The Scaling, Efficacy, and Timescales of Precipitation Change: A comparison between \( \text{CO}_2 \) and \( \text{CH}_4 \) perturbations using CESM CAM4

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Abstract

Precipitation patterns and rates change with global warming. These changes can be separately evaluated in fast and slow responses, the combination of the two are called apparent responses. The fast precipitation responses can be understood by energetics, while the slow precipitation responses scale with surface temperature change. Precipitation Driver and Response Model Intercomparison Project (PDRMIP) is a project investigating precipitation responses to separate climate drivers. One of their experiments, a tripling of atmospheric CH$_4$, proved too weak of a perturbation to compare to the other experiments in the project.

This thesis performs two stronger perturbations of CH$_4$ and compare precipitation responses to a doubling of CO$_2$, using one of the models in PDRMIP, CESM1 CAM4. Two configurations were used to separate responses in timescales, and each perturbation were run as an ensemble to reduce natural variability.

Both surface temperature and apparent precipitation responses scale well with forcing for CH$_4$. CO$_2$ does not scale equally to CH$_4$. The apparent surface temperature efficacy for methane was below 1, averaging at 0.96 ± 0.07, while the apparent precipitation efficacy was above 1, averaging at 1.24 ± 0.09. Fast precipitation changes has a negative correlation to atmospheric absorption, and the CO$_2$ simulation exhibited the strongest atmospheric absorption as well as the strongest negative fast precipitation response.
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Oslo, June 1, 2018
Kine Onsum Moseid
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Chapter 1

Introduction

Essentially, all models are wrong, but some are useful.

George E. P. Box, Empirical Model-Building and Response Surfaces (1987)

Climate change is the biggest self inflicted challenge humans have faced in recorded history. The future of Earth is in the hands of politicians and policy makers, and they depend on credible and accurate research to make educated decisions. Current climate change is caused by natural and anthropogenic emissions of aerosols and greenhouse gases (GHG), together with changes to incoming solar radiation. These drivers of climate change have altered the energy balance of the Earth, generating an increase in surface temperatures. We call this global warming. Global patterns and levels of precipitation are changing in response to global warming (Hartmann et al., 2013), and will continue to change in the future. Precipitation is an important source of freshwater not only in the developing world, but for food production around the globe. Infrastructure and human life are vulnerable to potential extreme weather caused by changes in precipitation rates (Myhre et al., 2017). Unfortunately, observational data for precipitation is sparse, and the model spread in future projections from computational models should be reduced. Projections of future climate is dependent on current and future anthropogenic emissions, and an understanding in how temperature and precipitation responds to the separate climate drivers will increase the accuracy in estimates of a future climate.

Changes in temperature, precipitation, and hydrological sensitivity are subjects of interest, and this thesis’ topic is inspired by the Precipitation Driver and Response Model Intercomparison Project (PDRMIP) lead by The Center for International Climate and Environmental Research (CICERO), Oslo, Norway. PDRMIP investigates precipitation responses through five experiments using ten climate models. One of these experiments triples the atmospheric concentration of methane. Their preliminary results from the tripling of methane showed weak signals and a large model spread, making a need for a study with stronger perturbations to methane apparent.
Chapter 1. Introduction

This thesis uses the coupled model CESM1 CAM4\(^1\), which is one of the models used in PDRMIP, to investigate responses following separate perturbations to the two most important greenhouse gases for global warming, carbon dioxide and methane. The concentration perturbations are a doubling of carbon dioxide, a five time increase in methane, and a ten time increase in methane, relative to present day atmospheric concentrations. It is useful to determine the potential difference in response of the two gases, as this can increase the accuracy of emission based projections in future studies. Associating climate responses to specific greenhouse gases can also help our understanding of how much of observed the climate change is anthropogenic, and how much is caused by natural variability.

When introducing a step-function increase in a GHG Earth’s energy balance is shifted, and the magnitude of this shift is called radiative forcing. The first question to be answered in this thesis is how well equilibrium responses of interest scale with forcing strength. If carbon dioxide and methane had equal strengths of radiative forcing, would their responses be the same? This question of scaling will determine if there is a basic difference in how the climate system responds to the two gases.

This potential difference will be highlighted in the next thesis question: what is the efficacy? The ratio between a response initiated by a methane forcing and the same response initiated by carbon dioxide forcing is called efficacy. The efficacy is the factor with which methane affects the response per forcing compared to carbon dioxide.

Precipitation responds on two different timescales, fast and slow. The fast adjustments can be understood through energetics, and slow responses are driven by surface temperature changes. The efficacy can be estimated separately for fast and slow precipitation responses, revealing at what timescale the potential difference in response occurs. This leads us to the final question: how do the responses and potential differences between carbon dioxide and methane develop over time?

The reader will know the motivation for this thesis by the first chapter, the introduction. Chapter 2 focuses on theory by providing relevant background information before explaining the atmospheric substances and its radiational properties, global precipitation patterns and important climate feedbacks to consider. A more in-depth explanation of the project PDRMIP along with a few preliminary results are found in Chapter 3. Chapter 4 will inform the reader of how and why the climate model was chosen, how the results were obtained, the methodology for the experiments, and how output from the model was analyzed. The result of the analysis is found in Chapter 5 with a following discussion. The last chapter, Chapter 6, contains a summary of the thesis together with final conclusions and recommendations for future work. The appendix contains ensemble results and a brief discussion on questions that arise during Chapter 5.

\(^1\) Community Earth System Model, Community Atmosphere Model 4.0

http://www.cesm.ucar.edu/models/ccsm4.0/cam/
Chapter 2

Theory

This chapter presents the scientific background of climate change. It also presents the most important greenhouse gases (GHG’s) together with climate feedbacks and responses. In order to categorize the responses the different timescales are introduced.

2.1 Climate change

Changes to the Earth’s energy balance induce climate change. An estimation of this energy balance is found in Figure 2.1. The yellow arrows represent short wave radiation from the sun, while the orange arrows represents the longwave radiation emitted by Earth and greenhouse gases.

![Figure 2.1: Global mean energy balance of the Earth for the beginning of the twenty first century as presented by Wild et al. (2013). Numbers are given in [W/m²] and the uncertainty ranges are listed below each average.](image)

Anthropogenic emissions of GHG’s and other radiative gases are increasing. Some of
the longwave radiation emitted by Earth is absorbed in the atmosphere by GHG’s, and the increase of such GHG’s will create an energy imbalance. The anthropogenic emission of \( \text{SO}_4 \) affects the energy balance by absorbing incoming solar radiation. Earth responds to a decrease in outgoing longwave radiation by increasing its surface temperature, and with time the energy budget will reach a new state of equilibrium. The instantaneous energy change following a change in atmospheric radiative content is called radiative forcing, and will be further explained in Section 2.1.1. In the far left of Figure 2.1 the reader can observe the residual. This is the estimated current imbalance of the energy budget, and is in the process of being balanced out by surface temperature increase. This is the climate change we observe today.

The so called atmospheric window is a specified range of wavelengths where the longwave radiation as emitted by the Earth can travel undistorted through the atmosphere and directly to space. This works as a way of “cooling” the Earth, and can be seen to the right in Figure 2.1.

Figure 2.1 also shows energy exchange between the surface and the atmosphere as latent and sensible heat fluxes. Sensible heat flux is defined as an increase of enthalpy added in hydrostatic balanced air. In Layman’s terms sensible heat flux is related to changes in temperature of a gas without any change in phase. Latent heat flux is related to phase changes between gases, liquids, and solids. Changes in latent heat flux and its effect on climate is explained in more detail in Section 2.4.

Trenberth et al. (2009) explains the complexity and simplifications made to create figures like Figure 2.1.

### 2.1.1 Radiative forcing

Radiative forcing (RF) is defined as the difference in energy entering the top of the atmosphere (TOA) and the energy exiting the TOA (Myhre et al., 2013), in an instantaneous response to an external perturbation (Stocker et al., 2013). When estimating RF clouds, surface temperature response, albedo and more are held constant. Positive and negative RF leads to heating and cooling of Earth, respectively. The definition of TOA can vary, but for purposes concerning weather and climate it is useful and common to measure RF in the tropopause.

There is little evidence of drastic changes in surface temperature before the industrial revolution, and 1750 is commonly used as a baseline year for calculating RF.

RF is defined as an instantaneous response to a climate forcer, not including feedback mechanisms of the climate forcer such as surface temperature change. In the practice of estimating RF it is complex to differ between the energetic response following emissions and the energetic response following feedback mechanisms of emissions. Different drivers have exerted different RF over the recorded history. This is illustrated by (Stocker et al., 2013) in Figure 2.2. The effect of volcanic outbreaks has a negative RF, but only for a couple of years at a time, and is therefore not included in the figure. Anthropogenic forcing agents are seen to have the largest order of magnitude...
Figure 2.2: Radiative forcing of climate change from year 1750 to 2011. Adapted from [Stocker et al., 2013]. The confidence levels are indicators of both evidence and agreement. WMGHG stands for well mixed greenhouse gases, AR4 is the former physical assessment report by IPCC (2007).

regarding RF. The only natural forcing agents to be included have a positive RF. CO\textsubscript{2} is the well mixed greenhouse gas (WMGHG) with the largest contribution to the total radiative forcing, not surprisingly. Note the confidence level for each forcing agent, where greenhouse gases are the forcing agents with the highest amount of confidence, and aerosol-cloud interactions have the lowest amount of confidence. The confidence term includes both uncertainty in evidence and scientific agreement [Stocker et al., 2013].

2.2 Greenhouse gases

Greenhouse gases are the dominating forcing agents to anthropogenic radiative forcing over the last 270 years. It is useful to take a closer look at their properties. Carbon dioxide and methane are two of the most important greenhouse gases regarding global warming.

2.2.1 Carbon dioxide

Carbon dioxide (CO\textsubscript{2}) is a well mixed greenhouse gas, and is responsible for most of the radiative forcing in recorded history. CO\textsubscript{2} has atmospheric absorption bands in both the longwave range and in the shortwave range, meaning the gas can absorb both irradiance from the sun and radiation emitted by the Earth. The shortwave bands are ineffective, and are often negligible. Etminan et al. (2016) performed a model experiment where they increased the atmospheric concentration of CO\textsubscript{2} and studied the variation in spectral
bands of the tropopause forcing. The result is shown in Figure 2.4b, and shows that the absorption lines in the shortwave range will give a negative adjustment to the much stronger absorption line in the longwave range. This negative adjustment was calculated to be only 5%. Since 1750 the atmospheric concentration of CO$_2$ has increased by over 40% (Hartmann et al., 2013). Figure 2.3a displays how atmospheric concentrations of CO$_2$ has developed from 1960 to present day according to observations. The rate of which CO$_2$ is increasing is accelerating.

Sources of CO$_2$ are both natural and anthropogenic. The natural sources include decomposing of organic material and respiration from plants, while the anthropogenic sources include fossil fuel burning and land use changes (removal of forests). The natural sinks for CO$_2$ is oceanic dissolving and removal by photosynthesis in organisms. Individual CO$_2$ molecules have a short residence time in the atmosphere, they are usually only swapping places with other CO$_2$ molecules from the ocean. The removal process by biosphere happens on a short time scale, as the vegetation that removes CO$_2$ will eventually die, decompose, and release the CO$_2$ again in addition to respiration. Dissolution in the ocean is effective, but the top layer of the ocean can be saturated by CO$_2$, and relies on the overturning circulation to replace the top layer. These circulations takes hundreds of years, so the excess content of CO$_2$ can be assumed to stay in the atmosphere for just as long. Currently about half of the emitted CO$_2$ is removed from the atmosphere by dissolving in the ocean and by land biosphere, while the rest accumulates in the atmosphere.

Future emissions of CO$_2$ are highly dependent on global policies, which are difficult to predict. Future projections of CO$_2$ are therefore highly uncertain.

![Figure 2.3: The observed development of atmospheric (a) CO$_2$ and (b) CH$_4$ mixing ratios. By NOAA.](image)
Figure 2.4: Spectral variation of tropopause forcing in the shortwave range following an increase in atmospheric (a) CH$_4$ and (b) CO$_2$. Adapted from Etminan et al. (2016).

2.2.2 Methane

In Figure 2.2 methane contributed about 20 % of the anthropogenic radiative forcing from 1750 to 2011, which makes methane (CH$_4$) the second most important greenhouse gas. The forcing over this period was found in Myhre et al. (2013) to be 0.48 W/m$^2$, but a recalculation by newer models in Etminan et al. (2016) suggest this forcing value should be updated to 0.61 W/m$^2$. Methane has atmospheric absorption bands in the longwave range and in the shortwave range. The most important absorption band is found in the longwave range around 7.7 µm. Figure 2.4a show the instantaneous shortwave forcing due to an increase in atmospheric methane content as performed by Etminan et al. (2016). The change in net irradiance shows that the shortwave absorption bands at approximately 3.3 µm are of larger importance than those of CO$_2$. These band will create a positive adjustment to the forcing caused by bands in the longwave range. The calculated positive adjustment was found to be 15 % Etminan et al. (2016).

In the last 50 years there has been not only an increase in methane concentration in the atmosphere, but also changes in the growth rate, as can be seen in Figure 2.3 made by NOAA 1.

Methane has both natural and anthropogenic sources, such as wetlands, fossil fuel, agricultural emissions and biomass burning (Isaksen et al., 2014). The contributions from the specific sources are considered to be highly uncertain (Dlugokencky et al., 2009). The main loss process for CH$_4$ is the chemical reaction with hydroxyl radical (OH), which makes methane a source for atmospheric water vapor and a precursor to ozone. The inter annual variability of OH will therefore have a significant impact on changes in atmospheric CH$_4$ concentrations. Dalsøren et al. (2016) modelled an increase in OH, and by that a decrease in the lifetime of CH$_4$. The lifetime of methane varies geographically, and depends on the fine balance between availability of OH, the emissions of methane itself, and NOx emissions. A short lived climate forcer is defined as gases and particles that contribute to warming, and that have a lifetime of a few days to approximately 10 years. Methane is as well mixed as long lived greenhouse gases, but is called a short lived climate forcer because of its average lifetime of 10 years (Aamaas et al., 2016).

1 https://www.esrl.noaa.gov/gmd/ccgg/trends_ch4/#global, Accessed 13.05.18
Projections of future atmospheric methane content have high uncertainties. This is related to the uncertainties in emission contributions from specific sources, feedback mechanisms, and oxidation capacity (the loss process). Dalsøren et al. (2016) modelled the atmospheric evolution in methane over the past 40 years using the Oslo CTM3 CTM model, and found that the model overestimates the growth rates in periods of large emissions of NOx’s. This is probably because NOx’s contributes to the loss process of methane. Previous estimates on the global methane budget have been conflicting, and the recent increase in growth rate had been of special interest. A recent study by Worden et al. (2017) suggest that a decrease in fires could be a reason for the conflicting budget numbers, as fires act as a source of methane in the atmosphere. Global fires decreased by about 12 % between the early 2000s and recent times, and the reduction of methane emissions form fires was twice as big. When removing this amount of methane from the budget the numbers balance correctly.

2.3 Feedbacks

A change to a climate forcer will create a climate response, and this response may have feedbacks. A feedback is when a change in our climate causes an impact that changes the climate even further. A positive feedback will enhance the initial change, while a negative feedback would weaken the initial change. A change to a climate forcer will create a climate response, and this response may have feedbacks. A feedback is when a change in our climate causes an impact that changes the climate even further. A positive feedback will enhance the initial change, while a negative feedback would weaken the initial change.

An example is the melting of snow on land. The forcing is an increase of a greenhouse gas, which makes the thermal downgoing flux larger. This triggers a response - a heating of the surface. Heating the surface will melt some of the snow, which will leave a larger surface area susceptible to absorb radiation which will heat the surface further, and melt more snow. This specific form of positive feedback is called ice-albedo feedback.

2.3.1 Lapse rate feedback

Another important feedback is the lapse rate feedback, which can be either positive or negative depending on the response. Lapse rate describes the vertical temperature variations, and this temperature distribution may change as a response to a radiative forcing. Lapse rate can be used to indicate the stability of the troposphere, i.e. if the temperature decreases rapidly in altitude the atmosphere is unstable, if the surface is cooler than the air above it the atmosphere is said to be stable.

A change in lapse rate can indicate a change in stability, which in turn could amplify or weaken the initial change caused by driver of the lapse rate change. A schematic of the feedback is found in Figure 2.5. The perturbed atmospheric temperature profile is shown in red for three different outcomes.

\[\text{https://www.nasa.gov/feature/jpl/nasa-led-study-solves-a-methane-puzzle}\]
Accessed 23.05.18

\[http://www.climate.be/textbook/chapter4_node7.html\]
Accessed 13.05.18
Figure 2.5: Schematic of the lapse rate feedback. The positive x-axis per panel is temperature change, and the y-axis is altitude. $\Delta Q$ is the RF following a perturbation to a climate forcer.

If the response temperature change is uniform along the vertical axis from the surface to the tropopause, there is no lapse rate feedback, as shown in the second panel of Figure 2.5. In the third panel the temperature increases more in the upper troposphere than at the surface, increasing the stability of the atmosphere. Warmer air radiate away heat more easily at the top of the troposphere than near the ground. A more stable atmosphere will therefore lose more energy, and deamplify the initial temperature change and works as a negative feedback. The last panel shows a decrease in stability, which will keep more energy close to the surface and then increase the temperature as a positive feedback. The lapse rate feedback is believed to be positive in regions where there are stable stratification conditions, such as the polar regions, which leads to a larger warming at the surface than in the upper troposphere. In lower latitudes where there are more convection the reverse happens, and the net global lapse rate feedback is considered to be negative.

2.3.2 Water vapor feedback

An increase in mean temperature in a column of air close to the surface will increase the amount of water vapor it contains (Held and Soden, 2006). In O’Gorman et al. (2012) the relationship between low level moisture and temperature using Clausius-Clapeyron dependence was calculated for a comparison of rates in several climate change scenarios. The goal was to see if the water vapor change follows surface temperature change linearly. This rate can be expressed as $\frac{dW}{dT}$ and has the unit [ % K$^{-1}$ ]. They showed that for an increase in global surface temperature $\Delta T = 1$ K, the corresponding water vapor (WV) rate was 7.6 % per Kelvin. For $\Delta T = 3$ K the WV rate was 8.2 % per Kelvin, and for $\Delta T = 6$ K the WV rate was 9.2 % per Kelvin. This shows that the water vapor content in a column of air and its dependence on the change in temperature, is not linear according to
Chapter 2. Theory

2.4. Fast and slow precipitation responses

Clausius-Clapeyron.
With this in mind it is widely accepted to approximate the $\frac{dW}{dT}$ to be 7 % per Kelvin, as this is the rate connected to the observed global surface temperature change today. An increase in water vapor concentrations will trap additional heat in the atmosphere, as water vapor reduce longwave cooling, in addition to absorb shortwave radiation. In other words, water vapor is a greenhouse gas. As previously mentioned, carbon dioxide is the most important greenhouse gas, but water vapor is the dominant one (Held and Soden 2000). The water vapor feedback is also the dominant positive feedback in our climate system (Gordon et al. 2013).
The water vapor feedback can be one of several sources to another feedback, the cloud feedback.

2.3.3 Cloud feedback
Clouds play a part in Earth’s energy budget, and changes in clouds are driven by changes in moisture, aerosols, and temperature. Low level clouds are more opaque than high level clouds, and have a higher albedo at their cloud top. This cloud top albedo makes low level clouds effective reflectors of incoming solar radiation. Low level clouds are relatively warm, meaning they emit more radiation to space compared to high level clouds. An increase in low level clouds will increase the outgoing radiation, and is a negative feedback.
High level clouds have a low albedo, and are relatively cold. An increase in high level clouds increase the downgoing radiation, and is a positive feedback. The cloud feedback differs in season, region, and forcing, but is estimated to be globally net positive (Ceppi et al. 2017).

2.3.4 Methane feedback
Natural storages for methane are vulnerable to changes in the worlds climate, and have the potential to increase natural CH$_4$ emissions. An increase in atmospheric methane will create a positive surface temperature response, which will help melt permafrost. Permafrost contains gas pockets of methane as well as organic material that will start decomposing once melted, and release methane into the atmosphere. This will result in further warming and the positive feedback loop is established (Dean et al. 2018).

2.4 Fast and slow precipitation responses

Figure 2.6 is a schematic diagram showing the responses of a perturbation on three different timescales: the instantaneous response, the rapid adjustments and feedbacks.
First panel of Figure 2.6 shows a simplified version of the Earth’s energy balance similar to Figure 2.1.
Yellow arrows represent the shortwave (SW) fluxes, and the red arrows show the longwave (LW) fluxes. Sensible heat (SH) and latent heat (LH) fluxes are also
Chapter 2. Theory 2.4. Fast and slow precipitation responses

represented and shown in green. If a climate perturbation is imposed, changes in the energy balance will trigger changes in other climatological variables as a response, and these responses work on different timescales (Bala et al. (2010), Lambert and Faull (2007)). The variable of interest in this section is precipitation. A perturbation may create changes in absorption and/or emission of LW radiation, as well as changes in absorption of SW radiation. This will in turn alter the atmospheric radiative cooling ($Q$). The relation between $Q$, SW, and LW is given in Equation 2.1

\[
\Delta Q = \Delta SW + \Delta LW
\]  (2.1)

Changes in the atmospheric radiative cooling is also related to changes in LH and SH fluxes. Latent heat can also be called $L\Delta P$.

\[
\Delta Q = \Delta SH + L\Delta P
\]  (2.2)

If one combines Equation 2.1 and 2.2, an expression for the change in LH flux is given as

\[
L\Delta P = \Delta SW + \Delta LW - \Delta SH
\]  (2.3)

Equation 2.3 is very useful as it is very difficult to measure changes in latent heat flux. This is further explained in Section 2.5.

Figure 2.6: Schematic diagram of fast and slow precipitation change processes following a change in radiative cooling. The blue temperature profile represents the unperturbed state, the orange represents fast adjustments and the red shows apparent adjustments. From Myhre et al. (2017).
The second panel of Figure 2.6 shows the instantaneous response - the immediate response to a climate perturbation. There is a change in the fluxes at the top of the atmosphere, $\Delta F_\uparrow$.

A change in the atmospheric radiative cooling, $\Delta Q$, will in turn affect the LH flux and the SH flux (Equation 2.2). The blue temperature profile represents the unperturbed state of the atmosphere, and show that temperature profile changes is not a part of instantaneous responses. On an instantaneous time scale a change in $\Delta Q$ will need to be balanced out by a change in SH flux and LH flux. It is this change in LH flux that will lead to a change in the precipitation, $\Delta P$.

The third panel is as well as the second considered to represent a fast precipitation change, and is called rapid adjustment. The instantaneous change of radiative cooling and the following change of LH flux and SH flux will further alter the temperature profile, atmospheric water vapor, precipitation, and clouds. These changes are shown in orange in Figure 2.6 panel three. Note that the surface temperature response by definition stays fixed during these fast adjustments.

In the final panel the surface temperature has adjusted, and several climate feedbacks follow the rapid adjustments as indicated by the color red in the figure. This will add up to what is called an apparent change in precipitation (Samset et al., 2016) which is defined as

$$\Delta P_{\text{Apparent}} = \Delta P_{\text{Fast}} + \Delta P_{\text{Slow}}$$

The timescales of such feedback processes are from years to decades, and by this time the averaged TOA energy imbalance has adjusted to zero.

To sum up, $\Delta P_{\text{Fast}}$ is a response to the change in the Earth’s energy balance and is relatively distinct from responses to global mean surface temperature change (Stocker et al., 2013), and $\Delta P_{\text{Apparent}}$ is a response to both the radiative changes and the feedback processes following a surface temperature change. Lastly $\Delta P_{\text{Slow}}$ is a response scaling with the change in surface temperature (Myhre et al., 2017).

In the example above the initial change was in the radiative cooling, and this change needed to be balanced out by changes in SH flux and LH flux. A recent study by Myhre et al. (2018) shows that changes in SH flux have been the dominating cause of precipitation changes in recorded history, and that the net radiative cooling term is negligible. The changes in SH flux is predicted to become more important in the future (Myhre et al., 2018).

### 2.5 Global precipitation patterns

Figure 2.7 shows the annual mean precipitation, and this figure is used as a benchmark for verifying precipitation data from the atmospheric models from National Center for Atmospheric Research (NCAR). There is a clear precipitation pattern

---

https://climatedataguide.ucar.edu/climate-data/gpcp-monthly-global-precipitation-climatology-p

Accessed 13.05.18
around the equator. This area is known as the inter tropical convergence zone (ITCZ), and acts as one of the joints of the Hadley circulation. Descending branches of the Hadley circulation occurs about 30° N or S and this is typically a dry zone. Storm tracks can be identified along the east coast of northerner continents, with the general moving direction to the north west. Figure 2.7 comes from NCAR climate data guide and is based on gauge stations, satellites and sounding observations on a 2.5 degree global grid. This dataset is based on observations, but it is important to note that precipitation observations are very sparse compared to temperature observations. The change in precipitation in the future is very much linked to surface temperature changes, lapse rate feedbacks and water vapor feedbacks.

![TRMM GPCP: 1979-2010](image)

**Figure 2.7:** Annual mean precipitation for 1979 to 2010 in [mm/day].
By NCAR Climate Data guide

The rate at which precipitation changes with surface temperature changes is called hydrological sensitivity and is observed and modelled to be lower than the WV rate of 7 % per Kelvin. The change in global mean precipitation as calculated by models is limited by energetic constraints ([Allen and Ingram] (2002), [Mitchell et al.] (1987), [O’Gorman et al. (2012)]) as explained in the previous subsection. Previous studies ([Lambert and Webb (2008), Stephens and Ellis (2008)]) found the hydrological sensitivity to be roughly 1 – 3.4%/K, but later studies have shown this to be highly variable between forcing agents when including fast adjustments, and between land and ocean ([Samset et al., 2018]). This will be further explained in the next Chapter.
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2.5. Global precipitation patterns
Chapter 3

PDRMIP

The Center for International Climate and Environmental Research (CICERO), Oslo, Norway, leads the Precipitation Driver and Response Model Intercomparison Project (PDRMIP). This project investigates the role of various climate change drivers for precipitation rates and changes, based on multiple models (Myhre et al., 2017). This chapter provides the background for this thesis.

3.1 Motivation

Precipitation responses to climate perturbations can be categorized as apparent, fast, and slow (Samset et al., 2016). Global mean fast precipitation responses are shown to be correlated with the atmospheric absorption, while the slow responses are correlated to the surface temperature response to the initial climate perturbation (Bala et al., 2010). The precipitation response, both fast and slow, is dependent on the physical properties of the climate forcing mechanism, therefore it is useful to evaluate the climate forcers and their respective responses separately.

By investigating the precipitation responses separately one can gain insight in future precipitation patterns and rates following future emissions. Furthermore, it will advance the understanding of what part of the observed climate change is caused by anthropogenic emissions and what is caused by natural variability. In addition to evaluating the responses of different drivers, the core experiments were performed as a multimodel study. This will help to verify the results, and point out differences in models that need to be taken into account in future studies. Increasing knowledge on model spread reduce multimodel uncertainty in precipitation. PDRMIP has a goal to investigate different climate forcers and diagnose the precipitation responses and the respective timescales of those responses (Myhre et al., 2017).
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3.2 Method and models

The list of models used in PDRMIP is found in Table 3.1. A thorough description of each of the models can be found in the PDRMIP protocol by Myhre et al. (2017). The models have either been used in Coupled Model Intercomparison Project Phase 5 (CMIP5) or will be used in CMIP6.

Section 2.4 defines apparent, fast and slow precipitation responses. To investigate these responses using models, two sets of configurations are needed. One configuration with prescribed sea surface temperatures and fixed sea ice (hereby called fSST), and one configuration coupled with either a full ocean or a slab ocean model. More information on these configurations can be found in Section 4.2.

The response of the fSST simulations represent the fast adjustments by definition, while the responses from the coupled simulations represent the apparent precipitation response (Samset et al., 2016). One can then calculate the slow precipitation response by

$$\Delta P_{\text{slow}} = \Delta P_{\text{Coupled}} - \Delta P_{\text{fSST}}$$  (3.1)

3.3 Experiments

Ten models were used to perform the core experiments as well as some additional experiments. The models each ran one baseline and five core perturbation experiments. All experiments were performed with both fixed sea surface temperatures and coupled ocean model configurations, this is to ensure the diagnosis of both fast and slow responses, as defined in Section 2.4. CESM1 CAM4 is the only model to be coupled with a slab ocean, the rest of the models were coupled to a full ocean. The baseline was specified by either preindustrial values of anthropogenic and natural climate forcings, or with present-day abundances (Myhre et al., 2017).

A list of the models and the five core experiments is found in Table 3.1. The experiments consist of a doubling of carbon dioxide concentrations relative to base, a tripling of the methane concentrations relative to base, an increase in solar irradiance by 2 %, a five time increase in anthropogenic sulfate concentrations or emission relative to base, and finally an increase in anthropogenic black carbon concentration or emission by 10 times relative to base.

3.4 Introduction to PDRMIP results

"Fast and slow precipitation responses to individual climate forcers: A PDRMIP multimodel study" by Samset et al. (2016) is the first published article from the project. This article present data from the five core experiments with the use of nine of the PDRMIP models.

Some basic results can be found in Figure 3.1. The yellow bar charts shows the
Chapter 3. PDRMIP

3.4. Introduction to PDRMIP results

<table>
<thead>
<tr>
<th>Models</th>
<th>Core Experiments</th>
</tr>
</thead>
<tbody>
<tr>
<td>CanESM</td>
<td>Base</td>
</tr>
<tr>
<td>NorESM</td>
<td>CO₂ x 2</td>
</tr>
<tr>
<td>HadGEM2</td>
<td>CH₄ x 3</td>
</tr>
<tr>
<td>HadGEM3</td>
<td>Solar + 2%</td>
</tr>
<tr>
<td>NCAR CESM1 CAM4</td>
<td>Sul x 5</td>
</tr>
<tr>
<td>NCAR CESM1 CAM5</td>
<td>BC x 10</td>
</tr>
<tr>
<td>IPSL-CM5</td>
<td></td>
</tr>
<tr>
<td>MPI-ESM</td>
<td></td>
</tr>
<tr>
<td>GISS ModelE</td>
<td></td>
</tr>
<tr>
<td>SPRINTARS</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.1: The ten models used for PDRMIP and the five core experiments they performed. More in depth information about the models are found in Myhre et al. (2017).

Figure 3.1: Top: Change in surface temperature, and bottom: Change in total precipitation relative to base. Adapted from Samset et al. (2016). The errorbars indicate ±1 standard deviation of interannual variability.

change in global annual mean surface temperature relative to base, for the nine models and the five core experiments. The annual means are based on year 51-100 of the coupled simulations. A change in global annual mean apparent precipitation can also be seen in blue bar charts. It is clear from these figures that a tripling of CH₄ gives a relatively weak signal from all of the models in both precipitation and temperature response.

The goal of PDRMIP was as mentioned in Section 3.1 to investigate the climate drivers separately and see how they compare in climatic responses. A comparison between the two greenhouse gases of the project seems natural and is shown in Figure 3.2. This Figure specifically investigates the apparent, fast and slow precipitation response. The doubling of CO₂ has a much stronger signal than the tripling of CH₄, and in this study of timescales, CH₄ was proven to give the weakest signal out of every experiment. The model mean for fast precipitation response following CH₄x3 was nonsignificant at all latitudes, which is connected to the weak atmospheric absorption for this same perturbation.
Figure 3.2: Mean total (apparent), fast, and slow precipitation response following two greenhouse gas perturbations from multimodel simulations. The hatched area shows where the multimodel mean is more than 1 standard deviation away from zero. Adapted from Samset et al. (2016).

Figure 3.3: Slow hydrological sensitivity. The hatched area shows where the multimodel mean is more than 1 standard deviation away from zero. Adapted from Myhre et al. (2017).

Hydrological sensitivity is a response of interest, and Figure 3.3 will come in use later in Chapter 5. This particular figure shows slow hydrological sensitivity. Hydrological sensitivity is further studied in a PDRMIP study by Samset et al. (2018). This study calculated the slow hydrological sensitivities per core experiment found in Table 3.1 and differ between global and regional hydrological sensitivies. Their results show that the slow hydrological sensitivity were 2-3 %/K independent of the climate driver. Samset et al. (2018) also showed that the slow hydrological sensitivity was noticeably weaker over land (0-2 %/K) than over ocean (3-5 /K).

The core experiment regarding methane gave a weaker signal than anticipated. The preliminary results shows that the goal of comparing the responses from a tripling of methane to other climate forcers is not satisfactory, and an experiment with a stronger perturbation is needed. This thesis will perform experiments with stronger perturbations, which are further explained in Chapter 4.
Chapter 4

Model and Methodology

In this thesis we have used a global climate model to perform a set of atmospheric experiments with several perturbations and configurations on the supercomputer ABEL, located in Oslo, Norway. The model is presented in Section 4.1.1 and the methodology regarding the experiments follows in Section 4.2.

4.1 Model

A climate model is a tool for simulating the physical processes of the climate system. The models are based on well-documented mathematical equations to simulate the transfer of energy and materials through the climate system (McSweeney, 2018). There are pure atmospheric models that represent the physical processes only occurring in the atmosphere, and other models representing each component of the earth system.

If an atmospheric model can exchange information regarding energy and material with an oceanic model, this is done by a coupling model. The coupling model shares information in between the other models, for example by exchanging energy from the atmosphere to the ocean, in a coupled atmosphere-ocean model. The expression ”fully-coupled model” occurs, and by that one usually speak of a model containing components such as the atmosphere, ocean, biosphere, cryosphere, and of course the coupling model itself. Despite this expression a model can never be fully coupled, as that would require a model for every single component of the earth, such as cities and human activity, which seems to be an impossible task.

Figure 4.1 shows when the individual parts of a climate model was made and when they were coupled. The first coupling of climate models was between the atmosphere and ocean in the 1960’s. In the late 1950’s chemistry and biochemical models were made, but they weren’t coupled until the 1990’s. The latest addition to the global coupled climate models are interactive vegetation, and ice sheets. Climate models are always in the process of improvement. The next section will introduce the reader to the ”fully-coupled” model used for this thesis. A visual representation of the model components and their interactions is seen in Figure 4.2.
Figure 4.1: The evolution of climate model complexity. Separate components have merged together to form coupled systems. Adapted from McSweeney (2018).

Figure 4.2: The model components of the NCAR CESM1 and their interactions. The coupling model exchanges information between the other models. The stick man represents in what model the perturbations in this thesis was performed, and the arrow to "output" indicates that even though the atmospheric model interacts with the other models only atmospheric data was stored for further analysis.

### 4.1.1 NCAR CESM1 CAM4

The model used for this thesis is made by the National Center for Atmospheric Research (NCAR) in Boulder, Colorado, USA, and is called the Community Earth System Model (CESM), more specifically CESM version 1.0.3.

Unlike a weather research and forecasting model, CESM is made to simulate the Earth’s past, present, and future on spatially global scales and climatic temporal scales. The CESM 1.0.3 is composed of separate models that simulate the Earth’s atmosphere, ocean, land, and cryosphere simultaneously.

A representation of how the models interact with each other is shown in Figure 4.2. There are four models, each representing one component of the Earth system, and
one coupling model that exchanges information between the rest of the models. The atmospheric model is called The Community Atmosphere Model (CAM4), and is the sixth generation of the atmospheric global general circulation model developed by NCAR. This is one of the models used in PDRMIP. The experiments of this thesis focuses on the atmospheric responses and feedbacks of given perturbations, and only results from CAM4 is used for analysis in Chapter 5, called output in Figure 4.2. This means that the fully coupled model is run, and the atmosphere interacts with the other components through the coupling model, but only atmospheric variables are stored for further processing and analysis. A more thorough explanation of the experiments is given in Section 4.2.

Our setup of CAM4 uses a horizontal resolution of 1.9 latitude x 2.5 longitude, and 26 levels in the vertical direction, the top level is at approximately 3 hPa. The vertical levels are described as quasi-Lagrangian, which functions like hybrid sigma pressure system as popularly used by previous versions of CAM. A hybrid sigma pressure system is a system where sigma represents pressure at the surface, which follows the topography of the model. The further up you move in altitude the more pressure affects the vertical levels rather than sigma (topography), and at the top of the model the levels are discretized by pressure only. The vertical levels affected by both sigma and pressure are in what’s called the hybrid sigma-pressure region, which can be observed in Figure 4.3.

![Figure 4.3: A very simplified schematic showing vertical levels in the model. The lowest level $\sigma_0$ is pure sigma following the topography, then comes the hybrid-sigma-pressure region, then at the top the pure pressure region $\sigma_N = p$.](https://upload.wikimedia.org/wikipedia/commons/a/a1/Sigma-z-coordinates.svg)

CAM4 has included longwave radiative effects from the greenhouses gases H$_2$O, CO$_2$, O$_3$, CH$_4$, N$_2$O, CFC11,n and CFC12. CO$_2$ is assumed to be well mixed, which means it is evenly distributed throughout the global atmosphere. CH$_4$ however has a specified zonally averaged and equatorial symmetric concentration distribution that is homogenous in the troposphere and decreasing above. The height of the troposphere is determined by seasonal average per latitude. The concentration distribution of CH$_4$ in the troposphere is specified as uniform, as the surface sources of CH$_4$ have a high uncertainty. As mentioned

[https://upload.wikimedia.org/wikipedia/commons/a/a1/Sigma-z-coordinates.svg](https://upload.wikimedia.org/wikipedia/commons/a/a1/Sigma-z-coordinates.svg)

Accessed 22.05.18
in Section 2.2.2 methane has an important atmospheric absorption band around 7.7\(\mu m\), and CAM4 accounts for this (Neale 2010).

![CH4 profile in CAM5](image)

**Figure 4.4:** The latitude-altitude distribution of atmospheric concentration of CH\(_4\) from NCAR CAM5 as shown in Modak et al. (2018) is comparable to that of NCAR CAM4.

When performing perturbations to atmospheric CH\(_4\) concentrations in CAM4, this will have further effects on the volume mixing ratio of water vapor. As explained in Chapter 2.2.2, the main loss process of methane is the reaction to the radical OH, which eventually creates H\(_2\)O. CAM4 parametrizes the source of water vapor as twice the CH\(_4\) sink (Neale 2010). In the atmospheric model used here, this CH\(_4\) sink is dependent on the volume mixing ratio of CH\(_4\), which then will increase with a larger amount of atmospheric CH\(_4\) relative to base. This means that when analyzing results of a strong perturbation to CH\(_4\), one need to keep changes in atmospheric water vapor in mind as well.

CAM4 includes a parametrization package \( P = \{ M, R, S, T \} \), where \( M \) denotes the moist processes, \( R \) denotes clouds and radiation, \( S \) denotes the surface model and \( T \) denotes turbulence. The \( M \) includes large-scale stable condensation, shallow convection and penetrative convection, among others. The process of deep convection is treated with a parameterization scheme where it is assumed whenever the atmosphere is conditionally unstable in the lower troposphere, an ensemble of convective scale updrafts may exist. The non-convective processes parametrization has two components: a macro scale component that describes the temperature change following an exchange of water substance between the condensate and the vapor phase, and a microphysical component that controls the conversion from condensate to precipitate. (Neale 2010)
4.2 Experiments

Several idealized experiments were conducted to simulate the responses and feedbacks to specific changes in atmospheric greenhouse gas concentrations. The simulations for this thesis were run by the use of two configurations. One configuration had prescribed sea surface temperatures (hereby called fSST) and prescribed sea-ice extent, while the other used a simplified ocean model, called a slab ocean model (hereby called SOM). These two configurations were chosen to study the differences from fast and slow responses.

An fSST simulation does not have an ocean response to climate change, and therefore represents fast responses as explained in Chapter 2.4. A slab ocean model simulates an ocean with a depth of approximately 70 m, and allows energy to be exchanged between atmosphere and ocean. The slab ocean model is a useful ocean model when investigating atmospheric data on decadal timescales. When looking at longer than decadal timescales, the ocean’s deep vertical circulation is of large importance and a full ocean model is more appropriate.

One baseline and three atmospheric concentration perturbations were chosen. The baseline including present day values of atmospheric content, a doubling of CO$_2$ concentration (hereafter denoted CO2x2), five times CH$_4$ concentration (CH4x5), and ten times CH$_4$ concentration (CH4x10), respectively. As seen in Figure 4.2, the alterations in atmospheric values was given as input in CAM4, and the values of the perturbations are found in Table 4.1 together with present day abundances known as the baseline value.

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>x 2</th>
<th>x 5</th>
<th>x 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO$_2$</td>
<td>380 ppm</td>
<td>760 ppm</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CH$_4$</td>
<td>1760 ppb</td>
<td>-</td>
<td>8800 ppb</td>
<td>17600 ppb</td>
</tr>
</tbody>
</table>

Table 4.1: Atmospheric concentrations of CO$_2$ and CH$_4$ for the different simulations.

4.2.1 Prescribed SST Simulations

A 33 year simulation was run for the prescribed SST and fixed ice extent configuration. This simulation was run with present day values for atmospheric concentrations of greenhouse gases, and will hereby be referred to as the baseline run for the fSST-case. A simulation run of this sort only needs a couple of years to spin up, so the cases with altered values of atmospheric gases was branched from year three and then run for 30 years.

It is of interest to have a clear signal from the perturbations as possible, this is done by reducing the signal from natural variability. To achieve this all branched simulations were run as 12-member ensembles, each member initialized by the first day of each month of the baseline year three.

A visualization to describe the specific case for CH4x5 is shown in Figure 4.5. In the figure, each arrow points from a baseline month to the branched simulation, each named by their initialization month, respectively.
Each case (CH4x5, CH4x10, and CO2x2) has a 12-member ensemble run branched from the baseline run. The 12 members per case is then averaged together to become one case, and the result is a signal close to clear of natural variability. A reduction of natural variability can also be done by running one very long simulation, but this is only for studies investigating the equilibrium values of the climate. Since we are performing a study of transient climate variables in the thesis, the method of ensembles is appropriate. This means that day 1 of every CH4x5_xx simulation as shown in Figure 4.5 is averaged together to become one file, and the same was done with day 2, months, years and so on. This average of a multiple ensemble members is valuable because one can achieve daily output data on an annual average, reducing the potential of noise from natural variability is our results. Each ensemble member was run for 30 years.

4.2.2 Slab Ocean Simulations

In addition to the baseline run, all cases with a climate perturbation were run as an ensemble, including the simulations for the slab ocean configuration. Figure 4.5 can be used to describe the branching with the SOM model configuration as well, with some small alterations. The baseline run with present day atmospheric concentrations of greenhouse gases was run for 111 years, not 33 as in the fSST-case. The spin-up time for this configurations is also longer than that of fSST. This is because the slab ocean uses a longer time to stabilize. With this in mind the baseline output year from which every ensemble is branched from is year 11, not 3 as in Figure 4.5. There was not enough time to run a full 12 member ensemble for the SOM configuration, so this is a 9 member ensemble. A 9 member ensemble will reduce natural variability substantially, and works well for this thesis’ statistical purposes. All ensemble members of the SOM simulation was run for 100 years. Figure 4.6 shows the annual surface temperature and annual total precipitation from the baseline. The figure is made with the models true grid size, and can be used as a visualization of the resolution of the model.

Figure 4.5: A visualization of the 12 member ensemble branched from each month of baseline year three for the case of CH4x5. Each ensemble member are further averaged together for a clearer signal.
When comparing Figure 4.6 to Figure 2.7, one finds the same precipitating patterns, especially the large oceanic areas to the west of continents with little precipitation in the southern hemisphere, and heavy precipitating areas in the southeast Asia. A list of all the cases that were run, together with the basics results, is found in the Appendix.

![Figure 4.6: (a) Annual surface temperature and (b) total precipitation averaged from year 50 to 100 from the SOM baseline run using 9 ensemble members.](image)

### 4.3 Methodology

All data output from the model are given on regular latitude-longitude grids. When calculating a global mean of a principal component an appropriate weighing is needed to accurately represent a globe. This is done by so-called cosine weighting, where the variable in question is multiplied by the cosine of the latitude the data is from, or

$$
\bar{\mu} = \frac{1}{N} \sum_{\text{lon,lat}} \mu(\text{lon, lat}) \times \cos(lat)
$$

(4.1)

where $\mu$ is some value at (lat,lon), $N$ is the number of grid points to calculate the mean from, and $lat$ is given to the cosine function in radians.

#### 4.3.1 Effective radiative Forcing and efficacy

Radiative forcing (RF) was defined in Section 2.1.1 and represent the net imbalance of the Earth’s energy, measured at the tropopause. In the definition of the radiative forcing of an external climate perturbation only the stratosphere was allowed to adjust to radiative equilibrium, keeping the tropospheric temperature profile along with the surface temperatures fixed.

A better metric was presented in IPCC AR5 called Effective radiative forcing (ERF). In the ERF definition the troposphere is allowed to adjust, including changes in water vapor, clouds and so on [Etminan et al., 2016]. The sea surface temperatures are
still kept fixed, so the ERF for the experiments are calculated by output from the fSST simulations explained in Section 4.2.1. This method for calculating ERF using fSST simulations has become standard in recent years after a recommendation by Forster et al. (2016). The field used for this calculations are explained in Table 4.2 in the end of this chapter.

\[
ERF_{\text{case}} = (FSNT_{\text{case}} - FLNT_{\text{case}}) - (FSNT_{\text{base}} - FLNT_{\text{base}}) \quad (4.2)
\]

Where case can be CO2x2, CH4x5 and so on. The field FSNT is defined to be positive downwards, while FLNT is defined to be positive in the upwards. A choice must be made to define the same positive direction for both fields, and this is defined to be downward (negative z-direction). This choice was made to make ERF a positive value, as the perturbations affect the energy imbalance so that more radiation is entering the atmosphere than leaving it. Since the positive direction is downward, the long wave fluxes is given a negative sign in the calculation of net flux at the top for both cases of case and base in the calculation of ERF.

Whenever energy fluxes are being investigated in this thesis the long wave fluxes are given a negative sign to fit with the chosen coordinate system. The ERF can be found by calculating a 20-year average of the fields and then use Equation 4.2 or the net flux is calculated per year for the last 20 years of the fSST-run, and then averaged to one value. The calculated values for ERF for each case is found in the Appendix.

The change in atmospheric absorption due to the climate perturbation was diagnosed using the ERF at the top of the model and the ERF at the surface. The atmospheric absorption is then obtained by

\[
\begin{align*}
ERF_{\text{TOA}} & = (FSNT_{\text{case}} - FSNT_{\text{base}}) - (FLNT_{\text{case}} - FLNT_{\text{base}}) \\
ERF_{\text{surf}} & = (FSNS_{\text{case}} - FSNS_{\text{base}}) - (FLNS_{\text{case}} - FLNS_{\text{base}}) \\
\text{Atm. abs} & = RF_{\text{TOA}} - RF_{\text{surf}}
\end{align*}
\]

(4.3)

It is of interest to check the scaling of a response to its climate forcer. This is found by investigating the relation between an effect of a forcing agent and the ERF by that same forcing agent. This diagnostic resembles the climate sensitivity parameter, \( \lambda = \frac{\Delta T}{RF} \), but in this thesis we use ERF instead of RF, the response in focus is not necessarily surface temperature change, and the parameter is not confined to CO\(_2\) being the forcing agent. We call the new parameter \( \lambda' \).

\[
\lambda' = \frac{X_{\text{case}} - X_{\text{base}}}{ERF_{\text{case}}}
\]

(4.4)

Where \( X \) represents the variable in question (see list of variables/fields in Table 4.2), and case is the forcing agent. \( \lambda' \) is useful to determine linearity between a response and the associated ERF, and to compare forcing agents.
CO₂ is a well studied greenhouse gas, and the resulting climate responses of a simulation of doubling of CO₂ concentrations has been done multiple times before. When investigating lesser known climate drivers it is useful to compare the results to that of CO₂x2. One way to do this is to calculate the efficacy of a certain response. Efficacy is usually defined as the ratio of a climate sensitivity parameter for a given forcing agent, to the climate sensitivity parameter for changes in atmospheric CO₂ [Joshi et al., 2003]. Efficacy in this thesis is defined by the "new" climate sensitivity parameter we call λ’, as we were interested in the efficacy of other variables than only surface temperature response. The general formula for efficacy used in this thesis is given by

\[
\text{Efficacy}_{X,\text{case}} = \frac{X_{\text{case}} - X_{\text{base}}}{\text{ERF}_{\text{case}}} \times \frac{X_{\text{CO₂x2}} - X_{\text{base}}}{\text{ERF}_{\text{CO₂x2}}}
\]

(4.5)

Where \(X\) represents the variable in question, either global annual total precipitation or global annual surface temperatures, and \(\text{case}\) represents the forcing agent in question, which could be CH₄x10.

Hydrological sensitivity is a specific term of interest in this thesis, and it seems natural to find the efficacy of methane regarding hydrological sensitivity. Hydrological sensitivity is the ratio between the change in precipitation and the change in surface temperature for a specific case, and Chapter 5.2 confirms that the response surface temperature change and the ERF of a certain case is scaling well with one another. Therefore a decision was made not to calculate the efficacy of hydrological sensitivity following the formula given in Equation 4.5, but rather a hydrological sensitivity ratio, defined as

\[
\text{HSR}_{\text{case}} = \frac{dP_{\text{case}}}{dT_{\text{case}}} \times \frac{dP_{\text{CO₂x2}}}{dT_{\text{CO₂x2}}}
\]

(4.6)

The term "apparent hydrological sensitivity" was used by Samset et al. (2016) as the combined result of both fast and slow adjustments, and the apparent hydrological sensitivity ratio will be presented together with other efficacies in Chapter 5.3. It is of interest to determine wether fast or slow adjustments dominate in precipitation changes. This is found by a response ratio, \(R_{\text{case}}\), as

\[
R_{\text{case}} = \frac{|\Delta P_{\text{fast}}| - |\Delta P_{\text{slow}}|}{|\Delta P_{\text{fast}}| + |\Delta P_{\text{slow}}|}
\]

(4.7)

If the response ratio is positive the fast adjustments dominate the precipitation responses, and the slow adjustments dominate if the ratio is negative (Samset et al., 2016).
4.3.2 PDRMIP-data

Data from the simulations run by CESM1 CAM4 in PDRMIP was used to verify experiment results, and to include more data in in the analysis. It is important to note that this data did not have multi member ensemble runs or daily temporal output of temperature distributions in the vertical direction. On some occasions data from several models in PDRMIP have been included in the analysis, and this will be clear in the text.

<table>
<thead>
<tr>
<th>Field name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>Temperature</td>
</tr>
<tr>
<td>TS</td>
<td>Surface temperature (radiative)</td>
</tr>
<tr>
<td>PRECT</td>
<td>Total (convective and large-scale) precipitation rate (liq + ice)</td>
</tr>
<tr>
<td>PRECL</td>
<td>Large-scale (stable) precipitation rate (liq + ice)</td>
</tr>
<tr>
<td>PRECC</td>
<td>Convective precipitation rate (liq + ice)</td>
</tr>
<tr>
<td>lat</td>
<td>Latitude</td>
</tr>
<tr>
<td>lon</td>
<td>Longitude</td>
</tr>
<tr>
<td>lev</td>
<td>Atmosphere hybrid sigma pressure coordinate</td>
</tr>
<tr>
<td>FSNT</td>
<td>Net solar flux at top of model</td>
</tr>
<tr>
<td>FSNS</td>
<td>Net solar flux at surface</td>
</tr>
<tr>
<td>FLNT</td>
<td>Net longwave flux at top of model</td>
</tr>
<tr>
<td>FLNS</td>
<td>Net longwave flux at surface</td>
</tr>
<tr>
<td>FLNSC</td>
<td>Clearsky net longwave flux at surface</td>
</tr>
<tr>
<td>FLNTC</td>
<td>Clearsky net longwave flux at top of model</td>
</tr>
<tr>
<td>FSNSC</td>
<td>Clearsky net solar flux at surface</td>
</tr>
<tr>
<td>FSNTC</td>
<td>Clearsky net solar flux at top of model</td>
</tr>
<tr>
<td>SHFLX</td>
<td>Surface sensible heat flux</td>
</tr>
<tr>
<td>LHFLX</td>
<td>Surface latent heat flux</td>
</tr>
<tr>
<td>SWCF</td>
<td>Shortwave cloud forcing</td>
</tr>
<tr>
<td>LWCF</td>
<td>Longwave cloud forcing</td>
</tr>
<tr>
<td>CLOUD</td>
<td>Cloud fraction</td>
</tr>
<tr>
<td>CLDTOT</td>
<td>Vertically-integrated total cloud</td>
</tr>
</tbody>
</table>

Table 4.2: Field names with description
Chapter 5

Results and Discussion

The present chapter will show and discuss the results of the simulations presented in the previous chapter. First the basic results will be presented. An investigation of the scaling of climate response to methane forcing follows, before a dive into the efficacy term. Finally, the response developments with time are laid out together with a discussion of our findings, along with a comparison to previous studies.

5.1 Results

The equilibrium surface temperature (TS) changes for the cases CH4x3, CH4x5, CH4x10, and CO2x2 are found in Figure 5.1a. The TS changes for the three cases in our thesis experiment are estimated using the last 50 years of the 9 member ensemble SOM simulation. The values for TS range from 1.1 K for the experiment from PDRMIP CH4x3 using the same model as ours, to 3.3 K from our own CO2x2 experiment. The TS change for the four cases increase by each perturbation, following the same pattern as their effective radiative forcing, presented in Figure 5.1c. This is further discussed in Section 5.2. The ERF values are estimated using the method explained in Section 4.3.1, using the averaged values for the 12 member ensembles.

Figure 5.1b shows the change in total apparent precipitation. Recall that the term "apparent" means the sum of fast and slow responses. The total apparent precipitation change does not increase in the same fashion as surface temperature change. The maximum equilibrium total apparent precipitation change measure to 6 % and is caused by CH4x10. The simulations of CO2x2 have the lowest percentage total apparent precipitation change per Wm$^{-2}$ forcing.

They also have the lowest percentage total apparent precipitation change per surface temperature change, which is defined as apparent hydrological sensitivity and can be observed in Figure 5.1d. The apparent hydrological sensitivities are similar between the methane cases. This is an important finding and the reason for this is discussed in the next section; Scaling with forcing strength. The total apparent precipitation change should be compared to the total fast precipitation
change, which can be found in Figure 5.1. Recall that the fast responses are products of the fSST simulations, so the results in Figure 5.1 are made from the average of 12 ensemble members, except for the case of CH4x3 which is from PDRMIP and never based on ensembles.

Change in fast precipitation is negative for all cases, and the signal from CO2x2 is double in magnitude compared to that of CH4x10. The atmospheric absorption is the difference between the ERF at the top of the atmosphere to the ERF on the surface, and is shown in Figure 5.1. CO₂ is the climate driver with the strongest atmospheric absorption out of the four cases with almost 1.9 W/m².

![Figure 5.1](image.png)

**Figure 5.1:** Change in global annual mean apparent (a) surface temperature, change in global annual mean total apparent (b) precipitation, the (c) ERF of the multiple simulations is shown in the top row. The bottom row contains the global annual mean (d) apparent hydrological sensitivity, (e) change in fast precipitation response, and (f) the atmospheric absorption. (a), (b), and (d) are made from the 9 member ensemble SOM simulations year 50-100, and (c), (e), and (f) are made from the 12 member ensemble fSST simulations year 10-30. No result from CH4x3 is based on ensembles. The error bars show the standard deviations from the annual means.

**Temperature profile changes**

Figure 5.2 shows the equilibrium change in global annual mean temperature profiles. The temperature profiles in Figure 5.2 represent the global net effect that the four cases would have on the lapse rate. The magnitudes of these changes increase with forcing strength, which is especially apparent in the different cases of methane.
Chapter 5. Results and Discussion

5.1. Results

Figure 5.2: Global annual mean change in temperature with altitude for our four cases. CH4x3 is estimated from the last 50 years in the 100 year SOM simulation performed by PDRMIP. The rest of the cases are estimated from the last 50 years in the 100 year SOM simulation with 9 ensemble members. The grey dashed line highlights where the temperature change is 0.

Changes to the temperature profile caused by CO2 are similar to the changes caused by methane in the low and middle troposphere. The maximum temperature change measures almost 4 K, and is reached on the border of mid to upper troposphere (300 hPa). The temperature change from CO2x2 rapidly decreases with altitude above the tropopause.

The temperature change measured at the bottom of Figure 5.2 matches the global mean surface temperature change shown in Figure 5.1b. The temperature increases more close to the surface than directly above it. There is a roughly uniformly heated profile until approximately 500 hPa. All of the temperature change profiles reach their maximum values around 300 hPa, before reducing in value until they reach the tropopause. The temperature increase can be observed to weaken during the transition from upper troposphere to lower stratosphere. Each case for methane has a uniform weak negative temperature change from the lower stratosphere and throughout the rest of the atmosphere.

The largest temperature change is found in the mid to upper troposphere, which indicates an increase in atmospheric stability. An increase in atmospheric stability leads to a negative lapse rate feedback, as warmer air in higher altitudes can radiate more undisturbed to space than warmer air at the surface.
Chapter 5. Results and Discussion

5.1. Results

Figure 5.3:
Annual mean (a) surface temperature change for CH4x5, (b) total apparent precipitation change for CH4x5
Annual mean (c) surface temperature change for CH4x10, (d) total apparent precipitation change for CH4x10
Annual mean (e) surface temperature change for CO2x2, (f) total apparent precipitation change for CO2x2. Averaged from year 50-100 from 9 ensemble members in the SOM simulation. All values above and below the color bar range are given the color equal to the maximum/minimum color bar value.
Regional surface temperature changes

Figure 5.3a, c, and e show the changes in surface temperatures and Figure 5.3b, d, and f show the changes in apparent total precipitation for our three cases. From the top these are: CH4x5, CH4x10, CO2x2. All data is averaged from the last 50 years of the SOM simulation, using 9 ensemble members.

Note that the maximum and minimum values for each map are shown, and that these values may be outside of the range of values shown on the color bar. All values above and below the color bar range are given the color equal to the maximum/minimum color bar value. This is to include more variation, which is especially relevant for the precipitation maps.

The surface temperature change maps show that the polar areas have the largest change. This is connected to the arctic amplification caused by (among others) the ice albedo feedback, as briefly mentioned in Chapter 2. The largest temperature differences are found in the CO2x2 map in Figure 5.3e, which is expected given its large ERF value.

Regional precipitation changes

The maps showing the change in annual mean total apparent precipitation all have a distinct increase along the equatorial line of the Pacific ocean. Note that the value for maximum annual change in total apparent precipitation from CO₂ is lower than that of CH₄, even though we know CO₂ has a larger ERF value. Both methane maps (Figure 5.3b and d) show the same pattern, but with a stronger signal for the CH4x10 case, as expected.

The patterns of precipitation changes are similar between CH4x10 and CO2x2 (Figure 5.3f and f), but their magnitudes differ between areas. CH4x10 has a significantly stronger increase in the eastern pacific, with a maximum value of 143% increase. The area with the strongest increase in precipitation by CO2x2 is in the northeastern Africa at approximately 15°N. This area also has an increase in the case of CH4x10, but with only half the value of increase compared to that of CO2x2. The Arabian Peninsula would experience an increase in precipitation in all cases. A noticeable increase in precipitation is observed in the ocean outside Namibia and Angola, and in the Indian ocean to the northwest of Australia. The pattern of increase in precipitation seem to occur with the southeasterly trade winds blowing from land to ocean.

Central America stands out as the area with the largest decrease in precipitation. There are substantially larger drying areas in the northern hemisphere than in the southern hemisphere. These areas follow the northeasterly trade winds over the Atlantic and east Pacific ocean. CH₄ is the strongest contributor to the increase in precipitation in the eastern Pacific, while CO₂ is the strongest contributor to the drying of this area. A doubling of CO₂ would create stronger drying patches along the southeasterly trade winds than perturbations to CH₄ would. The areas of increased precipitation are mostly found north of the equator, indicating a northerner shift of the ITCZ (See Chapter 2.5). This is most likely connected to the land area distribution. There is more land in the northern hemisphere than in the southern hemisphere, creating a stronger surface temperature response, which in turn affects the location of the ITCZ.
Geographical distribution of hydrological sensitivity
Maps showing the slow hydrological sensitivity for the PDRMIP multimodel mean is found in Figure 3.3 Chapter 3 for the case of CH4x3. This can be compared to our results in Figure 5.4.

Note that the map in Figure 3.3 shows the slow hydrological sensitivity while the maps presented in Figure 5.4 is showing the apparent hydrological sensitivity. The apparent response is the sum of fast and slow responses. The areas of increased apparent hydrological sensitivity are in accordance to that of the slow hydrological sensitivity, with main areas in the equatorial eastern Pacific and eastern Sahara. The areas of decreased hydrological sensitivity have a stronger signal in the maps showing the apparent response than in the map showing the slow response, which could indicate a decrease in hydrological sensitivity related to fast adjustments.

Figure 5.4:
(a) Apparent hydrological sensitivity for CH4x5, (b) CH4x10, and (c) CO2x2. Made by annual means from year 50-100 in a 9 member ensemble SOM simulation.

In conclusion, there seem to be differences in precipitation response areas and strength. This will be further investigated in the next section that will try to answer the first thesis question: how do CH4 and CO2 responses scale with forcing strength?
5.2 Scaling with forcing strength

**Apparent surface temperature change**

One can compare global mean apparent surface temperature change to each perturbation’s ERF by calculating the $\lambda'$ from Equation 4.4 for each case, and the results are shown in Figure 5.5. Recall that $\lambda'$ is the signal of a perturbation divided by the ERF of that perturbation, and that the term “apparent” means the sum of fast and slow responses. There has been drawn a regression line trough the methane data, and the function for the best linear fit is indicated in blue in Figure 5.5. The development of $\lambda_{TS,CH_4}'$ is linear, and that the global mean apparent surface temperature change is directly proportional to its ERF. One datapoint for the $\lambda_{TS,CO_2}'$ from the doubling of Carbon Dioxide is included in red. The data point does not perfectly fit on the linear line of $\lambda_{TS,CH_4}'$, even when considering its standard deviations. This means that if one were to increase the amount of atmospheric methane for it to match the ERF produced by a doubling of CO$_2$, the resulting apparent surface temperature change would still not be as great as for CO2x2. This result will be discussed throughout the rest of this chapter.

**Figure 5.5:** $\lambda_{TS}$ for CH$_4$ and CO$_2$ together with a regression line representing the best fit linear function for $\lambda_{TS,CH_4}'$. The values for apparent surface temperature change are estimated by annual mean for year 50-100 from the 9 member ensemble SOM simulations. The error bars are showing the standard deviations for the annual means.

**Apparent precipitation change**

The same was done for global mean total apparent precipitation change and is shown in Figure 5.6. The apparent precipitation responses from methane seem to scale well to their ERFs. The best fit regression line goes perfectly through each methane data point, indicating a linear relationship between the apparent precipitation response and ERF for methane. CO$_2$ does again not fit on regression line, but this time the data point is located below the regression line. This means that if one were to increase the amount of atmospheric methane so that its ERF was equal to that of CO2x2, the apparent precipitation response would be larger than that of CO2x2.
Figure 5.6: $\lambda'_P$ for $\text{CH}_4$ and $\text{CO}_2$ together with a regression line representing the best fit linear function for $\lambda'_{P,\text{CH}_4}$. The values for total apparent precipitation change are estimated by annual mean for year 50-100 from the 9 member ensemble SOM simulations. The error bars are showing the standard deviations for the annual means.

**Apparent hydrological sensitivity**

The response in apparent hydrological sensitivity appears independent from its ERF for methane, as Figure 5.7 shows. The best fit regression line for the methane data points is nearly horizontal, and a horizontal line is well within the error bars showing the standard deviations for the annual means from year 50-100. The appearance of independence between apparent hydrological sensitivity and ERF can be explained by Figure 5.5. Apparent hydrological sensitivity is defined as the change in apparent precipitation divided by the change in surface temperature. Since the change in surface temperature is scaling so well to its forcing regarding methane, the division of surface temperature will remove the ERF dependence in the apparent hydrological sensitivity term.

The datapoint for $\text{CO}_2$ is not on the best fit regression line for $\text{CH}_4$ in the case of apparent hydrological sensitivity, which could be predicted from Figure 5.5 and Figure 5.6. The error bars for the case of CH4x3 in Figure 5.5, Figure 5.6, and Figure 5.7 are made from calculations using PDRMIPs simulations from model CAM4, and shows the standard deviations from year 51-100.

In Chapter 3 we saw that the signal from CH4x3 in PDRMIP publications was weak relative to the other experiments performed. When using PDRMIP data from only one of the models such as done in most of this thesis the signals are comparable to our own experiments, but when using the multimodel mean results for CH4x3 the signal becomes more uncertain, for reasons to be explained.
Chapter 5. Results and Discussion

5.2. Scaling with forcing strength

Figure 5.7: $\lambda'_{HS,CH_4}$ and $CO_2$ together with a regression line representing the best fit linear function for $\lambda'_{HS,CH_4}$. The values for apparent hydrological sensitivity are estimated by annual mean for year 50-100 from the 9 member ensemble SOM simulations. The error bars are showing the standard deviations for the annual means.

Figure 5.8: Annual average apparent hydrological sensitivity for CH$_4$ (blue) and CO$_2$ (red) as estimated by the PDRMIP-models from years 51-100 (left), and as estimated by the experiments performed in this thesis (right). The error bars show the spread in estimated apparent hydrological sensitivity for year 50-100 for from the 9 member ensemble of the SOM simulation.

Figure 5.8 shows the apparent hydrological sensitivity for CH4x3 (blue) and CO2x2 (red). The left panel shows apparent hydrological sensitivity per model in PDRMIP as averaged from year 30-110 for CAM4 and year 51-100 for the rest of the models, and is made from simulations done for the PDRMIP-study [Samset et al., 2016]. The panel to the right show the average apparent hydrological sensitivity as estimated from year 50-100 by this thesis’ experiments, which is equal to Figure 5.1f. The error bars show the spread in the average apparent hydrological sensitivity between the 9 ensemble members of the SOM simulation.
Chapter 5. Results and Discussion

5.3. Efficacy

The range of apparent hydrological sensitivity between the models is significantly larger for CH4x3 than for CO2x2. GISS is the model with the lowest equilibrium climate sensitivities in CMIP5 (Samset et al., 2016). When DeAngelis et al. (2015) investigated CO2 forcing in a multimodel study they found GISS to be an outlier (outlier does not mean it is wrong). If the result from the GISS model is removed, the model spread difference between CO2 and CH4 is more pronounced. PDRMIP could not conclude that the precipitation response from CH4 is any different than for CO2. The model spread is to blame for the insignificant results in values of interest for CH4x3, and the reason for the model spread could lie in how the models parametrize methane. Section 5.5.3 further discusses the differences in how the models treat methane, and could provide insight as to why the multimodel mean proved unsatisfactory results.

The difference between CH4 and CO2 in response scaling with forcing strength is evident, and the next question to be answered is that of efficacy.

5.3 Efficacy

Efficacy is defined in Equation 4.5, and will illuminate differences in responses between CH4 and CO2. Figure 5.9 shows the efficacy of apparent surface temperature change (red), apparent total precipitation change (blue) and the apparent hydrological sensitivity ratio (teal). Recall that the term ”apparent” means the sum of fast and slow responses. The dark grey horizontal line shows where the efficacy and ratios will be equal to 1, which means the response to a forcing is independent of which of the two climate drivers in question created the forcing.

The average efficacy for apparent change in surface temperature (right panel) are all below 1, but becomes closer to 1 with an increasing methane forcing strength. This means that CH4 has a weaker temperature response per Wm$^{-2}$ forcing than CO2, although the standard deviations for the annual means shows there is a chance this efficacy is above or equal to 1. In the case of change in apparent total precipitation all of the perturbations including their error bars are above the 1 mark. CH4 has a more significant increase in apparent precipitation response per Wm$^{-2}$ forcing than CO2 for all perturbations. The same can be said for the apparent hydrological sensitivity ratio shown to the very right in Figure 5.9.

The values of apparent hydrological sensitivity ratio is close to that of the efficacy for apparent total precipitation change. Recall from Chapter 4.3.1 that in the fraction in the efficacy calculation the apparent total precipitation change is divided by ERF, while in the apparent hydrological sensitivity ratio fraction the total apparent precipitation is divided by the apparent surface temperature change. The previous section showed clearly how well surface temperature change and ERF scaled with one another, and is the reasoning behind the similar values in the two panels to the left of Figure 5.9.
Chapter 5. Results and Discussion

5.3. Efficacy

Figure 5.9: Efficacy for apparent surface temperature change (red), total apparent precipitation change (blue). The last panel shows the apparent hydrological sensitivity ratio (teal). The error bars show the standard deviations for 50-100 year annual average from the 9 member ensemble SOM simulation.

Zonally averaged efficacies

The efficacy for the same responses as in Figure 5.9 is shown as zonally averages in Figure 5.10. The efficacy for surface temperature change is seen in Figure 5.10a and is highly variable along the meridional axis. The efficacy reaches its maximum around the equator, and decrease towards the poles. The average efficacy for surface temperature change is shown to be below 1 in Figure 5.9. However, in the equatorial area all three cases have efficacy values measured above 1. Model dynamics are known for being highly uncertain in the immediate areas around the equator, and this area will not be further discussed here. The most significant feature of Figure 5.10a is the efficacy difference between the northern hemisphere and the southern hemisphere. All three cases show a significantly lower surface temperature efficacy in the northern hemisphere. This means that CO$_2$ warms the surface more per Wm$^{-2}$ forcing than CH$_4$ on all mid to high latitudes, and that this difference is largest in the northern hemisphere.

The reason for this difference is in the land distribution on Earth. The northern hemisphere has substantially larger land areas than the southern hemisphere. CO$_2$ has the strongest atmospheric absorption as can be seen in Figure 5.1f. The heating caused by the atmospheric absorption is easier mixed above land than above ocean. Therefore CO$_2$ will have a larger surface temperature response per Wm$^{-2}$ forcing than CH$_4$, especially in the northern hemisphere.

The zonally averaged efficacy for total apparent precipitation change is shown in absolute values in Figure 5.10b and apparent hydrological sensitivity ratio in absolute values in Figure 5.10c. The two figures have similar values, for the same reasons as explained under Figure 5.9. The precipitation efficacy for three cases are in agreement with each other, and show that the largest differences between the precipitation response of CO$_2$ and CH$_4$ are found close to the equator and in the northern hemisphere. There is only one area where CO$_2$ clearly produces a stronger precipitation signal than CH$_4$, around 25°N. The area of efficacy well below 1 is
Chapter 5. Results and Discussion 5.3. Efficacy

Figure 5.10: Zonally averaged (a) efficacy for surface temperature change, (b) absolute value efficacy for total precipitation change, and (c) absolute value apparent hydrological sensitivity ratio. The y-axis for (b) and (c) are logarithmic. Values are estimated from year 50-100 in the 9 member ensemble mean from the SOM simulation. Likely caused by the strong increase in precipitation over eastern Sahara found in the precipitation map for CO2x2 in Figure 5.3. The precipitation effect in the equatorial eastern Pacific is significantly greater in the case of methane than in the case of carbon dioxide. This is supported by multiple Figures (Figure 5.10b, 5.3bde), and can also be observed in the apparent hydrological sensitivity maps in Figure 5.4.

Apparent and slow hydrological sensitivity ratio
So far we have only investigated the apparent hydrological sensitivity, but as explained in Chapter 2.4 and Chapter 3.2, the climate system develops on different timescales. We have divided the hydrological sensitivity ratio in two timescales: apparent and slow, and the result is shown in Figure 5.11. The panel for fast hydrological sensitivity ratio is not shown, as hydrological sensitivity is defined by surface temperature changes, and the definition of fast adjustments exclude the surface temperature response. The fast response panel would be hard to physically interpret, and is not needed for the following discussion.

The dark grey line indicates where the apparent hydrological sensitivity ratio (AHSR for the rest of this section) would be 1, which is when the AHSR of CH4 is equal...
to that of CO$_2$. Notice how the error bars are getting narrower with the larger the perturbation is. The case of CH4x3 has the largest error bar which is expected as this is not an ensemble run. Still, the mean value for AH$_R$ for CH4x3 compares well with the two others. Recall that the slow responses are responses to the surface temperature change only, while the fast adjustments is a result of energetics. Figure 5.11 show that the AH$_R$ is above 1, which means that in the combined result of fast and slow adjustments methane increases more in precipitation per kelvin surface warming than carbon dioxide. The panel to the right show the slow hydrological sensitivity ratio, and one can observe how each case has a ratio of 1. This tells us that is does not matter which of the two investigated gases are responsible for the surface heating, the precipitation response to the surface heating will be the same. Since the apparent ratio shows a difference between the two gases, and the slow ratio shows no difference between the two gases, it is safe to say that the difference occurs in the fast adjustments.

![Figure 5.11: Hydrological sensitivity ratio. The error bars are standard deviations from annual calculation for the years 50 to 100 in the apparent (left) panel](image)

Methane responses scale well with its forcing, but carbon dioxide proved to have a different scaling. The efficacies show that carbon dioxide provides the strongest surface temperature increase per Wm$^{-2}$ forcing, while methane provides the strongest precipitation increase per Wm$^{-2}$ forcing. These results show a difference between the two gases. The slow hydrological sensitivity ratio is equal to 1, indicating that the fast adjustments are responsible for the differences found in apparent responses for the two gases. The next section will investigate the development of responses and efficacies with time.
5.4 Development of responses over time

The third question to be answered is how the responses of methane and carbon dioxide differ over time.

ERF

Each perturbation has its own ERF, that is estimated as an average TOA net forcing over the last 20 years by the fSST simulation as explained in Chapter 4.3.1. The energy imbalance at the top of the atmosphere varies over time, and Figure 5.12 shows the development of imbalance at the top of the model through the entire 30 years of the fSST simulation. Note that the CH4x10 simulation has a higher energy imbalance than CO2x2 in the first 30 days before stabilizing below CO2x2 after a few months. A brief discussion of this is found in Section 5.5.4 and the Appendix. Apart from some smaller yearly fluctuations the forcing values become stable after only 1 year of model run. This shows that our choice of using the average from year 10 to 20 to calculate ERF is a good approximation.

![Figure 5.12: Net radiative flux development at the top of the model for CH4x5, CH4x10, and CO2x2 estimated from the 12 member ensemble mean in the fSST simulation.](image)

With confidence in our ERF values we can take a look at the development of the altered climate sensitivity, $\lambda'$, for precipitation and its development over time. $\lambda'$ is defined in Equation 4.4 and is the signal of a perturbation divided by the ERF of that perturbation.

Apparent, fast, and slow responses

Figure 5.13 shows the total precipitation changes divided by their own ERF, $\lambda_p'$, for the apparent, fast, and slow adjustments. Recall that the term "apparent" means the sum of fast and slow responses. The apparent changes are found by an annual 9 member ensemble mean from year 50-100 in the SOM simulation, while the fast adjustments are found by an annual 12 member ensemble mean from year 10-30 in the fSST simulation.

The left panel shows the apparent change in precipitation per $Wm^{-2}$ forcing. The mean values for the methane cases are similar to each other at 1.8 %/$Wm^{-2}$, while the doubling of carbon dioxide has a smaller apparent value of almost 1.6 %/$Wm^{-2}$. The slow $\lambda_p'$ (to the far right) shows similar values among all the cases, with CO2x2
Recall that the efficacy of a certain methane case is defined as $\lambda'$ of that case divided by the $\lambda'$ of CO2x2. Since Chapter 5.2 showed the excellent scaling between the surface temperature response and the ERF for each case, the efficacy of precipitation and the hydrological sensitivity ratio are comparable.

![Figure 5.13: Change in total precipitation divided by ERF, $\lambda'$ on different timescales. The error bars show the standard deviations from the annual mean.](image)

Both Figure 5.11 and Figure 5.13 show that the slow response values are similar between CH$_4$ and CO$_2$. The apparent responses on the other hand, show a difference between the two climate drivers. In Chapter 5.3 it was suggested that the cause of the discrepancy was found in the fast precipitation responses, and Figure 5.13 confirms this. The fast adjustment in precipitation response is negative, and the CO2x2 perturbation has a stronger negative signal per W m$^{-2}$ forcing than the rest. The fast adjustments are responsible for the difference in apparent precipitation response per W m$^{-2}$ forcing.

The response ratio tells whether the fast or slow adjustment dominates the precipitation change, and was further explained in Chapter 4.3.1.

<table>
<thead>
<tr>
<th>Case</th>
<th>$R_{Case}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CH4x3</td>
<td>-0.76</td>
</tr>
<tr>
<td>CH4x5</td>
<td>-0.76</td>
</tr>
<tr>
<td>CH4x10</td>
<td>-0.76</td>
</tr>
<tr>
<td>CO2x2</td>
<td>-0.54</td>
</tr>
</tbody>
</table>

**Table 5.1:** Response ratio, estimated from ensemble means from both fSST and SOM simulations, except for CH4x3 which is estimated from one simulation.

The response ratio for CH4x5, CH4x10, and CO2x2 is estimated from the year 50 - 100 in the 9 member ensemble of SOM simulation and from year 10-30 in the 12
member ensemble of fSST simulation is found in Table 5.1. The response ratio for CH4x3 is estimated from one simulation from PDRMIP. The response ratio is negative in all cases, which means the slow precipitation response dominates the long-term precipitation response. Methane perturbations have a stronger negative value than the doubling of CO₂, which can be interpreted as the fast adjustments affecting the long-term precipitations changes more in the CO₂ case than in the CH₄ cases. This is supported by Figure 5.13.

**Correlating adjustments**
The correlation between the fast precipitation response and the atmospheric absorption is shown to the left in Figure 5.14. There is a strong negative correlation between atmospheric absorption and fast precipitation changes. The dark blue squares represent all 12 ensemble members for both CH4x5 and CH410, the red dot represents all 12 ensemble members for CO2x2. It is hard to tell the ensemble members apart because of their consistency. CO2x2 is the perturbation with the strongest atmospheric absorption and the most significant decrease in fast precipitation. This can be explained by the suppression of convection following the change in absorption in an atmospheric column. When less convection is present, latent heating and precipitation is also suppressed.

![Figure 5.14](image_url)

**Figure 5.14:** Fast precipitation change versus atmospheric absorption (left) and slow precipitation change versus surface temperature change (right). The dark blue squares represent the two methane cases and the pink dot represent CO2x2. The grey data points are from a previous PDRMIP study by Samset et al. (2016).

Figure 5.14 (right) shows a strong positive correlation between slow precipitation response and apparent surface temperature change. The dark blue squares represent all 9 ensemble members for both CH4x5 and CH410, the red dot represents all 9 ensemble members for CO2x2. This correlation has been indicated in previous figures (Figure 5.11, Figure 5.13), and supports the claim that fast adjustments are driven by atmospheric absorption while slow responses are driven by surface temperature change.
Chapter 5. Results and Discussion

5.4. Development of responses over time

Figure 5.15: (a) Global mean apparent surface temperature change development and (b) global mean apparent surface temperature change development divided by ERF ($\lambda'_{TS}$).

Development of surface temperature changes

Figure 5.15(a) shows that the global mean apparent surface temperature change differs between the cases with time, as expected. In 5.15(b) the temperature change developments are divided by their own ERF, also called $\lambda'_{TS}$. $\lambda'_{TS}$ for each case is found to be close to 1 from year 40 to 100, which is an indicator of how well the surface temperature response scales with forcing, as already discussed in 5.2. Apart from day 25-30 $\lambda'_{TS,CO2x2}$ is higher than $\lambda'_{TS,CH4}$ on all timescales.

Efficacy for surface temperature is defined as $\frac{\lambda'_{TS,CH4}}{\lambda'_{TS,CO2}}$, and the efficacy for a certain case would be values representing that case of methane in Figure 5.15(b) divided by the values representing CO2x2, shown in red.

Development of precipitation changes

Figure 5.16(a) shows the development of global mean total apparent precipitation change over the timescales of days, months, years and decades for the three experiments. Both of the methane perturbations give similar responses in the first 30 days, and stay close in values to one another until the first year has passed. After 10 years they reach a difference that they keep throughout the rest of the simulation. CH4x5 and CH4x10 have mostly negative values until month three, from where they stay weakly positive throughout their first year. CO2 gives a stronger negative precipitation response than CH4 in the first 30 days, apart from day 25. The precipitation response
5.4. Development of responses over time

Figure 5.16: (a) Global mean total apparent precipitation change development and (b) global mean total apparent precipitation change development divided by ERF ($\lambda'_P$) for the three cases.

from CO2x2 is negative until the turn of the first year. The precipitation value for CO$_2$ keeps below the values for both of the CH$_4$ perturbations until year three. After that the precipitation value for CO2x2 develops similar to that of CH4x10, with values slightly lower.

In all cases there is an initial negative adjustment for change in apparent total precipitation. Although this figure is made based on values from the SOM simulation, the fSST simulation gives the same negative change in precipitation response throughout its 30 year run for all cases (as shown in the tables in the Appendix 6). This is in compliance with what Figure 5.16a show as we recall that fSST represents the fast adjustments.

Figure 5.16b shows the same values as in (a) while divided by their respective ERFs, $\lambda'_P$. Figure 5.16b has the same overall pattern as (a) with negative values of total precipitation change that turns positive within the first year. The difference is that both of the methane cases stay close to each other throughout the simulation, and that CO2x2 keeps below both of the methane cases for the most part, except for fluctuations in day 24-30. This is expected from what we learned in Section 5.3.

Figure 5.15b and 5.16b both show the $\lambda'$ for each case. If we divide $\lambda'$ for each methane perturbation by the $\lambda'$ for the carbon dioxide perturbation we obtain efficacy.
Chapter 5. Results and Discussion

5.4. Development of responses over time

Figure 5.17: Efficacy of (a) global mean apparent surface temperature and (b) total apparent precipitation change for the two perturbations of methane. In (b) values below -5 is chosen to be -5, to remove a negative spike in month 8 caused by $\lambda'_{P,CO2x2}$ being close to 0.

Efficacy development with time

The efficacy for apparent surface temperature change is found in Figure 5.17a. The temperature efficacy for CH4x5 is initially above CH4x10, they both have a negative trend during the first 15 days, before having a positive trend. From day 24 there is a strong increase, and the efficacy is above 1 for both methane cases on day 25. This can be traced back to Figure 5.15b where $\lambda'_{TS}$ for CO2x2 is below both methane cases in this time period. In Figure 5.15a one can see that CO2x2 has a negative trend from day 21 to day 26, while the methane cases both have a positive trend from day 22. These small fluctuations on surface temperature response gives a large signal in efficacy.

Apart from day 25 for CH4x10 and day 25 to 30 for CH4x5 The temperature efficacy stays below 1, meaning CO2 creates a larger surface temperature response per $Wm^{-2}$ forcing than CH4.

Figure 5.17b shows the efficacy for annual mean total apparent precipitation change. The initial efficacy is below 1, which means CO2 triggers a larger precipitation response per $Wm^{-2}$ forcing than CH4, which can be confirmed for the first 22 days in Figure 5.16a and b. Some fluctuations in the precipitation efficacies are seen before they both become negative after 4 months. For an efficacy to be negative either the precipitation response caused by CO2x2 or the one caused by methane must be negative, but not both. Figure 5.16b shows that the $\lambda'_P$ (precipitation response...
Chapter 5. Results and Discussion

5.4. Development of responses over time

divided by ERF) for CO2x2 stayed negative between month 4 and 11, and that the \( \lambda_p \) for both methane cases were positive in this same period. \( \lambda_p \) for CO2x2 is the numerator of precipitation efficacy, and if this value is close to 0 one can get spikes in the efficacy. Such is the case for month 8 and 12, where Figure 5.16 clearly shows a negative value close to 0 in month 8 for \( \lambda_p \) for CO2x2, and a positive value close to 0 in month 12. Both these months have resulting spikes in Figure 5.17. The efficacy for precipitation stabilizes at a value of 1.24 after only five years.

Temperature profile changes with time

Both the precipitation and surface temperature responses are apparent from the first couple of days of the simulation. The temperature will change in the vertical as well as in the horizontal direction. Figure 5.18 shows the vertical temperature profile change divided by ERF develop over time. The temperature responses throughout the atmosphere can be observed quickly after the perturbations are introduced, this is a sign of the slab ocean model. All three cases (CH4x5, CH4x10 and CO2x2) exhibit the same tropospheric patterns of heating. This is illustrated in Figure 5.18, which also shows the timescales of atmospheric dynamics. The boundary layer warms and is evenly mixed during the first 2 days. Within 3 months most of the troposphere has been mixed to reach the same temperature increase. After 6 months the tropopause moves higher in altitude as the temperature increases. The development of the temperature changes have finished after only 9 months.

\( \text{Figure 5.18: Global mean vertical temperature change development divided by their ERF} \ [K / Wm}^{-2}] \). The y-axis represents the model levels in unit [hPa]. All panels are based on 9 member ensemble means from the SOM simulation.

CO2x2 creates stronger temperature signals per forcing in the troposphere as well as in the stratosphere. The tropospheric temperature development for CO2x2 in
first 30 days may be a sign of the large atmospheric absorption. The most significant difference between the cases is the cooling of the stratosphere caused by CO2x2. This strong cooling is established within the first couple of days, and starts at the top of the model spreads to lower altitudes in time. This cooling is a fast adjustment that persist throughout the simulation, and will be further discussed in Section 5.5.1. A weak stratospheric cooling can be observed in the methane cases as well.

The last 50 years of the simulation presented in the last panel of Figure 5.18 have already been presented as temperature profiles (not divided by ERF as in Figure 5.18) in Figure 5.2. There is a heating in the mid to upper troposphere that will enhance stability.

Changes in radiative flux
The fast adjustments are initialized by a change in atmospheric cooling, and all further changes in water vapor, temperature profile, and precipitation are defined as fast adjustments as long as climate feedback processes in response to a surface temperature change are excluded (Myhre et al., 2017). Since fast adjustments are can be understood by energetics it is of interest to look further into changes in radiative fluxes, and their development over time.

Figure 5.19 shows the development of four radiative parameters together with the net flux at TOA for the three perturbations, made from the 9 member ensemble SOM simulations. The top panel shows the change in clear sky longwave (LW) fluxes in solid line, and the change in clear sky shortwave (SW) fluxes in the dashed line. Recall that the positive sign is pointed downward in our radiative flux coordinate system, which means a positive change in LW clear sky flux is associated with a decrease in outgoing LW radiation. A decrease in outgoing LW radiation can be caused by more absorption in the troposphere. It seems that the CH4x10 perturbation create an equally strong decrease in outgoing clear sky LW than CO2x2 in the timescale of days to months. During the first 10 days one can observe a weak negative trend in both of the methane perturbations, while CO2x2 has an equally weak positive trend in the same time period. The reason for this could be a stratospheric cooling occurring the first few days that is stronger in the CO2 case (Figure 5.18), reducing outgoing LW radiation and thus increasing the LW clear sky flux for CO2 in this same period.

After about six years the LW clear sky fluxes become negative, meaning an increase in outgoing LW radiation. This can be caused by the surface temperature response making Earth emit more LW radiation. CO2 has a stronger signal for the increasing outgoing LW radiation, which is supported by the observed result that the CO2 perturbation creates a stronger surface temperature response.

The dashed lines of the top panel shows the SW clear sky flux, which increases slowly until it stabilizes after 30 years. The three perturbations start out with equal values and slowly diverges. An increase in clear sky SW flux is caused by less reflection of SW radiation back to space by the surface and atmosphere, and by absorption of incoming SW radiation by water vapor. Surface temperature increases
in time, and so will SW clear sky flux, which could be a result of the increase in atmospheric water vapor following an increase in atmospheric temperatures. The pattern of development in SW clear sky fluxes is a good fit with the signals in surface temperature response by the three perturbations (Figure 5.15), and the development of this flux can be used as a visualization of the water vapor feedback.

![Figure 5.19](image)

**Figure 5.19:**
Top panel: change in LW clear sky flux (solid) and SW clear sky flux (dashed)
Mid panel: change in LW cloud flux (solid) and SW cloud flux (dashed).
Bottom panel: Net flux at the top of the model. All data is from the 9 member ensemble mean of the SOM simulation.

The mid panel of Figure 5.19 show the cloudy sky fluxes. The solid lines represent longwave flux and the dashed lines represent the short wave flux. The magnitude of the change of cloudy sky fluxes are unsurprisingly smaller than the clear sky fluxes. Longwave cloudy sky fluxes (LWCF) tells us how cloud cover can trap outgoing LW radiation, a positive change shows more outgoing LW radiation is trapped from leaving Earth’s atmosphere, and is associated with an increase in high-level clouds, or a decrease in low level clouds, or both. LWCF have little difference between their starting point and their respective ending point in year 100. The largest change of the LWCF is caused by CH4x10 and stabilizes at $\sim 0.9 \text{ W/m}^2$. LWCF for CH4x5 starts and ends at $\sim 0.5 \text{ W/m}^2$, and has the most fluctuations between 10 days and 6 months. The LWCF from the CO$_2$ perturbation has a starting point in between the two methane perturbations at $\sim 0.7 \text{ W/m}^2$, a maximum after about 26 days and an ending point at $\sim 0.5 \text{ W/m}^2$. These values will be relevant in Section 5.5.2.
In the last 50 years the LWCF for CO2x2 and CH4x5 have similar values. All changes are positive, and CH₄ gives a stronger signal per ERF than CO₂, throughout the simulation.

The shortwave cloud fluxes (SWCF) are connected to the reflection of insolation by clouds, and a positive change in SWCF represents a decrease in reflection by clouds, probably caused by a decrease in low level clouds. The SWCF starts out as positive for all cases, although fluctuating. It slowly decreases and stabilizes over time. Apart from the first three years the change in SWCF for CO2x2 and CH4x10 are equal, and stabilizes close to 0. The weaker methane perturbation follows the same pattern of fluctuations as the two others but with a slightly lower value, and stabilizes as a weak negative of ∼-0.09 W/m². A negative value for SWCF indicated an increase in low level clouds that are effective reflectors.

Since the values for the SWCF are so closely related to low level clouds, and the stabilized values are so close to 0, one can assume that the long-term cloud changes mainly affects the high level clouds. With LWCF being positive there is most likely an increase in high level clouds, and it seems as if CH₄ is more effective in increasing the amount of high level clouds than CO₂ is.

The bottom panel shows the sum of the values from the upper panels, the net flux at the top of the model. The long wave clear sky flux creates the trends, while the cloudy sky fluxes creates the noise in this panel. The net forcing for CO2x2 has similar values to that of CH4x10 in the first year. After that the CO2x2 forcing stays right below CH4x10 until year 10 when the difference between them increases, and the stabilized net forcing of CO2x2 is barely larger than that of CH4x5. The difference between the two methane perturbations becomes smaller over time, due to the development in LW clear sky forcing. We can see that the net forcing for CH4x10 does not reduce to the value of the two others in the last 50 years, which could indicate that the model has not yet reached equilibrium. This should not be the case when using a slab ocean model, and shows limitations of CAM4. A discussion on how CAM4 compares to other models is found in Section 5.5.2 and Section 5.5.3.
5.5 Discussion

5.5.1 Scaling, efficacy, and timescales

Apparent precipitation and apparent surface temperature responses scale well with forcing strength for methane. The correlation between TOA forcing, surface temperature changes, and precipitation changes has been discussed in previous studies (Andrews et al. (2010), Kvalevåg et al. (2013), Samset et al. (2016)), with similar findings to ours. Carbon dioxide scales differently than methane, and this is especially apparent when calculating the efficacy. The efficacy shows that the apparent surface temperature response would be larger to a forcing caused by CO$_2$ than to an equal forcing strength caused by CH$_4$. The result is opposite for apparent precipitation.

The slow hydrological sensitivity ratio has been estimated to be 1 in our investigation (Figure 5.11), which is in agreement with Kvalevåg et al. (2013) and Samset et al. (2018). Apparent hydrological sensitivity ratio was above 1, which reveals that the difference between responses are in the fast adjustments. Figure 5.14 shows a strong negative correlation between atmospheric absorption and fast precipitation changes, and a strong positive correlation between slow precipitation changes and apparent surface temperature changes. This result is supported in Kvalevåg et al. (2013), Samset et al. (2016), and Myhre et al. (2017). The $\lambda'$ for fast precipitation in Figure 5.13 show that CO$_2$ causes a stronger negative precipitation change than CH$_4$ per Wm$^{-2}$ forcing. CO2x2 has the largest atmospheric absorption (Figure 5.1f), which correlates well with the strong negative fast precipitation signal in Figure 5.14.

CO$_2$ creates a strong negative precipitation response because of its strong atmospheric absorption. A change in absorption in an atmospheric column will increase the stability in that column, suppressing convection. An increase in atmospheric stability leads to reduced precipitation and latent heat release. CO$_2$ increases the stability of the atmosphere more than CH$_4$, and this is the main reason for the differences found between the two gases.

CO$_2$ creates a strong stratospheric cooling within the first couple of days of the simulations that CH$_4$ does not have. This cooling is a fast adjustment and could play a role in the large atmospheric absorption values for CO$_2$ compared to the two others. If stratospheric cooling causes increased values for atmospheric absorption, the source of the difference in responses lie in the distribution properties of the two gases.

5.5.2 Comparison to Modak et al. (2018)

Model comparison

One of the main references in this thesis is Modak et al. (2018), as they perform a similar investigation with a different model and different experimental design. Modak et al. (2018) (hereby referred to as M18) used CESM1 CAM5 and chose perturbations to create equal equilibrium global surface temperature change between both experiments. The baseline values were pre-industrial, and perturbations were a
ten times increase in atmospheric methane concentrations \((\text{CH}_4 \times 10)\) and a one third increase in atmospheric carbon dioxide concentrations \((\text{CO}_2 \times 1.3)\). The experiments had two configurations, fSST and a coupled slab ocean.

CAM5 is different from CAM4 in a number of ways. The most relevant difference is how CAM5 parametrizes methane’s absorption bands. Methane has atmospheric absorption bands at 1.6, 2.3 and 3.3 \(\mu\text{m}\), which is in the shortwave range, and one important band in the longwave range around 7.7 \(\mu\text{m}\). The model used in this thesis does not account for methane’s shortwave absorption bands, while CAM5 does. Main results from the experiment of \(\text{CH}_4 \times 10\) from M18 and this thesis is shown together in Table 5.2.

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Variable</th>
<th>CAM5</th>
<th>CAM4</th>
</tr>
</thead>
<tbody>
<tr>
<td>fixed SST</td>
<td>(\Delta T S) [K]</td>
<td>0.09 ± 0.02</td>
<td>0.14 ± 0.03</td>
</tr>
<tr>
<td></td>
<td>(\Delta P) [%]</td>
<td>-1.24 ± 0.01</td>
<td>-0.95 ± 0.18</td>
</tr>
<tr>
<td></td>
<td>ERF [W/m(^2)]</td>
<td>1.73 ± 0.12</td>
<td>3.15 ± 0.25</td>
</tr>
<tr>
<td>Slab ocean</td>
<td>(\Delta T S) [K]</td>
<td>1.72 ± 0.04</td>
<td>2.63 ± 0.08</td>
</tr>
<tr>
<td></td>
<td>(\Delta P) [%]</td>
<td>3.22 ± 0.10</td>
<td>6.10 ± 0.22</td>
</tr>
<tr>
<td></td>
<td>HS [K/%]</td>
<td>1.87 ± 0.08</td>
<td>2.32 ± 0.09</td>
</tr>
<tr>
<td></td>
<td>Efficacy TS</td>
<td>0.84 ± 0.09</td>
<td>0.98 ± 0.06</td>
</tr>
</tbody>
</table>

Table 5.2: \(\text{CH}_4 \times 10\) changes as estimated by CAM5 in Modak et al. (2018) and by CAM4 in this thesis. Slab ocean results are from 50 year averages and fSST results are from 20 year averages. The uncertainties from CAM5 are represented by 2 standard error from annual means. The uncertainties from CAM4 is standard deviations from annual means.

Table 5.2 shows significant differences in the responses to \(\text{CH}_4 \times 10\) between CAM4 and CAM5. The ERF value is greater for CAM4 than for CAM5, and the reason for this may be in the methane parametrization in the models. M18 finds a strong heating of the upper troposphere/lower stratosphere within the first 30 days of the simulation, that they believe is linked to the SW absorption bands for methane. Warmer air radiates more, and a strong heating at such high altitudes will let more radiation emit undisturbed to space, thus reducing the ERF. CAM4 does not include SW absorption bands for methane, nor exhibit a strong warming of the upper troposphere/lower stratosphere in the first 30 days\(^1\), and has a larger ERF value. Table 5.2 underlines the fact that CAM4 and CAM5 are different atmospheric models, and should be treated as such.

Radiative flux comparison

The following investigation is a comparison of Figure 5.20 (Modak et al. (2018, Fig. 7)) to our Figure 5.19. The development of LW clear sky fluxes in Figure 5.20 follows the same overall pattern as our results, but with a weaker signal.

The SW clear sky flux in M18 slowly increases just as in our results, but the starting point is different. Where our SW clear sky fluxes have the same starting point and slowly diverges, M18’s SW clear sky fluxes have different starting points for

\(^1\)See https://folk.uio.no/krisomos/images/gif/Tprofile.gif
CO2x1.3 and CH4x10. This can be explained by the SW absorption bands for methane in CAM5 enhancing SW absorption in the lower stratosphere, creating an instantaneous increase in SW clear sky absorption that carbon dioxide will not create. Since CAM4 does not include these absorption bands, we do not observe this instantaneous difference between CH4 and CO2 in the SW clear sky flux in Figure 5.19.

Figure 5.20: Changes in global and annual mean TOA (a) net radiative flux, (b) LW clear sky flux, (c) SW clear sky flux, (d) LW cloud flux and (e) SW cloud flux on daily to monthly to yearly timescale for CO2x1.3 (black) and CH4x10 (blue). Daily and monthly mean changes are estimated from the average of the 12 member ensemble runs. Fluxes downward are given positive sign for the SW and net fluxes but negative sign for LW fluxes. Adapted from Modak et al. (2018).

The cloudy sky fluxes in M18 differs a lot from our results. The LWCF is overall negative, which speaks of a larger outgoing LW flux from clouds from the signal than from baseline, or a decrease in high level clouds. M18 explains this by the heating of the upper troposphere caused by the shortwave absorption bands from methane, which removes high clouds that would normally trap LW radiation from
clouds. Our LWCF results are positive, indicating an increase in high level clouds. The SWCF in M18 initially has weak positive values but become negative within the first 30 days for both of their simulations. They then stay negative until around three years when they both become positive again. Our results are comparable in having a period when all simulations are negative, although this is from year 3 to 6. Our results have a larger initial difference in the perturbations, while M18’s two perturbations have the same starting point to one another.

The magnitude of the signals are larger in our results than for that of M18. This is compatible to the results seen in Table 5.2 and could well be a signal of the completely different atmospheric models used for the two studies. Modak et al. (2018) concludes that the warming of the upper troposphere/lower stratosphere is caused by shortwave absorption bands of methane, and is the reason for their low ERF value, and that this low ERF value is then the reason for their temperature efficacy to be less than 1. This result is not in agreement with our results as we have a greater value for ERF, no shortwave absorption bands, and still an average temperature efficacy below 1 for all of our methane perturbations.

CAM4 and CAM5 has the same equatorially symmetric and zonally averaged distribution of methane, and the same globally uniform distribution of CO$_2$. Being greenhouse gases and having such different distributions can raise the question if the change in temperature with altitude and time as viewed in Figure 5.18 is just a symptom of the atmospheric distribution. Methane has a very low concentration in the stratosphere compared to the troposphere, and it might be natural to connect the weak temperature signal in the stratosphere by methane to the low concentrations in this area. In Modak et al. (2018) they performed an experiment with a spatially homogenous distribution of methane, and found that the stratospheric temperature response for methane remained the same as with the experiment including the zonally averaged and equatorially symmetric distribution.

5.5.3 Methane in the models of PDRMIP

Methane setup in models

The list of models used in PDRMIP is found in Table 3.1 in Chapter 3.3. Both CAM4 used in this thesis and CAM5 used in Modak et al. (2018) are among the models in PDRMIP, and the change in both surface temperature and total precipitation can be seen in Figure 3.1. Note that CAM5 has a slab ocean in Modak et al. (2018) while it has a coupled full ocean in PDRMIP. CAM4 is the only model in PDRMIP with a slab ocean. It is clear from Figure 3.1 that for the surface temperature response in all of the core experiments performed in PDRMIP, CAM4 gives a larger signal than CAM5. The change in total precipitation shows the same signal difference between CAM4 and CAM5, with the exception of the core experiment of SO4x5.

The basis for this thesis was that the experiment of methane in PDRMIP was designed with a signal that turned out to be too weak relative to the other core
experiments, and that the weak signal created large variations between the models. That the signal is weak compared to some of the other core experiments is obvious from Figure 3.1, but the variation between the models could have various reasons in addition to the signal strength.

As previously discussed, the reason for CAM5 giving a weaker signal than CAM4 is how CAM5 parametrizes methane. Another factor that can affect the responses is the global atmospheric distribution of methane in the models. CAM4 and CAM5 has the same model set up for methane distribution, and is shown in Figure 4.4. The models have different set ups for methane, and an overview is found in Table 5.3.

<table>
<thead>
<tr>
<th>Model</th>
<th>CH$_4$ distribution</th>
<th>Absorption bands</th>
</tr>
</thead>
<tbody>
<tr>
<td>CESM1 CAM4</td>
<td>Zonally averaged and equatorially symmetric</td>
<td>LW only</td>
</tr>
<tr>
<td>CESM1 CAM5</td>
<td>Zonally averaged and equatorially symmetric</td>
<td>SW and LW</td>
</tr>
<tr>
<td>NorESM</td>
<td>Zonally averaged and equatorially symmetric</td>
<td>LW only</td>
</tr>
<tr>
<td>SPRINTARS</td>
<td>Spatially homogeneous</td>
<td>unknown</td>
</tr>
<tr>
<td>HadGEM3</td>
<td>Spatially homogeneous</td>
<td>LW only</td>
</tr>
<tr>
<td>HadGEM2</td>
<td>Spatially homogeneous</td>
<td>unknown</td>
</tr>
<tr>
<td>IPSL</td>
<td>Spatially homogenous</td>
<td>unknown</td>
</tr>
<tr>
<td>CanESM2</td>
<td>Spatially homogenous</td>
<td>unknown</td>
</tr>
</tbody>
</table>

Table 5.3: Some of the models in PDRMIP and their treatment of methane.

**ERF and efficacies**

Figure 5.21 show the estimated ERF values from the models in PDRMIP, made from their fSST simulations. The ERF values seem to be on two levels, and CAM4 is on the level giving the large ERF value, while CAM5 is in the lower level. NorESM and CAM4 have similar model treatment of methane but still has different results. The efficacies for both apparent surface temperature and apparent precipitation is found in Figure 5.22.

The ERF showed various values between models, but the models are in agreement on the efficacy for surface temperature shown in the top panel of Figure 5.22. Most of the models show a surface temperature efficacy below 1, and are compatible to my results, shown in the upper right panel. Modak et al. (2018) states that CAM5 gives a smaller ERF value for their methane experiment because of the SW absorption bands, and that climate models without SW absorption bands for CH$_4$ representation are likely to overestimate the efficacy of CH$_4$ forcing. This is not evident in Figure 5.22.

Notice in Figure 5.22 that CAM4 has a precipitation efficacy close to 1 for the experiment of CH4x3, while our calculations for this efficacy was above 1. This may be related to the time period used in the calculation, as the previous results have shown average values from year 50 to 100, this CAM4 shows the average value for a time period of 80 years. CAM4 is the only one of the PDRMIP models in Figure 5.22 with this long averaged time period. The rest of the models averages over 50
Figure 5.21: ERF for the case of CH4x3 from the models in PDRMIP.

Figure 5.22: Top left: efficacy for apparent surface temperature for CH4x3 per model in PDRMIP. Top right: Efficacy for apparent surface temperature from the experiments performed in this thesis. Bottom left: efficacy for apparent total precipitation for CH4x3 per model in PDRMIP. Bottom right: Efficacy for apparent total precipitation from the experiments performed in this thesis. The error bars are showing the ensemble spread.
The models with equal methane parametrization can give different results, meaning other parts of the coupled models will play equally a big part of the signal as the methane parametrization. This could be the case for the difference shown between CAM4 and CAM5 as well.

5.5.4 Water vapor and Ozone

Chapter 2.2.2 states that methane is an important precursor to Ozone, and a source of water vapor in the stratosphere. The documentation for CAM4 (Neale, 2010) states that the source of water vapor in the atmosphere is the double to the sink of atmospheric methane. The sink of methane is connected to the volume mixing ratio in the model, and therefore a step function increase in methane would also result in a step function increase in water vapor. An increase of water vapor from a methane perturbation in addition the increase following water vapor feedback could describe the large equilibrium values shortwave clear sky flux in Figure 5.19. Allan (2006) states that water vapor is a key parameter determining atmospheric radiative cooling, and that an increase in tropospheric humidity would reduce radiative cooling to space. This can be used to further discuss why CH4x10 had an equally large net flux at TOA in the first year from the SOM simulation (Figure 5.19). An increase in water vapor could also help explain why the net flux at the top of the model as estimated from the fSST 12 member ensemble simulation was larger for CH4x10 than for CO2x2 in the first 30 days of the simulations (Figure 5.12). The water vapor increase was not investigated in this thesis, but a deeper insight in how the model and other models treat water vapor in response to perturbations to methane is of interest to investigate in a future study, and another radiative flux figure along with a brief water vapor discussion is included in the Appendix on the subject. The source of ozone in CAM4 is not connected to the sink of atmospheric methane, so the results shown in this chapter is not affected by an increase in ozone.
Chapter 6

Summary and conclusion

In this thesis, simulations have been carried out with the model CESM1 CAM4 to investigate the difference in climate responses between methane and carbon dioxide perturbations. The responses were investigated on different timescales. To divide responses in timescales two configurations were used. The first configuration represents the fast adjustments, is called fSST and had fixed sea surface temperatures and fixed sea ice extent. A slab ocean model (SOM) was used for the second configuration to represent the apparent responses, the slow response was calculated using the two configurations fSST and SOM. In addition to one baseline run per configuration there were three climate perturbations: CH4x5, CH4x10, and CO2x2. To reduce noise from natural variability in our simulations the configurations with a climate perturbation were run as ensembles. The fSST configuration had one baseline run lasting 33 years and 12 ensemble members per climate perturbation running 30 years each. The SOM configuration had one baseline run lasting 111 years, and 9 ensemble members per climate perturbation running 100 years each. This adds up to 65 simulations, or 3924 modelled years. The ensemble means, together with a non-ensemble run from PDRMIP’s experiment CH4x3 from CAM4 were used to study the differences in the climate responses.

The results show that both surface temperature response and apparent precipitation response to the cases CH4x3, CH4x5, and CH4x10 scales well with their forcing. The CO2 perturbation does not scale equally to that of CH4 in either apparent surface temperature or apparent precipitation response. The investigation of scaling showed that when increasing the amount of atmospheric methane to create an equal effective radiative forcing as CO2x2, the surface temperature response would be lower than the one caused by CO2x2. In the case of apparent precipitation the situation is opposite, as CO2x2 creates a smaller response relative to a perturbation to methane with the same effective radiative forcing.

With evidence of the difference in scaling, the next question to be answered is that of efficacy.

The efficacy for apparent surface temperature change averaged from year 50 to 100 agree among the methane perturbations to be below one, averaging on 0.96, confirming the results of the scaling investigation. The standard deviation for the
annual means include the possibility of an apparent surface temperature efficacy equal to one for all three methane cases. The efficacy for apparent precipitation change averaged from year 50 to 100 is averaged among the three methane cases to be 1.24. All of the methane cases including their standard deviations have apparent precipitation efficacy values above one. The apparent hydrological sensitivity ratio is above one, with an average value of 1.30, while the slow hydrological sensitivity ratio are approximately equal to one for each methane perturbation. The division of hydrological sensitivity ratio into timescales revealed that the differences between the two greenhouse gases are found in the fast precipitation response.

We then performed a deep dive into the time development of the responses and efficacies. The fast precipitation response was negative for all cases, and the largest negative fast response was caused by CO2x2. CO2x2 is also the case with the largest value for atmospheric absorption, which is no coincidence. A strong negative correlation between fast precipitation responses and atmospheric absorption was evident, which can be explained by an increase in atmospheric stability following changes in absorption through the atmospheric column.

The doubling of carbon dioxide has a strong stratospheric cooling signal that is established within the first few days of the simulation. None of the methane cases exhibit a stratospheric cooling of this magnitude. This cooling is a fast adjustment, and may be connected to the large values for atmospheric absorption of CO2, and thereby the negative fast precipitation changes.

The results of this thesis were compared to the results of Modak et al. (2018) and we find that in both studies the efficacy for surface temperature is below one. In Modak et al. (2018) they reason this efficacy with the lower stratospheric warming caused by SW absorption band for methane. However we obtain the same result without SW absorption bands for methane in our model. PDRMIP has a large variety of methane handling in between models, but the intermodel variability is at least as big as the signal from other dynamical model differences. Modak et al. (2018) states that lower ERF values will give lower efficacy values for surface temperature. The results from PDRMIP does not exhibit this correlation.

The limitations to our study include the use of a slab ocean model rather than a full ocean model, and a lack of a signal to noise ratio estimation. These limitations are of interest to perform in future work. The thesis topic was inspired by a model intercomparison project with weak perturbations to methane. A multi model analysis with the perturbations used in this thesis would provide a greater insight in the robustness of our results, and the potential limitations of PDRMIP. A further investigation into how methane is parametrized in models, especially regarding the indirect effect of methane on ozone and water vapor would increase the credibility of the results.

The results from this thesis will be included in future publications by PDRMIP regarding precipitation responses and timescales.
Appendix

fSST data

This section will provide the reader with averaged change in surface temperature, precipitation, and ERF from every ensemble member from the fSST configuration simulations, averaged from year 10-30.

<table>
<thead>
<tr>
<th>Name</th>
<th>dT [K]</th>
<th>dP [%]</th>
<th>ERF [W/m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>CH4x5_F.01</td>
<td>0.10 ± 0.05</td>
<td>-0.63 ± 0.22</td>
<td>2.07 ± 0.23</td>
</tr>
<tr>
<td>CH4x5_F.02</td>
<td>0.10 ± 0.04</td>
<td>-0.59 ± 0.21</td>
<td>2.06 ± 0.34</td>
</tr>
<tr>
<td>CH4x5_F.03</td>
<td>0.10 ± 0.05</td>
<td>-0.62 ± 0.22</td>
<td>2.00 ± 0.27</td>
</tr>
<tr>
<td>CH4x5_F.04</td>
<td>0.09 ± 0.05</td>
<td>-0.56 ± 0.21</td>
<td>2.04 ± 0.31</td>
</tr>
<tr>
<td>CH4x5_F.05</td>
<td>0.10 ± 0.04</td>
<td>-0.53 ± 0.35</td>
<td>1.99 ± 0.31</td>
</tr>
<tr>
<td>CH4x5_F.06</td>
<td>0.09 ± 0.04</td>
<td>-0.63 ± 0.23</td>
<td>2.08 ± 0.26</td>
</tr>
<tr>
<td>CH4x5_F.07</td>
<td>0.10 ± 0.04</td>
<td>-0.66 ± 0.21</td>
<td>2.11 ± 0.27</td>
</tr>
<tr>
<td>CH4x5_F.08</td>
<td>0.08 ± 0.04</td>
<td>-0.55 ± 0.23</td>
<td>2.02 ± 0.32</td>
</tr>
<tr>
<td>CH4x5_F.09</td>
<td>0.09 ± 0.04</td>
<td>-0.60 ± 0.29</td>
<td>1.95 ± 0.23</td>
</tr>
<tr>
<td>CH4x5_F.10</td>
<td>0.11 ± 0.05</td>
<td>-0.56 ± 0.26</td>
<td>1.95 ± 0.27</td>
</tr>
<tr>
<td>CH4x5_F.11</td>
<td>0.09 ± 0.04</td>
<td>-0.60 ± 0.23</td>
<td>2.05 ± 0.22</td>
</tr>
<tr>
<td>CH4x5_F.12</td>
<td>0.10 ± 0.04</td>
<td>-0.63 ± 0.23</td>
<td>1.95 ± 0.32</td>
</tr>
<tr>
<td>CH4x5_F</td>
<td>0.10 ± 0.03</td>
<td>-0.60 ± 0.17</td>
<td>2.02 ± 0.20</td>
</tr>
</tbody>
</table>

Table 6.1: Change in surface temperature, change in precipitation and ERF for every ensemble member. The bottom row shows the ensemble mean. The uncertainties are the standard deviation from the annual means from year 10-30.
<table>
<thead>
<tr>
<th>Name</th>
<th>dT   [K]</th>
<th>dP   [%]</th>
<th>ERF [W/m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>CH4x10_F_01</td>
<td>0.16 ± 0.04</td>
<td>-1.01 ± 0.24</td>
<td>3.15 ± 0.25</td>
</tr>
<tr>
<td>CH4x10_F_02</td>
<td>0.17 ± 0.05</td>
<td>-0.90 ± 0.20</td>
<td>3.07 ± 0.29</td>
</tr>
<tr>
<td>CH4x10_F_03</td>
<td>0.16 ± 0.06</td>
<td>-0.10 ± 0.27</td>
<td>3.19 ± 0.29</td>
</tr>
<tr>
<td>CH4x10_F_04</td>
<td>0.15 ± 0.06</td>
<td>-1.02 ± 0.22</td>
<td>3.21 ± 0.21</td>
</tr>
<tr>
<td>CH4x10_F_05</td>
<td>0.15 ± 0.05</td>
<td>-0.96 ± 0.24</td>
<td>3.10 ± 0.23</td>
</tr>
<tr>
<td>CH4x10_F_06</td>
<td>0.14 ± 0.05</td>
<td>-0.97 ± 0.28</td>
<td>3.14 ± 0.26</td>
</tr>
<tr>
<td>CH4x10_F_07</td>
<td>0.14 ± 0.05</td>
<td>-0.89 ± 0.24</td>
<td>3.18 ± 0.25</td>
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<tr>
<td>CH4x10_F_08</td>
<td>0.13 ± 0.04</td>
<td>-0.91 ± 0.22</td>
<td>3.20 ± 0.29</td>
</tr>
<tr>
<td>CH4x10_F_09</td>
<td>0.14 ± 0.04</td>
<td>-0.99 ± 0.24</td>
<td>3.19 ± 0.24</td>
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<td>CH4x10_F_10</td>
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<td>-0.95 ± 0.24</td>
<td>3.17 ± 0.20</td>
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<td>CH4x10_F_11</td>
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<td>CH4x10_F_12</td>
<td>0.16 ± 0.04</td>
<td>-0.94 ± 0.27</td>
<td>3.13 ± 0.29</td>
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<tr>
<td>CH4x10_F</td>
<td>0.15 ± 0.03</td>
<td>-0.95 ± 0.18</td>
<td>3.15 ± 0.18</td>
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</tbody>
</table>

**Table 6.2:** Change in surface temperature, change in precipitation and ERF for every ensemble member. The bottom row shows the ensemble mean. The uncertainties are the standard deviation from the annual means from year 10-30.

<table>
<thead>
<tr>
<th>Name</th>
<th>dT   [K]</th>
<th>dP   [%]</th>
<th>ERF [W/m²]</th>
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<tr>
<td>CO2x2_F_01</td>
<td>0.27 ± 0.05</td>
<td>-2.44 ± 0.22</td>
<td>3.63 ± 0.22</td>
</tr>
<tr>
<td>CO2x2_F_02</td>
<td>0.26 ± 0.03</td>
<td>-2.51 ± 0.27</td>
<td>3.69 ± 0.25</td>
</tr>
<tr>
<td>CO2x2_F_03</td>
<td>0.26 ± 0.04</td>
<td>-2.47 ± 0.24</td>
<td>3.72 ± 0.25</td>
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<tr>
<td>CO2x2_F_04</td>
<td>0.26 ± 0.03</td>
<td>-2.47 ± 0.22</td>
<td>3.70 ± 0.23</td>
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<tr>
<td>CO2x2_F_05</td>
<td>0.27 ± 0.05</td>
<td>-2.43 ± 0.23</td>
<td>3.71 ± 0.35</td>
</tr>
<tr>
<td>CO2x2_F_06</td>
<td>0.26 ± 0.04</td>
<td>-2.40 ± 0.30</td>
<td>3.74 ± 0.22</td>
</tr>
<tr>
<td>CO2x2_F_07</td>
<td>0.27 ± 0.05</td>
<td>-2.48 ± 0.28</td>
<td>3.64 ± 0.31</td>
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<tr>
<td>CO2x2_F_08</td>
<td>0.26 ± 0.05</td>
<td>-2.45 ± 0.20</td>
<td>3.65 ± 0.26</td>
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<tr>
<td>CO2x2_F_09</td>
<td>0.26 ± 0.05</td>
<td>-2.48 ± 0.29</td>
<td>3.71 ± 0.25</td>
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<tr>
<td>CO2x2_F_10</td>
<td>0.26 ± 0.05</td>
<td>-2.49 ± 0.27</td>
<td>3.76 ± 0.22</td>
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<tr>
<td>CO2x2_F_11</td>
<td>0.27 ± 0.03</td>
<td>-2.45 ± 0.24</td>
<td>3.66 ± 0.33</td>
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<tr>
<td>CO2x2_F_12</td>
<td>0.27 ± 0.04</td>
<td>-2.46 ± 0.24</td>
<td>3.60 ± 0.26</td>
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<tr>
<td>CO2x2_F</td>
<td>0.26 ± 0.03</td>
<td>-2.46 ± 0.18</td>
<td>3.68 ± 0.19</td>
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</tbody>
</table>

**Table 6.3:** Change in surface temperature, change in precipitation and ERF for every ensemble member. The bottom row shows the ensemble mean. The uncertainties are the standard deviation from the annual means from year 10-30.
This section will provide the reader with averaged change in surface temperature, precipitation, and hydrological sensitivity from every ensemble member from the SOM configuration simulations averaged from year 50-100.

<table>
<thead>
<tr>
<th>Name</th>
<th>dT [K]</th>
<th>dP [%]</th>
<th>HS [%/K]</th>
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<tbody>
<tr>
<td>CH4x5_E_01</td>
<td>1.68 ± 0.10</td>
<td>3.84 ± 0.39</td>
<td>2.28 ± 0.21</td>
</tr>
<tr>
<td>CH4x5_E_02</td>
<td>1.73 ± 0.11</td>
<td>3.92 ± 0.38</td>
<td>2.26 ± 0.18</td>
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<tr>
<td>CH4x5_E_03</td>
<td>1.69 ± 0.12</td>
<td>3.91 ± 0.38</td>
<td>2.31 ± 0.19</td>
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<tr>
<td>CH4x5_E_04</td>
<td>1.63 ± 0.11</td>
<td>3.75 ± 0.35</td>
<td>2.30 ± 0.18</td>
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<tr>
<td>CH4x5_E_05</td>
<td>1.69 ± 0.14</td>
<td>3.87 ± 0.44</td>
<td>2.29 ± 0.20</td>
</tr>
<tr>
<td>CH4x5_E_06</td>
<td>1.71 ± 0.12</td>
<td>3.84 ± 0.38</td>
<td>2.24 ± 0.17</td>
</tr>
<tr>
<td>CH4x5_E_07</td>
<td>1.67 ± 0.11</td>
<td>3.78 ± 0.39</td>
<td>2.25 ± 0.19</td>
</tr>
<tr>
<td>CH4x5_E_08</td>
<td>1.66 ± 0.10</td>
<td>3.83 ± 0.36</td>
<td>2.30 ± 0.19</td>
</tr>
<tr>
<td>CH4x5_E_09</td>
<td>1.65 ± 0.12</td>
<td>3.84 ± 0.43</td>
<td>2.32 ± 0.24</td>
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<tr>
<td>CH4x5_E</td>
<td>1.68 ± 0.09</td>
<td>3.84 ± 0.29</td>
<td>2.29 ± 0.14</td>
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Table 6.4: Change in surface temperature, change in precipitation and hydrological sensitivity for every ensemble member. The bottom row shows the ensemble mean. The uncertainties are the standard deviation from the annual means from year 50-100.

<table>
<thead>
<tr>
<th>Name</th>
<th>dT [K]</th>
<th>dP [%]</th>
<th>HS [%/K]</th>
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<tr>
<td>CH4x10_E_01</td>
<td>2.65 ± 0.10</td>
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<td>2.32 ± 0.13</td>
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<td>CH4x10_E_02</td>
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<td>CH4x10_E_03</td>
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<td>6.08 ± 0.41</td>
<td>2.33 ± 0.14</td>
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<td>6.18 ± 0.36</td>
<td>2.33 ± 0.10</td>
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<td>2.62 ± 0.10</td>
<td>6.14 ± 0.39</td>
<td>2.34 ± 0.12</td>
</tr>
<tr>
<td>CH4x10_E_06</td>
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<td>6.02 ± 0.46</td>
<td>2.32 ± 0.14</td>
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<tr>
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<td>2.65 ± 0.14</td>
<td>6.14 ± 0.43</td>
<td>2.31 ± 0.13</td>
</tr>
<tr>
<td>CH4x10_E_08</td>
<td>2.64 ± 0.11</td>
<td>6.13 ± 0.37</td>
<td>2.31 ± 0.13</td>
</tr>
<tr>
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<td>5.95 ± 0.36</td>
<td>2.31 ± 0.11</td>
</tr>
<tr>
<td>CH4x10_E</td>
<td>2.62 ± 0.09</td>
<td>6.10 ± 0.30</td>
<td>2.32 ± 0.09</td>
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</tbody>
</table>

Table 6.5: Change in surface temperature, change in precipitation and hydrological sensitivity for every ensemble member. The bottom row shows the ensemble mean. The uncertainties are the standard deviation from the annual means from year 50-100.
### Table 6.6: Change in surface temperature, change in precipitation and hydrological sensitivity for every ensemble member. The bottom row shows the ensemble mean. The uncertainties are the standard deviation from the annual means from year 50-100.

<table>
<thead>
<tr>
<th>Name</th>
<th>dT  [K]</th>
<th>dP  [%]</th>
<th>HS  [%/K]</th>
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<tr>
<td>CO2x2_E_01</td>
<td>3.24 ± 0.11</td>
<td>5.92 ± 0.39</td>
<td>1.82 ± 0.10</td>
</tr>
<tr>
<td>CO2x2_E_02</td>
<td>3.24 ± 0.14</td>
<td>6.02 ± 0.51</td>
<td>1.85 ± 0.12</td>
</tr>
<tr>
<td>CO2x2_E_03</td>
<td>3.18 ± 0.12</td>
<td>5.79 ± 0.43</td>
<td>1.81 ± 0.10</td>
</tr>
<tr>
<td>CO2x2_E_04</td>
<td>3.22 ± 0.12</td>
<td>5.86 ± 0.38</td>
<td>1.81 ± 0.09</td>
</tr>
<tr>
<td>CO2x2_E_05</td>
<td>3.20 ± 0.11</td>
<td>5.73 ± 0.41</td>
<td>1.79 ± 0.11</td>
</tr>
<tr>
<td>CO2x2_E_06</td>
<td>3.21 ± 0.12</td>
<td>5.84 ± 0.44</td>
<td>1.82 ± 0.11</td>
</tr>
<tr>
<td>CO2x2_E_07</td>
<td>3.27 ± 0.11</td>
<td>5.95 ± 0.44</td>
<td>1.81 ± 0.11</td>
</tr>
<tr>
<td>CO2x2_E_08</td>
<td>3.20 ± 0.13</td>
<td>5.84 ± 0.38</td>
<td>1.82 ± 0.10</td>
</tr>
<tr>
<td>CO2x2_E_09</td>
<td>3.20 ± 0.41</td>
<td>5.81 ± 0.83</td>
<td>1.80 ± 0.10</td>
</tr>
<tr>
<td>CO2x2_E</td>
<td>3.22 ± 0.11</td>
<td>5.86 ± 0.34</td>
<td>1.82 ± 0.08</td>
</tr>
</tbody>
</table>
Net top flux first 30 days

In Figure 5.12 one could observe that the ensemble mean representing CH4x10 had a slightly higher net flux at TOA than the ensemble mean representing CO2x2. The net flux can be divided into clear sky and cloudy sky fluxes, which is done in Figure 6.1. The remarkable feature of this figure is that the SW clear sky flux is larger for both methane cases than for CO2x2 in the first 30 days. Figure 6.1 is made out of the ensemble mean, but if one makes a similar figure for each ensemble member the result remains the same: methane has a higher SW clear sky flux change than carbon dioxide in the first 30 days.

Figure 6.1: CH4x5 (blue), CH4x10 (green), CO2x2 (red).  
Top panel: change in LW clear sky flux (solid) and SW clear sky flux (stippled)  
Mid panel: change in LW cloud flux (solid) and SW cloud flux (stippled).  
Bottom panel: Net flux at the top of the model. All data from the ensemble mean of the 12 member fSST simulation.

The flux developments per month for the first 6 months of each ensemble member shows the same pattern. Both methane cases exhibit a positive SW clear sky flux value in the first month, while CO2 has a value of zero. SW clear sky is usually affected by changes in water vapor, so this difference in value in the short timescale can be linked to our discussion on methane and Water vapor in Section 5.5.4. However we do not see this difference in SW clear sky flux in the SOM-simulation (Figure 5.19).

In Figure 5.19 there is no initial difference between the SW clear sky fluxes, but the LW clear sky are exhibiting similar values between CH4x10 and CO2x2. This could be a sign of an increase in tropospheric water vapor for methane. An
investigation of methane and water vapor in CAM4 is needed.
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<td>Radiative forcing of climate change from year 1750 to 2011. Adapted from Stocker et al. (2013). The confidence levels are indicators of both evidence and agreement. WMGHG stands for well mixed greenhouse gases, AR4 is the former physical assessment report by IPCC (2007).</td>
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<td>12</td>
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<tr>
<td>2.5</td>
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<td>14</td>
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<td>16</td>
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<td>18</td>
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<td>22</td>
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<td>Mean total (apparent), fast, and slow precipitation response following two greenhouse gas perturbations from multimodel simulations. The hatched area shows where the multimodel mean is more than 1 standard deviation away from zero. Adapted from Samset et al. (2016).</td>
<td>23</td>
</tr>
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<td>23</td>
</tr>
</tbody>
</table>
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5.6 $\lambda_{P}$ for CH4 and CO2 together with a regression line representing the best fit linear function for $\lambda_{P,CH4}$. The values for total apparent precipitation change are estimated by annual mean for year 50-100 from the 9 member ensemble SOM simulations. The error bars are showing the standard deviations for the annual means.

5.7 $\lambda_{HS}$ for CH4 and CO2 together with a regression line representing the best fit linear function for $\lambda_{HS,CH4}$. The values for apparent hydrological sensitivity are estimated by annual mean for year 50-100 from the 9 member ensemble SOM simulations. The error bars are showing the standard deviations for the annual means.

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