regions where GNIP stations are minimal (such as over the ocean). To our knowledge, there are no systematic, or even point wise, observations of evaporative flux over the open ocean that can offer a direct comparison with the CAM5 modeled evaporative flux.

To help identify if evaporation isotope ratios are responsible, near-surface vapor (which if depleted would indicate depleted surface fluxes), is compared to water vapor above the boundary layer (indicating rain-out if erroneously depleted). Figure 8 shows the δD for vapor at the lowest model layer, and the difference between the model and the interpolated surface data from Good et al., [2015], which used a combination of Tropospheric Emission Spectrometer (TES) retrievals [Worden et al., 2006] and surface observations to generate an estimate of low-level vapor δD. The average for the model was calculated using output for the months for which a sufficient volume of TES observations were available (September 2004 to May 2011, excluding June 2005, January, 2010, and February 2010). We focus on oceanic regions where the observations are of higher quality, and thus the possible influence of remote land sources should be borne in mind. Outside of the maritime continent, the model is in fact enriched relative to the Good et al., 2015 data, with a global average bias of +9.87 ‰. This indicates that isotopic
surface fluxes, at least from the ocean, are most likely not the cause of the global precipitation bias.

Figure 8: The water vapor δD at the lowest atmospheric model layer in iCAM5, averaged over September 2004 to May 2011, excluding June 2005, January, 2010, and February 2010 (a), and the difference between the model and the Good et al., 2015 water vapor δD dataset (b). All units are in permil (‰).

Figure 9 shows simulated vapor δD over the same time period as figure 8, but now at ~750 mb, which is close to the top of the boundary layer and the level of maximum TES retrieval sensitivity. It also shows the difference between the model and vapor δD as measured by TES. Given the enhanced sensitivity of TES at this vertical level, the direct TES retrievals can be used, as long as the model output is convolved with the TES averaging kernel using the so-called “observational operator” [e.g. Worden et al., 2006; Jones et al., 2009]. The model is depleted almost everywhere, with a global average bias of -41.40 ‰. This change in the sign of model
bias, from overly-enriched near the surface to greatly-depleted above the boundary layer, indicates that water isotopologue mass decreases too quickly in the vertical. The only physical processes that can directly remove water isotopologue mass from the atmosphere once it has left the surface is precipitation. Thus the water isotopologue data suggests that CAM5 produces too much precipitation as water is lifted upward from the surface to the free troposphere, and that this bias is not just a response to the overly strong surface evaporation rate. In fact, from mass balance considerations, the surface evaporation bias must result in part as a response to the overly strong vertical rain out. The use of isotopic information to diagnose the cause of these biases in the model isotopic partitioning similarly sheds light on the underlying reason for some of the biases in the model’s hydrologic cycle.

Figure 9: The water vapor δD at ~750 mb in iCAM5, averaged over September 2004 to May 2011, excluding June 2005, January, 2010, and February 2010 (a), and the difference between the model and water vapor δD as measured by TES at the same vertical level and over the same time period (b). The units are in permil (‰).
4. Parameter experiments

Model biases in precipitation rates are linked to a set of specific physical process or parameterizations which have remained difficult to diagnose by conventional means. Given that the isotopic distribution in the atmosphere was strongly influenced by the precipitation bias, it stands to reason that a particular free parameter or set of parameters in the model that influences precipitation should also strongly modify the isotopologue values. This will not only help lead one to determine what the underlying driver of the isotopologue and precipitation biases are, but also what parameters in the model the water isotopologue values are sensitive to, which could help in terms of future bias corrections.

The precipitation in iCAM5 is generated by three different parameterizations, a deep convective scheme [Zhang and McFarlane, 1995], a shallow convective scheme [Park and Bretherton, 2009], and a large-scale, or stratiform, cloud microphysics scheme [Morrison and Gettelman, 2008]. Thus parameters in each of these schemes was modified in an attempt to reduce either the frequency of precipitation events, or the intensity of precipitation per event. An extra experiment was performed to evaluate the credibility of the assumption that falling rain isotopically equilibrates, regardless of the rain intensity or the thickness of the layer through which it is falling. This was done to examine the importance of the new parameterization scheme used in iCAM5 (eq. 32) in determining the role of post-condensation processes on the final isotopic values. This is particularly critical since post-condensational exchange is known to have a strong influence on model results [e.g., Risi et al., 2008].

Table 1 lists all of the sensitivity experiments that were performed, including the parameter that was modified, and by how much the value was changed. All sensitivity experiments were branched from the control run in the year 1995, and run until 2014, with the
first five years ignored for spin-up. This provides 15 years of data covering the entire isotopologue-measuring satellite era, which will allow for an examination of isotopologues in both precipitation and water vapor. It should be noted that the main focus will be on improving the $\delta^D$ and $\delta^{18}O$, as opposed to the d-excess, given that the d-excess is highly sensitive to kinetic effects, which do not necessarily have as large of an effect on the isotopologue mass itself.
Table 1: A list of the different sensitivity experiments as shown in figure 8. The run name is the name as shown in figure 10. The Parameter is the name of the free parameter(s) that were modified for each run, the description explains what each parameter represents, the original value is the default value the parameter has at model set-up, and the modified value is what the value
was changed to in the run. It should be noted that only the parameters listed were modified for each run. Everything else was left as its default value.

Figure 10 shows the change in the average bias for each tuning run compared against GNIP (Figure 10a) and SCIAMACHY (Figure 10b), relative to the control run. A value of zero would indicate the simulations has a bias equal the control run, while a negative value indicates a bias that is worse. The error bars are ± one standard deviation of the annual averages from the model. If one looked at precipitation alone, which was done in the past due to a lack of isotopic vapor measurements, one would assume that simply equilibrating rain would produce the best values. However, when one also examines vapor it can be seen that completely equilibrating rain produces a very large vapor bias. This is not surprising, given that if a bias exists in precipitation, isotopically equilibrating it with vapor will simply pass that bias over to the vapor. Thus one should include an isotopic post-condensation or rain evaporation scheme that modulates the amount of equilibration or isotopic exchange based off of the environmental conditions.
Figure 10: The top plot (a) shows the difference in the average $\delta^{18}$O bias in permil in precipitation as compared to GNIP for the years 2000-2014 for each model run relative to the control run, with a positive bar indicating a smaller bias. The error bars indicate $\pm$ one standard deviation in the global annual average precipitation $\delta^{18}$O for that particular simulation. The bottom plot (b) is the same as the top, except for the $\delta$D bias in permil in integrated water vapor compared against SCIAMACHY. All of the simulation names are listed in Table 1.

Although all of the changes modify the precipitation by decreasing either the frequency or intensity, only changes to the deep convection resulted in a better comparison with the observations. This indicates that the shallow convection and cloud microphysics are accurately simulating the processes that impact water isotope ratios, or at least are as well tuned as possible. The specific tests that produce the biggest improvement in both precipitation and vapor is when the amount of CAPE needed to trigger deep convection is increased. This indicate that deep convection is triggering too frequently, which would not only explain the non-isotopic
precipitation amount bias, but also the positive specific humidity bias as well (as deep convection tends to inject moisture into the mid- and upper- troposphere). Thus the “4xcape” experiment will be examined more closely to see how it influences the water isotopologue distribution in the model, and to determine if it can fully explain the isotopic biases seen in the model.

Figures 11 and 12 are equivalent to Figures 4 and 9, except that now the comparison is only with the 2x2 degree resolution “4xcape” simulation. The δD in vapor shows there is a noticeable global improvement (global bias = -32.48 ‰ versus -41.40 ‰ for the control), particularly in regions where one expects deep convection to occur, such as in the ITCZ. However, for δ18O in precipitation the enrichment is much less noticeable (global bias = -2.36 ‰), except for in high-latitude regions, which is surprising given that those regions are not locations of frequent or intense deep convection. Thus it’s possible that a larger-scale change in atmospheric circulation or hydrology may be producing the isotopic precipitation changes.
Figure 11: Same as Figure 4, except for annual averages from the 2x2 “4cape” sensitivity experiment.
Figure 12: Same as Figure 9, except for the 2x2 “4xcape” sensitivity experiment.

To emphasize this point, Figure 13 shows the difference between the “4xcape” run and the control run in δ18O of precipitation (top plot) and in average precipitation rate (bottom plot). One can see that there is a large change in precipitation in the tropics, which one would expect given the prevalence of deep convection in tropical regions. The figure shows that on average the precipitation changes are inversely-correlated with the changes in precipitation δ18O. This indicates that the main driver for isotopic precipitation changes in the tropics is the amount effect, although the actual cause of the amount effect is still unclear [Lee and Fung, 2008; Risi et al., 2008; Moore et al., 2014; Conroy et al., in review]. Outside of the tropics, one can see a large enriched signal in the polar and mid-latitude continental regions. However, the change in precipitation amount is minimal. Thus non-local processes must be causing the enriched precipitation values.
Figure 13: The difference in the $\delta^{18}$O of precipitation in permil between the “4xcape” experiment and the control run, averaged over the years 2000-2014 (a), and the difference between those two runs in terms of average precipitation rate in mm/day over the same time period (b).

Although the net precipitation may not change substantially, the amount of precipitation from convection alone might. Figure 14 shows the change in precipitation from convective sources between the “4xcape” and control simulations for DJF (a) and JJA (b). One can see that in the mid-latitudes the amount of convective precipitation decreases substantially. It can also be seen that this decrease is largest over the oceans during winter, when extratropical cyclones are
generating a large amount of poleward moisture transport. By decreasing the isotopic mass loss, or distillation, caused by deep convection in extratropical cyclones, it means more isotopologue mass can be transported poleward and landward via the large-scale flow, resulting in more enriched precipitation values in those regions. It also indicates that CAM5 is not accurately simulating convective mixing in the atmosphere, which could have a strong influence on global climate sensitivity [Sherwood et al., 2014].
Figure 14: The difference in the average convective precipitation rate between the “4xcape” run and the control run, averaged over December-January-February for the years 2000-2014 (a), and the same difference plot, except averaged over June-July-August (b). Units are in mm/day.

Finally, given that the net precipitation did not change substantially, it indicates that different physical processes are compensating for the decrease in deep convective precipitation. However, both the shallow convection and the resolved vertical flow resulting from large-scale cloud physics tend to not transport moisture upwards as much as the deep convection. This results in more isotopic mass being present in the lower troposphere, as seen in Figure 15, which shows the zonally averaged difference in water vapor $\delta D$ between the “4xcape” and control simulations (a), along with the zonally-average meridional moisture flux (b). It can be seen that the enriched signal in the “4xcape” run occurs in the same region regions as the largest poleward moisture fluxes, indicating enhanced isotopic moisture transport by extratropical cyclones, particularly through the warm conveyor belt which tends to transport moisture upward from the lower troposphere/boundary layer [Browning, 1971]. This demonstrates that increasing the amount of isotopic mass in the lower troposphere, by decreasing deep convection, has allowed for more effective transport of water isotopologues poleward and landward, resulting in more enriched precipitation in those regions. Finally, given that this improves the overall isotopic biases, it indicates that the model is, by default, tuned to trigger deep convection more frequently than in nature, especially during winter in the mid-latitudes. Therefore future refinements to the Zhang and McFarlane [1995] convection scheme in CAM5, or new parameterizations of moist convection, should be cautious of the need to raise the trigger threshold for deep convection in order to simulate a more accurate hydrologic cycle in the atmosphere of CAM5, and CESM.
Figure 15: The difference in the zonally averaged water vapor δD in permil between the “4xcape” run and the control run (a), and the average meridional moisture flux (positive = northwards) for the control simulation in units of kg m/s. Also plotted is the zonally averaged potential temperature (black contours) in units of K. All quantities are averaged over the years 2000-2014.

5. Conclusions

Simulations of water isotopologues in climate and earth system models enables a wide range of new research possibilities within fields of paleoclimatology, cloud physics, large-scale hydrology and land-atmosphere exchange. Many paleoclimate proxy records are based on water isotopologues, and thus being able to simulate them in a climate model can allow for one to use proxy system models [Dee et al., 2015b], and avoid the need to create additional uncertainty by converting the proxy record into temperature or precipitation. However, another advantage of water isotopologues is that they provide an extra constraint on the simulated hydrologic cycle, and can be particularly sensitive to cloud and convective processes, which can be quite poorly constrained otherwise [Bolot et al., 2013; Field et al., 2014]. This additional information could
be used to eventually produce better-tuned models, or even more physically accurate parameterizations.

Water isotopologue physics has been added to the NCAR Community Atmosphere Model Version 5 (CAM5). This isotope-enabled CAM5 (iCAM5) should be comparable to other isotope-enabled climate models (e.g., GISS, ECHAM, MIROC, LMDZ), and is capable of simulating the overall isotopic distribution in the atmosphere, including in water vapor and precipitation, with fidelity. However, biases were present in a simulation of the modern era, including a large global depleted bias in precipitation as well as a depleted bias in tropical mid-tropospheric water vapor. In design of the isotopic fractionation scheme, a choice was made to include processes in a manner which was consistent with the physics of the underlying cloud and evaporation parameterization schemes, which had the advantage of both limiting the number of free parameters within the isotopic scheme and allowing the accuracy of isotopic simulations to be used to directly infer errors in the model hydrology. This is in contrast with a scheme in which there are sufficient free parameters as to enable the simulation to be tuned to match observations. Specifically, by using a new isotopic rain evaporation scheme, one no longer needs to tune the relative humidity during evaporation [e.g. Bony et al., 2008], nor set the fraction equilibrated to a constant number [e.g. Hoffmann et al., 1998]. This allows for a closer examination of the underlying atmospheric physics, instead of focusing on the particular parameters used in the isotopic scheme.

In order to determine causes of the biases in the model hydrological cycle that give rise to the isotope ratio simulation errors, it was found that the δD in water vapor is overly-enriched in the lowest model layer, but quickly becomes more depleted with height. This indicates that iCAM5 produces too much precipitation, independent of the surface evaporative flux, and thus
could be creating an unrealistic hydrologic cycle in the model. This result of too much precipitation producing overly-depleted isotope ratios was also found for the older CAM2 [Lee et al., 2007], and demonstrates a potential problem in the underlying physics routines. At first, precipitation was forced to isotopically equilibrate with the surrounding vapor. However, although this did improve the isotopic precipitation bias, it greatly increased the bias in water vapor. This shows that with satellite and in-situ measurements of water isotopologues in vapor, the isotopic budget can be more tightly constrained observationally, resulting in more physically accurate solutions to isotopic model biases. This also allows for water isotope ratios to be a good tool in constraining certain atmospheric processes that are important for the global climate, such as vertical mixing [Bailey et al., 2013; Bailey et al.; 2015b; Sherwood et al., 2014].

In an attempt to diagnose what was causing the increased precipitation bias in iCAM5, a series of sensitivity experiments were performed to evaluate the relative magnitude which with the variety of model processes control the isotopic simulation. It was found that by reducing the frequency with which convection triggers (by increasing the CAPE limit required before deep convection is initiated), the model improved both its vapor and precipitation isotopologue biases. However, an interesting result was that for precipitation, the isotopic values in the extratropical land and polar regions became strongly enriched, even though there was no major change in the local precipitation. Instead, it was found that by decreasing the frequency of deep convection over the mid-latitude oceans during winter, more isotopic mass was present in the lower troposphere, which in-turn meant that more was available to be transported by extratropical cyclones poleward and landward, resulting in an enriched precipitation signal in those locations. Ultimately, given that these changes improved the isotopic simulation without noticeably degrading the rest of the climate (not shown), it indicates that the current CAPE limit is set to too
low of a value, and that deep convection, at least in certain regions in certain seasons, is triggering too frequently. It also has strong implications for examining polar climates using isotope ratios in water, particularly in terms of proxy records of past climates [e.g. Sime et al., 2009], as it shows that changes in tropical or midlatitude convective processes, even without a major global temperature change, could produce substantial shifts in the average isotopic ratio of precipitation over the poles and high-latitudes, including Greenland and Antarctica.

Although convection frequency has a strong influence on the water isotopologues, the model is still depleted on average, both in precipitation and in mid-tropospheric water vapor. The cloud physics is partly responsible, but the overall simulation emerges from the balance between evaporative fluxes at the surface, turbulent exchange, large-scale transport, and precipitation, and each of these components are associated with model error. While the experiments here have demonstrated significant error in the cloud transport and condensation rates, we have also shown the feedback between the atmospheric transport of water vapor and the simulated latent heating profiles. This implicates large-scale systemic adjustments of the hydrological cycle in CAM 5 are essential to improve the isotopic simulation, and consequently improve the underlying hydrology and climate simulations.

Model testing also revealed possible dynamical biases in the model which could be contributing to the errors in the isotopic and hydrologic simulation. For example, it was found that the surface winds were too strong in the subtropics, and too weak in the midlatitudes (not shown), at least when compared to reanalyses. This could help explain the bias in ocean surface evaporation, independent of any bias in the atmospheric moisture gradient. It also implies that the lower level winds in the storm track regions may be too weak. Thus even if the humidity values were correct in the model, the transport of moisture poleward and landward in the
midlatitudes would be biased low, producing an isotopic bias similar to the one observed. There could also be biases in atmospheric convergence or divergence, which drives large-scale precipitation production in the atmosphere and thus could produce the biases in precipitation even if the sub-grid scale physics behaved perfectly.

Finally, it is also unclear what influence the model resolution in the vertical has on water isotopologue values, as well as the impact of using different numerical schemes for resolved-scale advection, as we restricted our analysis by using only a finite-volume dynamical core. Ultimately, we have shown here that within NCAR’s CESM, the use of water isotopologues, along with more traditional climatological observations, can enable evaluation, and consequently development, of a more physically realistic and robust model of the water cycle, which will allow for more accurate and reliable climate projections for both the past and the future.
CHAPTER IV

A numerical evaluation of the sources of moisture for atmospheric rivers that impact the West Coast of the United States in the modern era and 2100.

1. Introduction

Atmospheric Rivers (ARs) are long, thin plumes of enhanced lower-tropospheric water vapor transport usually present over the subtropical and midlatitudes ocean regions [e.g. Newell et al., 1992; Ralph et al., 2004]. When exposed to a lifting mechanism, such as orography, ARs can produce extreme precipitation and flooding [e.g. Smith et al. 2010]. In fact, ARs have been known to produce flooding events in the Western United States [Ralph et al., 2006; Neiman et al., 2011], Central United States [Moore et al., 2012], the United Kingdom [Lavers et al., 2011], Norway [Stohl et al., 2008], the Central Andes [Viale and Nuñez, 2011], and the Iberian Peninsula [Ramos et al., 2015]. They are also known to be important to the water resources of California, so a lack of ARs could produce water shortages [Dettinger et al., 2011]. Finally, it has been found that the majority of poleward moisture fluxes in the midlatitudes are generated by atmospheric rivers, and thus they also play an important role in the global water and energy cycles [Zhu and Newell, 1998].

Given their strong influence on flooding and droughts, it is important to understand how ARs might change due to global warming. Several studies have found that for both the West Coast of the United States and the United Kingdom, ARs should become more intense (i.e., have larger water vapor fluxes), and, depending on how one defines AR events, become more frequent as well [Lavers et al., 2013; Warner et al., 2015]. These changes are mostly caused by the increase in water vapor due to the Clausius-Clapyeron relationship [Held and Soden, 2006].
Thus even if the atmospheric circulation remained constant, the increased amount of water vapor would result in larger moisture fluxes, and in-turn more intense precipitation.

Although ARs are a major part of the atmospheric hydrologic cycle, the mean length of water vapor transport, from evaporative source to eventual precipitation, remains unclear. Understanding variability in atmospheric river moisture transport therefore involves consideration of the geographic location from which the systems gain moisture. Understanding the sources of moisture for a region is beneficial if one wants to better understand and predict a region’s precipitation or humidity. Also, variations in water source are known to influence the isotope ratios of precipitation [e.g. Berkelhammer and Stott 2008; Steen-Larsen et al., 2015]. Given that water isotope ratios are one of the main quantities used for reconstructing past climates, changes in moisture source could thus leave a change in the proxy record that could be misinterpreted. This is of particular concern with atmospheric rivers, given that they are extreme events, can make up a large fraction of a region’s annual precipitation amount [Dettinger et al., 2011], and are known to impact regions where proxy data is recorded, including Greenland [Neff et al. 2014] and Antarctica [Gorodetskaya et al., 2014].

Several studies have made use of weather models and Lagrangian back trajectories to try and determine the sources of moisture for atmospheric rivers, with varying results [Bao et al., 2006; Stohl et al., 2008; Sodemann and Stohl, 2013]. However, there are issues with these studies. For starters, several of them are only looking at specific AR events, and thus their results may not represent the true, average climatological pattern. Another issue is that Lagrangian back-trajectories do not always represent the underlying sub-grid scale physics of a model, and can only be integrated over several days, and thus can miss small-scale and very long distance moisture transport [Sodemann et al., 2008]. There also remains a need to examine ARs in a
climate that is different from the modern era, including a future, warmer climate. Thus it is unclear if the hydrologic relationships found for the current climate will still hold a hundred years from now.

This study seeks to resolve issues associated with identifying moisture sources and the changes in moisture transport characteristics in warmer climates. This will be done via a water tag and water isotope-enabled version of the NCAR Community Atmosphere Model, version 5 (iCAM5), which will be used to simulate the change in moisture sources for the West Coast of the United States, and the ARs impacting the West Coast of the United States, for both the modern era and the warmer 2100-era.

In the following section we describe the modelling approach, including the water tag scheme, and the simulations from which transport statistics are derived. Section 3 describes the results from these simulations, for both time periods, and for both average moisture sources, and for moisture sources associated with ARs. It also will demonstrate how water isotopes can be used to provide additional information. Section 4 then discusses what these results mean in terms of changes in atmospheric hydrology. Finally, section 5 provides a renewed perspective on understanding hydrological change associated with global warming, and offers a perspective on the capacity to better monitor and understand the impact of changing moisture pathways.

2. Methods

2.1 Water tracers in iCAM5

The model used in this study is the water tracer and water isotope-enabled NCAR Community Atmosphere Model Version 5 (iCAM5) [Nusbaumer et al., in prep]. The scheme to trace isotope ratios of water is built on top of the standard CAM5, which is the atmospheric
component of NCAR’s Community Earth System Model Version 1 (CESM1) [Neale et al., 2010; Hurrell et al., 2013]. The water isotope physics routines are described in detail in Nusbaumer et al., in prep, while the underlying model is described in Neale et al., [2010]. iCAM5 was also coupled to the isotope-enabled Community Land Model Version 4 (iCLM4) [Lawerence et al., 2011; Wong et al., in prep] in order to properly simulate the land-surface, including its influence on water isotope ratios.

An important advantage of the water and isotopic tracking scheme in iCAM5 is that an arbitrary number of water tracers can be included in the model, each of which track the underlying hydrology in a manner similar to isotopic tracers, but exclude fractionation effects. Within the model code this is accomplished by setting isotopic fractionation factors equal to unity. Water tracers are passive, and do not impact any other aspect of the model’s climate (including the radiation, convection, and cloud microphysics). Thus one can modify these tracers without modifying the underlying climate or circulation, and thus “tag” specific geographic areas or physical processes to determine what their impact is on the global and regional hydrologic cycle. However, they still follow the standard moisture budget in the model:

$$\frac{\partial q_i}{\partial t} = -\nabla \cdot (\mathbf{V} q_i) + \nu \nabla^2 q_i + E_i - C_i$$

(1)

Where $q_i$ is the water tracer mass (or specific humidity), $\mathbf{V}$ is the wind velocity field, $\nu$ is the eddy (or sub-grid scale) diffusivity, $E_i$ is the tracer evaporation rate, and $C_i$ is the tracer condensation rate. A useful quantity when working with water tracers or tags is the tracer ratio, or “tag fraction”, defined as the ratio:

$$R_i = \frac{q_i}{q}$$

(2)

Where $q$ is the standard (or total) model water mass. In practice, care must be taken to avoid
numerical artifacts resulting from instances where the specific humidity becomes extremely small. Thus any time the standard model water is below a pre-defined minimum (usually set to be $10^{-18}$ kg, kg/m$^2$, or kg/kg), then $R$ is automatically set to a constant value of unity.

2.2 Water tag setup

This study uses 21 water tags in iCAM5, along with extra tracers to match total water ($H_2O$), and the isotopologues HDO and $H_2^{18}O$. The tags represent the evaporative flux from 21 different regions, as shown in Figure 1. Table 1 lists the specific latitude and longitude boundaries of those tags. The water tags were set-up such that they cover the entire earth’s surface, this implies:

$$q = \sum_{i=1}^{21} R_i q_i$$  \hspace{1cm} (3)

This is because the sum of all evaporation from the earth’s surface must equal the total evaporation. Thus the sum of all water tag mass that covers the entire earth’s surface must equal the regular model water, i.e., the total ratio must equal unity. The water tracers were also designed such that locations that one would expect to be dominant moisture sources, such as the North Pacific, or North America, are represented by multiple water tags, while regions that are expected to contribute little, such as the Polar Regions, and the Southern Hemisphere, are represented by only a single tag. This allows for a more detailed examination of the moisture source distribution while at the same time not becoming overly computationally expensive.
Figure 1: A map of all of the different water tags used in this study. Each colored box indicates the evaporation region for a specific water tag. The three letter text is simply used to associate each colored region with the information provided in Table 1. There is also no difference between the black and white text, as the difference purely exists to help make the map more easily readable.

<table>
<thead>
<tr>
<th>Tag Name</th>
<th>Latitude Expanse</th>
<th>Longitude Expanse</th>
<th>Land or Ocean</th>
</tr>
</thead>
<tbody>
<tr>
<td>WHM</td>
<td>50°N - 60°N</td>
<td>130°E - 180°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>WML</td>
<td>40°N - 50°N</td>
<td>130°E - 180°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>WSB</td>
<td>30°N - 40°N</td>
<td>120°E - 180°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>WDS</td>
<td>20°N - 30°N</td>
<td>105°E - 180°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>WTR</td>
<td>10°N - 20°N</td>
<td>100°E - 180°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>WDT</td>
<td>0°N - 10°N</td>
<td>100°E - 180°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>EDT</td>
<td>0°N - 10°N</td>
<td>180°E - 270°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>ETR</td>
<td>10°N - 20°N</td>
<td>180°E - 270°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>EDS</td>
<td>20°N - 30°N</td>
<td>180°E - 260°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>ESB</td>
<td>30°N - 40°N</td>
<td>180°E - 260°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>EML</td>
<td>40°N - 50°N</td>
<td>180°E - 260°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>EHM</td>
<td>50°N - 60°N</td>
<td>180°E - 260°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>ATL</td>
<td>20°N - 60°N</td>
<td>260°E - 30°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>TRA</td>
<td>0°N - 20°N</td>
<td>270°E - 30°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>GOM</td>
<td>20°N - 40°N</td>
<td>260°E - 280°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>NIN</td>
<td>0°N - 60°N</td>
<td>0°E-360°E</td>
<td>Land</td>
</tr>
<tr>
<td>LND</td>
<td>0°N - 60°N</td>
<td>30°E-100°E</td>
<td>Ocean</td>
</tr>
<tr>
<td>NAM</td>
<td>10°N - 60°N</td>
<td>220°E-310°E</td>
<td>Land</td>
</tr>
<tr>
<td>USW</td>
<td>30°N - 50°N</td>
<td>235°E-240°E</td>
<td>Land</td>
</tr>
<tr>
<td>POL</td>
<td>60°N - 90°N</td>
<td>0°E-360°E</td>
<td>Both</td>
</tr>
<tr>
<td>SHM</td>
<td>60°N - 90°N</td>
<td>0°E-360°E</td>
<td>Both</td>
</tr>
</tbody>
</table>
Table 1: This table lists the latitude range and longitude range for all of the water tags shown in Figure 1, along with whether the tag uses only oceanic evaporation, land evapo-transpiration, or both. For tags that cover the same geographic region, the smaller tag will be the one that actually contains the fluxes from that region, while the larger tag will simply have a flux of zero in the overlap region.

2.3 Model experiments

In this study we focus on a comparison between a simulation depicting contemporary climate and a projection of climate near 2100. Both simulations involved forcing iCAM5 with prescribed SSTs, sea ice, and greenhouse gas concentrations. The first simulation (labeled “modern-era”) uses observed SSTs and sea ice averaged over each month from 1974 to 1999, such that an average annual cycle was repeated continuously during the entire simulation. The greenhouse gases were also averaged from 1974 to 1999, but instead of averaging over each month, the entire dataset was averaged to produce a single value for each constituent. The model was configured to use a computational grid of 0.9° latitude x 1.25° longitude resolution, and with 30 vertical levels in the hybrid sigma-pressure coordinate system extending from the surface up to the lower stratosphere. The model was then run for 25 years, with the first 5 years ignored due to spin-up. The initial land surface state for each simulation was generated from a separate 40 year isotopic run, which was used to ensure that the hydrology of deep soil water was near equilibrium.

The second simulation (denoted “2100”) was set-up in the same way as the first, except the SSTs and sea ice were taken from a fully-coupled CESM simulation for the years 2074-2099 forced using the RCP8.5 forcing scenario. The greenhouse gases were also averaged from 2074-2099 using the RCP8.5 estimates. This was done in order to capture the impact of global warming on the simulated water source results. Along these lines, the reason the boundary conditions were
averaged over such a long time period was to ensure that any differences that are seen between
the simulations are due purely to the impact of global warming, and not from internal modes of
climatic variability, such as ENSO or the PDO. It is also possible that some of the differences
could be due to biases in the SSTs from the fully-coupled run. However, given that only long-
term monthly averages are used, it is expected that many of the model biases, particularly in
terms of oceanic variability, will be averaged out.

2.4 Atmospheric River detection method

This study examines atmospheric rivers that impact the West Coast of the United States. In this case, the “West Coast” will be defined as a box going from 30° N to 50° N and from 235° E to 240° E. The area covered by this box is shown in Figure 2. The ARs themselves are
defined as any vertically-integrated moisture flux, up to 300 hPa, in this region that surpasses the
99th percentile. This is very similar to the methods used by Warner et al., [2015], and verified by
Nusbaumer and Noone, [in prep]. An example of one of these 99th percentile events, along with
a composite average of the events over the entire modern-era simulation are shown in Figure 2.
As one can see, the general features of an AR being a long, thin plume of elevated moisture
transport holds for this particular definition at this midlatitude location. It also has been shown
that CAM5 can simulate ARs at the horizontal resolution chosen for this study, although the
actual flux magnitudes for each event may be too weak [Nusbaumer and Noone, in prep].
Finally, it is likely that by setting such a high percentile as our limit, some of the weaker ARs are
missed, but prior analysis indicates that these neither contributed substantially to the annual
mean poleward moisture transport nor are associated with the most extreme rainfall events. On
the other hand, the decision not to use a lower threshold emphasizes a desire to exclude
precipitating weather systems other than ARs that would get erroneously included. Thus by
picking the 99\textsuperscript{th} percentile, we are ensuring that only ARs, or at least only extreme moisture flux events, are being examined in this study.

**Figure 2:** A map of the vertically-integrated moisture flux (vectors) and moisture flux magnitude (color contours) in kg/m/s for a single AR event as simulated in the modern-era run (a) and a composite of all such events over the run (b). The black box indicates the “West Coast”, which is the region where all water tag fractions are calculated, and where the 99\textsuperscript{th} percentile of moisture flux is calculated in order to detect the presence of ARs.

### 3. Results

Figure 3 shows the average fraction of moisture in the “West Coast” that comes from each water tag in December-January-February (DJF) and June-July-August (JJA), along with the difference between the two seasons, for the modern-era. For both seasons, >33 % of the moisture comes from the Eastern North Pacific. However, while the North Pacific is the dominant moisture source for DJF (52.6 %), more of the moisture in JJA is recycled from land sources, including other continents (30.2 % versus 9.0 %).
Figure 3: Maps of the average fraction of moisture in the “West Coast” region that comes from each respective water tag for DJF (a) and JJA (b), along with the difference in moisture tag fractionation between DJF and JJA (c), and that difference normalized against each tag’s 12-hourly standard deviation of moisture fraction (d). Shading in plot d indicates that the change is not statistically significant at the 99% confidence interval according to a Mann-Whitney U test.

To help place the magnitude of the change in tag fractions due to the seasonal cycle in context, the changes between the two seasons are normalized relative to the standard deviation of the moisture fraction statistic itself, which is 12-hourly. The results are shown in Figure 3d. In general, most changes are larger than ± 1, which means the average seasonal cycle change is larger than the 12-hourly standard deviation for that particular water tag. Two exceptions include the Tropical North Pacific, near the equator, and the upper Northeast Pacific where the normalized statistic is 36.5 % and 2.7 %, respectively. Given the small changes relative to the 12-hourly variability, there is a concern that the changes in these regions may not be statistically significant. To rectify this issue, a Mann-Whitney U test was applied to the different water tag time series, to determine significance at the 99th percentile confidence level. The only tag change that failed the significance test was the Tropical Eastern Pacific (EDT), which is shaded out in Figure 3d. The figure also shows that all of the other seasonal changes are significant,
even if the magnitudes of the fractional contribution to the final precipitation in the US West are not very large.

Although the average seasonal fractions help set a baseline to compare against, they do not necessarily represent the average source regions during precipitation events, particularly for extreme AR events. Figure 4 shows the average modern-era source distribution averaged over all instances where a grid point over the West Coast experienced a moisture flux in the 99\textsuperscript{th} percentile, or higher, in DJF along with the difference between the 99\textsuperscript{th} percentile events and the average DJF climatological source fractions. The JJA results are excluded because a small fraction of high moisture flux events occurred during the summer season, which corresponds to the observation that ARs are driven by the frontal dynamics of extratropical cyclones that dominate in DJF [e.g. Sodemann et al., 2013]. Just like with the average DJF values, the majority of moisture during AR events comes from the Northeast Pacific. In fact, the magnitude is even stronger for ARs then for the average DJF climate. Still, it is important to note that a small fraction of the precipitable water comes from locations outside the North Pacific Ocean (7.1\%) indicating that alternative regions also have at least a second-order effect on ARs.
Figure 4: Map of the average moisture fraction for each tag for all 99th percentile (AR) events that impact the West Coast region in DJF in the modern-era (a), along with the difference in moisture fraction between AR events and the DJF climatological average (b), and that difference normalized against the 12-hourly standard deviation of moisture fraction for each tag (c).

Although the general pattern between ARs and the DJF climatology are similar, there are
substantial differences as well. In particular, a larger fraction of the moisture originates from South of 30° N (+19.4 %), while a smaller fraction originates from North of 40° N (-14.3 %). This again is well aligned with the well understood linkages between midlatitude frontal circulations with which ARs are associated and the southwest-to-northeast orientation of ARs, and provides evidence that at least some of the moisture in ARs is tropical in origin. To emphasize this point, Figure 4d shows the differences in tag fraction normalized against the 12-hourly standard deviation for each tag. The figure shows that the Tropical Eastern Pacific (+58.3 %), the Tropical Atlantic (+58.4 %), and even the Southern Hemisphere (+34.5 %) increase substantially, while land-based and higher-latitude source regions decrease. Finally, all of the changes in the tags were significant, which demonstrates that the sources of moisture for precipitable water in ARs is appreciably different from the average seasonal values.

Figures 5 and 6 show the average DJF and JJA water tag fractions for the warmer climate projected for 2100 under an RCP8.5 scenario, along with the differences in the seasons relative to the modern-era fractions. At first glance, the results show that the tag fractions haven’t really changed, which indicates that compared to the magnitude of the seasonal cycle, the global warming signal, at least over 100 years, is relatively small. However, there are robust patterns in the differences for the respective seasons. The most obvious pattern is the decrease in moisture that comes from the Eastern Pacific (-3.5 % in DJF, -5.4 % in JJA), and an increase in moisture that comes from continental and tropical moisture sources, including cross-equatorial moisture from the Southern Hemisphere (+0.7% in DJF, +2.3% in JJA). Compared to the magnitude of the 12-hourly variability (Figure 5C and 6C), it is found that many of the changes are of the same magnitude as the high-frequency variability, and, excluding some areas in the Northern Tropical Pacific, North America in DJF, and the Northwest Pacific in JJA, all of the changes are
statistically significant.

**Figure 5:** Map of the average DJF moisture fraction for each tag in the 2100-era run (a), along with the difference in moisture fraction between the 2100 and modern-era climatological averages (b), and that difference normalized against the modern-era 12-hourly standard deviation of moisture fraction for each tag (c). Shading in plot c indicates that the change is not statistically significant at the 99% confidence interval according to a Mann-Whitney U test.
Figure 6: Same as Figure 5, except for the JJA season.

Figure 7 shows the average water tag fractions for West Coast ARs for the 2100-era, which again are simply defined as any region with a moisture flux in the 99th percentile or
higher. It should be noted that this percentile is for 2100, which means that the total number of ARs is the same between the two simulations, although the magnitude is approximately 38% larger (696 kg/m/s in 2100 vs 503 kg/m/s in the modern-era). Along with the climatological average, Figure 7b and 7c show the difference and normalized difference in tag fraction, respectively, between ARs in 2100 and the modern-era. Just like with the average climate for both DJF and JJA, ARs in 2100 have smaller fractions in the Eastern Pacific (-3.4 %), and larger fractions almost everywhere else. Also, all of the changes are significant, demonstrating that, at least for the climate as simulated by CAM5, the hydrology of atmospheric rivers for the West Coast of the United States will change in the future, assuming greenhouse gases continue to be emitted at the RCP8.5 rate.
Figure 7: Map of the average moisture fraction for each tag for all 99th percentile (AR) events that impact the West Coast region in DJF in 2100 (a), along with the difference in moisture fraction between AR events in 2100 and AR events in the modern-era (b), and that difference normalized against the 12-hourly modern-era standard deviation of moisture fraction for each tag (c).
3.1 Implications for observing hydrological change

Although numerical water tags can reveal the characteristics and variability of a model’s hydrologic cycle, there remains the matter of how well the results represent the actual atmospheric water cycle. While even the mean atmospheric water balance remains a challenge to constrain from observations [e.g. Bosilovich et al., 2015], a decomposition into specific regional flux components is a further challenge that extends beyond the capacity of traditional observational data - because there are no direct observations that can be used to quantify any biases or errors in the water tag results. However, the stable hydrogen and oxygen isotope ratios in water vapor are well recognized as indicators of moisture, the source locations of the vapor, as well as the rainout processes that the water vapor experiences as it is transported from the source region to the region of interest [e.g. Dansgaard 1964; Noone et al., 2011; Noone et al., 2013; Steen-Larsen et al., 2015]. Because the isotope ratios are an observable quantity and share some characteristics with the numerical tags, analyzing the simulations of stable isotope ratios of water in the atmosphere can allow for an evaluation of different moisture pathways within the model hydrologic cycle. The simulation of isotope ratios in CAM5 for the modern-era, and the biases that the isotopic comparison exposes, is discussed in Nusbaumer et al., in prep. Here we use isotope ratio information to decompose changes in hydrology between 2100 and the modern era into different contributing causes.

Isotope ratios in water are usually represented in “delta” notation. For the ratio of heavy hydrogen (deuterium) to regular hydrogen in water, the delta value is calculated as:

\[ \delta D = \left( \frac{R}{R_{std}} - 1 \right) \times 1000 \]  

(4)

Where R is the ratio of deuterium to hydrogen in the water mass of interest, and R_{std} is a ratio based off a geochemical standard, usually V-SMOW, which is representative of the average
ocean value [Gonfiantini, 1978]. In analogy to the budget for water tags given in Section 2, a change in the isotopic values over a particular region (West Coast of the United States) can be decomposed into several terms. To simplify, let’s first assume that the water isotope ratios can be modeled as a Rayleigh process [e.g. Jouzel and Merlivat, 1984; Noone, 2012]:

\[
R = R_0 f^{\alpha-1}
\]

Where \( R \) is the isotopic ratio at the location of interest, \( R_0 \) is the isotope ratio of the source region, \( f \) is the fraction of the water mass that was lost during transport from the source region to the region of interest, and \( \alpha \) is the isotopic fractionation factor. If one then treats the change as a small linear perturbation of the mean, then one can represent the isotopic change as:

\[
\Delta R = R_0 f^{\alpha-1}(f^{\Delta \alpha} - 1) + R_0 \Delta f^{\alpha-1} + \Delta R_0 f^{\alpha-1}
\]

Where \( \Delta \) is the change of the quantity over some length of time (i.e., 2100 vs modern-era). In this equation, the first term on the right hand side is the change in the ratio caused by a change in the fractionation factor, the second term is the change in the fraction of water mass lost during transit, and the third term is the change in isotopic ratios at the source. If one assumes that the initial rain out amount is zero (i.e. \( f=1 \)), then the equation simplifies even further to:

\[
\Delta R = R_0 \Delta f^{\alpha-1} + \Delta R_0
\]

Although that assumption is questionable, it does reduce the number of terms such that the relationship can be examined in at least a limited way here. By substituting the delta values in for \( R \), the equation becomes:

\[
\Delta \delta D = \delta D_0 \Delta f^{\alpha-1} + \Delta \delta D_0
\]

Finally, the change in the source region can be further split into a change in the distribution of moisture source locations, and the change in the actual isotopic values for each source:

\[
\Delta \delta D_0 = \Delta(\delta D_0)S + \Delta S(\delta D_0)
\]
Where $S$ represents the change in the source regions, which is equivalent to the change in the water tag moisture fraction for any particular region.

Figure 8a shows the change in the $\delta D$ of vapor for the West Coast of the United States as simulated by the model for DJF between the modern-era and 2100. There is an increase in the amount of heavy isotope mass in water everywhere, with a larger increase over the continent. Figure 8b shows the change in $\delta D$ due to the $\Delta(\delta D)S$ term, or the change in evaporative flux of $\delta D$ for each source region. The change is positive and almost spatially uniform over this region. The change of 4.2 ‰ is consistent with a reduction in fractionation over ocean water that has warmed 2.66° C, which is consistent with the increase in global temperatures at the surface over most of the globe. Figure 8c shows the change in $\delta D$ due to the $\Delta S(\delta D)$ term, or the change in the fractional contribution of moisture from each source region, and which can be directly evaluated from the tag fractions described above. Unlike the change in the net isotope values, this change is negative almost everywhere, which could be due to a shift away from the North Pacific subtropics, where the $\delta D$ can be quite high, to farther away regions where the $\delta D$ is lower. Finally, Figure 8d represents the remaining change in $\delta D$ that’s not explained by changes in the source conditions ($\Delta \delta D_0$), which is essentially the $\Delta f$ term, or the change in the rainout amount. This term is the largest of all three terms in the isotopic change over the 100 year time period and is also positive everywhere. A positive value corresponds to a reduction in the rainout rate of the atmosphere. This is due to two complementary effects. First, with higher condensation temperature at 2100, the fractionation is weaker. Second, with a higher atmospheric temperature and a broadly weaker poleward atmospheric transport, the fractional precipitation change relative to the fractional precipitable water change identified by Held and Soden [2006] accounts for a change in the rainout fraction “$f$”. It should be noted that within this “Rayleigh-like” paradigm,
the meaning of the fractionation, $\alpha$, is convoluted by the role of moisture recycling in clouds in a manner similar to the precipitation efficiency explored elsewhere [Noone et al., 2011; Bailey et al., 2015b]. In terms of atmospheric rivers, this implies that the increase in water vapor in ARs due to the Clausius-Clapeyron relationship will overwhelm any increase in rainout along the AR itself, resulting in increased overall moisture fluxes and potentially increased precipitation rates at the terminal end of the AR.

**Figure 8:** Maps of (a) the average change in δD for DJF between 2100 and the modern-era, (b) the change due to changing δD at the source regions, (c) the change due to the changing fraction of moisture that comes from the respective source regions, and (d) the remaining change after the source region contributions have been taken into account, which corresponds to the change in the amount of rainout experienced by the water vapor as it transits from the source region to the
West Coast of the United States.

An advantage of this analysis is that all of these terms, except the change in the source fraction, can be observed. Thus, the change in the source fraction can be evaluated by accounting for observed changes in isotope ratios of water vapor and precipitation. Indeed, this contrast also provides confidence that the simulation of water tags and their changes can be at least partially validated.

As an example, Figure 9 shows the annual trend in the δD of the vapor at ~750 mb as measured by the Tropospheric Emission Spectrometer (TES) instrument on the NASA Aura satellite [Worden et al., 2006], which made measurements from September, 2004 to May, 2011. The reason this instrument was chosen was because it had the longest time series of any satellite-derived data, and 750 mb was chosen because it is the altitude where TES has the highest accuracy. As one can see, much of the region has a positive trend in δD (Average over entire region is +0.023 ‰/year), although smaller than what the model projects. Still, the TES record is short enough that the signal could be dominated by internal climate variability, so the fact that the signal is even the same sign can provide some confidence in the model results, and shows the type of observations one would use to examine the model results in more detail.
4. Discussion

These results have provided a synthesis of several studies of atmospheric rivers and moisture transport, which have postulated changes in different aspects of the midlatitude water budget. First, the moisture flux intensity (measured by the vertical convolution of specific humidity and wind speed) in ARs that impact the West Coast of the United States increases by almost 40% over the 100 years from present day to 2100. Using a fixed threshold to define ARs in terms of the water mass flux, this implies an increase in the frequency of AR events by 2100 as well. This supports the synthesis results from projections from the Fifth Coupled Model Intercomparison Project (CMIP5) archive for the West Coast of the United States [Warner et al., 2015] as well as the United Kingdom [Lavers et al., 2013], and demonstrates that CAM5
simulates changes in ARs as well as most CMIP5 models. If this increase in moisture flux directly corresponds to a change in precipitation, then the risk of extreme precipitation events in these regions will increase substantially.

Second, the results have provide a climatology of moisture sources for the West Coast of the United States, which has previously been only described qualitatively and without numerical evaluation. We have found that for DJF, most of the moisture comes from the Northeast Pacific, while in JJA more moisture comes from continental regions. This helps demonstrate that the land surface scheme in CESM is properly capturing changes in the land surface’s energy and moisture budgets. It’s also important to note that this finding is specific for the US West Coast, which is a region in which most of the air mass that enters the region will have spent time over the ocean. An analysis that focuses on more central continental regions would be likely to expose the land-based evapotranspiration and continental recycling as even more significant.

When examining AR moisture sources, it was found that in general, most (71.4 \%) of the moisture which falls as precipitation in the US West came from the Northeast Pacific. This matches well with previous studies, including Bao et al., [2006] who argue that the majority of the water in ARs is from the convergence of locally-sourced moisture. However, it was also found that there is a significant increase in moisture coming from regions below 30° N, including moisture directly from the tropics. Our comprehensive Eulerian budget agrees with several case studies based on Lagrangian (trajectory) methods including Stohl et al., [2008] and Sodemann and Stohl, [2013] who found that ARs in the Atlantic that struck Scandinavia tended to obtain a large (>10 \%) fraction of their moisture from subtropical and tropical locations. Individual AR events will of course vary in terms of the amount of moisture that comes from local mid-latitude sources as opposed to tropical sources, but the fact that there is a hydrologic connection, on
average, between ARs and the tropics indicates that they do in fact play a role in global tropical-extratropical moisture transport.

In the year 2100 experiment, both the climatological moisture sources, and the moisture sources of ARs, move away from the Northeast Pacific, and instead came from regions that are more distant geographically. This essentially argues that there is less locally-source moisture, and instead more long-distance moisture transport. This result is not just unique to the West Coast of the United States, as another study has found it to be a more or less global signal [Singh et al., submitted]. Essentially, one can imagine that the change in the average moisture transport distance is proportional to the change in the evaporation of moisture from the source region divided by the change in the precipitation rate along the transport path. Given that most global warming projections show a ~7%/°C increase in atmospheric moisture, but only a ~2%/°C increase in average precipitation [e.g. Held and Soden, 2006], the average moisture transport length scale must increase, and thus a larger fraction of moisture at any one location must come from sources that are farther away.

Finally, it should be noted that there are limitations to these results. These limitations are mostly because the model is known to have errors in its representation of the global climate and hydrologic cycle [e.g. Nusbaumer et al., in prep]. These could result in potentially significant errors in the quantitative results shown here, although the qualitative results are believed to be robust. One way to alleviate this issue is to nudge the model results using observed wind and temperature fields, which would allow the model to more faithfully reproduce the modern climate. However, given that this is not possible to do for future climate states, this technique was not applied in order to try and accurately capture the shift in the hydroclimate due to global warming. For future studies that are more focused on the modern climate, though, this would be
5. Conclusions

Atmospheric Rivers are one of the major drivers of extreme precipitation in the West Coast of the United States [e.g. Ralph et al., 2006; Neiman et al. 2011], and recent studies have shown that their intensity, and potentially their frequency, could increase as the climate warms [Dettinger, 2011.; Lavers et al., 2013; Warner et al., 2015]. There has also been studies that show that ARs play a major role in the global transport of moisture poleward [Zhu and Newell, 1998], and thus changes in ARs could influence the global climate system outside of just precipitation in certain geographic regions. However, it is unclear where the moisture in ARs comes from, with different studies finding different results [Bao et al., 2006; Stohl et al., 2008; Sodemann and Stohl, 2013], which thus makes it hard to determine what role ARs play in the larger hydrologic cycle.

By using water tags in the isotope-enabled Community Atmosphere Model version 5 [Nusbaumer et al., in prep], 20 year climatologies of moisture sources were constructed for both the modern-era and the end of the 21s century. It was found that the majority of moisture in the region comes from the Northeast Pacific, although in summer a higher fraction comes from land-based sources. For ARs, it was found that although most of the moisture still came from the Northeast Pacific, there was a shift towards more moisture coming from south of 30° N. This supports the findings of Sodemann and Stohl, [2013] who found that a substantial fraction of the moisture comes from lower latitudes as well as from local midlatitudes sources, and that this relationship holds on a climatological time scale, instead of just being a product of some unique AR events that were used as case studies. It was also found that in 2100, a larger fraction of the
moisture came from remote sources outside of the Northeast Pacific, including moisture from the Southern Hemisphere. This relationship held for both seasons, as well as for ARs. It thus supports the idea of a longer moisture transport length scale, which has been found in other studies as well [e.g. Trenberth et al., 1998; Singh et al., submitted].

The change in water isotopes between the modern-era and 2100 was used to expose a more integrated approach to evaluating the hydrological change that is provided by the source region tags alone. It was found that the $\delta^D$ values became more enriched over time, which matches the expectation from simple theoretical considerations that water isotope values increase as the ocean temperature increases [e.g. Craig and Gordon, 1965]. However, it was found that the majority of this change is due to changes in atmospheric processes rather than source region effects. Specifically, there is reduction in the rate at which water is removed from the atmosphere (i.e., a decrease in rainout), which counteracts the increase in the $\delta^D$ of the source regions. This finding reveals a strong motivation to use isotopic observations alongside more traditional meteorological observations to determine how the distribution of source regions might change. Thus, it provides an opportunity to validate the results of water tagging studies, and the theory put forward in the synthesis study of Held and Soden [2006].

The analysis reported here leaves several pertinent questions unresolved. In particular, it is expected that there is significant variability in water sources associated with internal climate variability, such as ENSO. Given that the simulations only used 20 year averages of SSTs and sea ice, the model could be forced using SSTS from just one mode of a particular low-frequency climate mode or oscillation. This could result in a water source distribution that is not actually representative of the long-term average climate state. Along with that, it is known that the fully-coupled CESM has biases in the simulation of modern day SSTs and sea ice. This implies that
SST biases in the 2100 simulation might be present relative to the modern-day simulation, resulting in shifts in the water tag source distribution that are unphysical, and are purely a result of biases in the coupled model.

There is also some future analyses which could be done to examine the results shown here in more detail. For example, by using isotopic observations from satellites, such as TES [Worden et al., 2006], SCIAMACHY [Frankenberg et al., 2009], or GOSAT [Frankenberg et al., 2013], one can determine what the changes in δD for both the source and sink regions are, allowing one to directly constrain the model results. Also, by comparing the results from this model to other water tag and isotope-enabled models, like GISS [Jouzel et al., 1987; Kelley, 2003], one can determine how the results differ between different models. Finally, by directly calculating the rainout fraction instead of just assuming a value, one can separate the different physical influences on the rainout, including the impact of temperature. Eventually, all of this work will lead to a more complete understanding of the global hydrologic cycle, including atmospheric rivers, and thus allow for better hydrologic and climatic forecasts and projections.
1. Questions examined

Floods and drought can have a major impact on a society. The recent California drought alone has cost almost $2.7 billion [Howitt et al., 2015], while the current El Niño is producing fears of both droughts and floods all over the world [e.g. Ward et al., 2014]. Thus there is a strong incentive to understand the drivers of precipitation, and ultimately to be able to predict changes in the atmospheric water cycle as a whole, from a weather forecast a few days out all the way to global climate projections for a hundred years from now.

This collection of studies partially addresses these issues, particularly for the Community Atmosphere Model Version 5 (CAM5) [Neale et al., 2010], which is the atmospheric component of the Community Earth System Model Version 1 (CESM1) [Hurrell et al., 2013] and a modelling tool in wide use for climate and climate change research. The three major questions examined here were: A. How well does CAM5 simulate extreme transient eddy moisture transport, as well as ARs, compared against MERRA reanalysis [Reinecker et al., 2011]? B. What additional information can be gathered through adding water isotopes to CAM5, particularly in regard to cloud and convective processes, and C. can we use water tags in CAM5 to determine what the sources of moisture are for the West Coast of the United States, and for ARs that impact that region, both for the present and for the end of the next century under global warming? Together these have shown that there are future long-term changes to ARs that will occur, but that there are also biases inherent to the model that must also be addressed if one is to have confidence in the model’s results and projections.

2. Key findings
Although there have been studies examining extreme precipitation in models, as well as extreme atmospheric moisture transport [e.g. Lavers et al., 2015], there has been no published examination of global extreme moisture transport in CAM5, including ARs. Thus several simulations were performed with year 2000 boundary conditions, all with either different horizontal resolutions, or different dynamical cores. These results were then compared against the MERRA reanalysis, which is known to at least accurately simulate ARs on the West Coast of the United States [Payne and Magnusdottir, 2014]. It was found that compared to MERRA, although the global average fluxes matched well, the average flux magnitude per extreme event or AR event in CAM5 was significantly weaker, particularly in the midlatitude ocean regions. This means that any extreme precipitation events generated by ARs or transient eddies would be under-estimated, and that some aspect of the model physics was lacking, which could cause an under-prediction in the strength of extreme midlatitudes moisture flux events, both now and in any future projections.

However, it was also discovered that by increasing the horizontal resolution, this moisture flux bias decreased. The width of these events also decreased, and eventually seemed to converge to the MERRA results. The results also seemed to be more or less independent of the dynamical core used, which helps eliminate that aspect of the model as a major source of uncertainty. Still, even at the higher resolution, CAM5 had a negative moisture flux magnitude bias. This indicates that an issue with the model’s subgrid parameterizations is most likely generating the negative biases, at least compared to MERRA. Finally, it was found that extreme transient eddy transports and ARs have very similar characteristics. Thus ARs could potentially be just a subset of transient eddy events, which would allow for a more dynamically-based, and potentially global, definition for atmospheric rivers.
To better understand and constrain CAM5’s moist physics and atmospheric hydrology, new physics were added that can allow CAM5 to simulate water isotopes. Combined with a new isotope-enabled land surface model (iCLM4) [Wong et al., in prep], CESM can now simulate the stable isotope ratios of hydrogen and oxygen for water vapor, cloud liquid and ice water, and precipitation. A simulation was done with 1974-2014 boundary conditions, and the results were compared against several observational datasets, including satellite data [e.g. Worden et al., 2006; Frankenberg et al., 2009]. It was found that precipitation globally was too depleted, as well as water vapor above the boundary layer. However, water vapor near the surface was actually too enriched. This demonstrated that CAM5 produces too much precipitation, and thus causes too strong of a rainout effect as the water mass is transported from the region of evaporation, both horizontally and vertically.

Although determining that a precipitation bias exists in CAM5 is beneficial, it is more useful in terms of model development if one can track down a specific issue. By performing multiple sensitivity experiments, it was found that the parameter that most strongly decreased the global isotopic bias for both precipitation and vapor was the CAPE limit used to trigger deep convection. In particular, it was found that this limit was set to too low of a value, which allowed deep convection to trigger too frequently in the winter midlatitudes. This in-turn removed too much moisture from the lower troposphere, where most of the poleward moisture transport occurs. Thus with fractionation occurring during rainout, water vapor with low isotope ratios is advected to higher-latitude regions, resulting in the large depletion bias poleward of the extratropics. This result has implications for the model’s ability to simulate ARs, as too much deep convection could remove moisture from the AR transport region, resulting in horizontal
moisture fluxes that are too weak, and possibly not able to produce the extreme precipitation events generated by ARs and transient eddies in the real earth system.

An advantage to adding water isotopes to a climate or weather model is that one also automatically adds water tracing capabilities. This capability was then exploited to determine what the major sources of water vapor where for the West Coast of the United States, as well as for ARs that impacted this region, at least as simulated by CAM5. This was done both for the end of the 20\textsuperscript{th} century (1974-1999) and for the end of the 21\textsuperscript{st} century (2074-2099), to determine how the sources of moisture will change due to global warming. It is found, perhaps unsurprisingly, that most of the moisture comes from the Northeast Pacific, essentially right off the coast of North America. However, there was a significant amount of moisture that came from land-based sources during JJA, including from land in the Eastern Hemisphere. It was also found that ARs export more moisture from subtropical and tropical regions than the climatological average. This shows that although local moisture may still be a dominate source, there is a significant amount of moisture from outside of the midlatitudes, which helps validate the results from previous case studies [e.g. Stohl and Sodemann, 2013].

When comparing the differences between the 20\textsuperscript{th} and 21\textsuperscript{st} century results, it is found that the fraction of moisture that comes from the local Northeast Pacific decreases, and is replaced by moisture from more distant locations, including the Southern Hemisphere. This relationship holds for both the climatological average (for both seasons), and for ARs. These results provide evidence for the idea that the average moisture transport length scale increases as the global climate warms, resulting in more long-distance transport of moisture into any one location of interest.
Finally, the change in water isotope values was examined for the two different time periods, again over the West Coast of the United States. A simple framework was used to relate the change in the water isotope ratios with changes in the source regions as determined via the water tags. It was found, though, that the largest influence on water isotopes was not the change in the source, but instead the change in the rainout processes experienced by the water as it traveled from its source to the US West Coast. This examination also presents a pathway to validate the water tracers, or “tags”, which are purely a theoretical construct in the numerical model, with actual water isotope observations, including from satellite. The analysis demonstrated that this technique is a powerful method to analyze and constrain CAM5’s hydrologic cycle, and, ultimately, refine the climate simulations of CESM as a whole.

3. Perspectives and final thoughts

These collection of studies provide new, unique insights into the ability of an IPCC-class climate model to simulate the atmospheric hydrologic cycle, and in-turn the global hydroclimate. It also provided insights into the hydrology of the US West Coast, including atmospheric rivers, and how they might change in the future. However, these studies have exposed a deeper set of problems related to hydrological cycling within models and in nature, and now offers several pertinent opportunities for future research.

For example, even with the adjusted deep convective triggering conditions, iCAM5 still has a substantial negative isotopic mass bias in precipitation and upper-tropospheric water vapor, and a positive isotopic mass bias in surface vapor. Thus there are still errors in the underlying physics that are generating these biases, which could also be causing biases in the overall climate of CAM5 and CESM1. Understanding and correcting these biases would be beneficial, as it would increase one’s confidence in the model projections, which is needed if the projections are
to be used to make major policy or infrastructure decisions. Doing this sort of research also matters because numerical models are ultimately just an expression of our theoretical understanding of a particular physical or chemical system. If biases and errors exist in the model, it shows that there is a missing piece to the theory that still needs to be discovered, and that is what water isotopes really provide, an extra tool to help find those missing pieces.

By demonstrating how water sources change with global warming, and in-turn how those changes impact water isotopes, there is also an opportunity to re-examine paleoclimate reconstructions, particularly those related to hydrogen and oxygen isotope ratios. The reason this matters is because much of our understanding of the earth system comes from paleoclimate reconstructions, which themselves are developed using numerous physical assumptions. If one of those assumptions, for example, that the moisture source region remains the same, turns out to be false, then the reconstruction itself could have misleading or unrealistic values. Thus any scientific results built off that reconstruction, such as estimates of climate sensitivity or the state of ice sheets in warmer climates, could also become suspect. Thus any new paleoclimate research should be done with the tools and findings presented here in order to examine the assumptions on which the reconstructions are based. By ensuring that we understand the past, we can better prepare ourselves for what’s coming in the future.

One of the goals of science is to help people better understand the world around them, which can then be used to predict, mitigate, or adapt to any threats to one’s livelihood brought about by the surrounding environment. That is the ultimate goal for the scientific studies presented in this thesis, and for which the detailed analysis of the CAM5 hydrology allows success to be claimed. By better understanding where atmospheric rivers acquire their moisture, and by better diagnosing any shortcomings in the models we use to predict atmospheric rivers
and other weather and climatic phenomena, one can hopefully produce more accurate and robust forecasts and projections. This then allows societies to prepare for extreme precipitation events, floods, and droughts, and thus lessen the damage they do to not only individuals, but to society as a whole.
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