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ENSO DRIVEN INTER-ANNUAL VARIABILITY OF THE OLR FROM SATELLITE
OBSERVATIONS AND CLIMATE MODELS

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Abstract

The thermal radiation emitted by the Earth-atmosphere system in the longwave, also known as the outgoing longwave radiation (OLR), is one of the components of the top-of-atmosphere (TOA) Earth energy budget (EEB). Many satellite missions have been dedicated to monitor the broadband and the spectrally resolved OLR from space, contributing to improve the knowledge of surface and atmospheric physical processes that drive its variability. Past and present-day OLR measurements constitute also a fundamental benchmark to assess the reliability of climate models. Since long-term stable records of OLR observations are still not long enough to accurately quantify the radiative response of the climate system to external forcings (e.g. the increase of greenhouse gases concentration), many studies have focused on the inter-annual variability to improve our understanding of feedback processes. In this context, the El-Niño Southern Oscillations (ENSO) is the most important mode of variability of the system on the interannual time scale. The tropical OLR is strongly affected by ENSO, showing positive or negative anomalies in response to El-Niño or La-Niña phases, respectively.

Within this thesis, the ENSO-driven variability of the TOA OLR is investigated using both broadband and spectral OLR measurements and outputs from global climate models participating to the Coupled Model Intercomparison Project, phase 6 (CMIP6). In the first part of the work, the OLR variability induced by ENSO as simulated by 38 CMIP6 models has been assessed. Clear-sky OLR outputs from CMIP6 Atmospheric Model Intercomparison Project (AMIP) and coupled atmosphere-ocean historical experiments are evaluated against the corresponding broadband observations from the Cloud and Earth Radiant Energy System (CERES) instrument, considering the models' ability in reproducing the phase, amplitude and magnitude of the radiative response to ENSO. The understanding of the factors behind climate models biases has been at the center of the rest of the work, which considered - for the first time - the spectral dimension of the ENSO OLR response.

The second part of the analysis focused on the study of the physical processes that drive the OLR response to ENSO. These have been investigated by means of clear-sky OLR spectral fluxes derived from measurements acquired by the Infrared Atmospheric Sounding Interferometer (IASI) and the Atmospheric Infrared Sounder (AIRS). Unlike CERES' broadband fluxes, which are mostly used in climate science, the spectral measurements allow to isolate the wavenumbers that contribute the most to the OLR response and study the physical processes behind. These have been further investigated employing a spectral kernel analysis to assess the individual contribution of water vapor, surface and atmospheric temperature, the three main variables shaping the clear-sky OLR flux.

The spectral analysis shows how the total radiative response to ENSO is driven by different feedback mechanisms that compensate each other. The calculation of ENSO spectral radiative feedbacks allow to test whether the response in climate models is given by the correct balance among feedback mechanisms of different signs. The final step of the work involved the calculation of the spectral radiative response to ENSO in climate models. Water vapor, surface and air temperature fields as simulated by CMIP6 AMIP and historical models have been calculated using the same spectral radiative kernels and compared to the results obtained using spectral OLR observations.

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Chapter 1

Introduction

The modern era is characterized by a warming of the climate system, related to the increase in anthropogenic emission of greenhouse gases (GHGs) into the atmosphere (D. Chen et al. [2023](#)). The increased concentration of GHGs has the effect to trap more energy within the climate system than what is emitted to outer space to accomplish the Earth energy budget (EEB). This has caused an imbalance between the net incoming and outgoing energy fluxes, quantified by a top-of-atmosphere (TOA) Earth energy imbalance (EEI) to which the climate system responds by warming to increase the OLR and reach a new state of equilibrium. The climate system response can, in turn, be dampened or amplified by feedback mechanisms, which determine the ultimate warming of the planet. Predicting the long-term impact of the climate change is important for the development of mitigation and adaptation strategies to cope with the effects of the climate change that pose an unprecedented threat for humanity and the whole biosphere. In this context, it is of primary importance to understand and quantify the physical processes that drive the radiative response of the climate system to the increase in GHGs concentrations.

Currently, we can rely on climate models estimates to calculate the long-term feedback related to the increase in carbon dioxide concentration - the main GHG. Global climate models (GCMs) show that the long-term contributions of climate feedbacks to the global warming is larger than that of carbon dioxide itself, implying that climate feedbacks strongly amplify the magnitude of the warming (D. Chen et al. [2023](#)). However, their estimate is still uncertain, especially for the clouds feedback, and GCMs struggle to agree on a precise value (Zelinka et al. [2020](#)). This in turn affects estimates of equilibrium climate sensitivity (ECS), which is defined as the change in global mean surface temperature that will be reached by the planet in response to a doubling of carbon dioxide concentration. Our current best estimate of the ECS is around 3°C, but with a large uncertainty (AR6 very likely range: 2-5°C, K. Armour et al. [2021](#)).

A common approach to test climate models performances in reproducing the variability of the TOA EEB is to compare their simulated and observed values of TOA fluxes. To do so we can rely on accurate and stable measurements of the EEB acquired by satellite

instruments. Indeed, the information provided by satellite observations represents the bulk of the data assimilated into weather models (reference) and plays a crucial role in the evaluation, tuning and refinement of climate models (Wild 2020). However, the length of available satellite records consists of only a few decades of measurements, and it is not yet enough to accurately quantify the long-term effect of the climate change (Uribe, Bender, and Mauritsen 2024). Nevertheless, several research efforts have focused on the short-term changes of the EEB to improve our knowledge of feedback mechanisms on the long-term (A. Dessler, Zhang, and P. Yang 2008; Andrew E Dessler 2010; Andrew E Dessler 2013; Uribe, Bender, and Mauritsen 2022).

The OLR is one of the components of the TOA EEB. It is the energy flux emitted by the planet towards space across the thermal and far Infrared (IR) spectral regions, constituting the main cooling process of the climate system. The OLR variability contains the signal related to both natural climate variability and external radiative forcings. Its great sensitivity to surface and atmospheric properties makes it a good candidate to study the radiative response of the climate system to the processes that take place at the surface and within the Earth atmosphere.

Several satellite missions have been dedicated to monitor the OLR from space. The first systematic measurements of the OLR date back to the 1960s with the Wide Field Of View (WFOV) instrument on board the Explorer VII (Suomi 1960). It has been followed by the High Resolution Imaging Spectrometer (HIRS) (Dozier and Goetz 1989) launched in 1976 on board NOAA TIROS-N and MetOp platforms, and by Earth Radiation Budget (ERB) (Jacobowitz et al. 1979; Herbert Jacobowitz et al. 1984) launched in 1975 on board Nimbus-6,-7, who paved the way for the Clouds and Earth Radiant Energy System (CERES) instrument (Wielicki, Bruce R Barkstrom, et al. 1996), whose measurements has started in 2000 and has now accomplished more than 20 years of continuous observations. In addition to broadband CERES observations, which measure the integrated OLR, we can rely also on hyperspectral sounders, such as the Infrared Atmospheric Sounding Interferometer (IASI) (Simeoni et al. 2004), launched in 2008, and the Atmospheric Infrared Sounder (AIRS) (Aumann et al. 2003), active since 2002, which provide spectrally resolved OLR measurements. Spectral observations have proven to be particularly suitable in disclosing compensating errors that may affect broadband OLR fluxes in climate models (X. Huang, X. Chen, B. J. Soden, et al. 2014). The main advantage of the spectral dimension is the possibility to isolate single contributions by examining different spectral regions and to identify the atmospheric layers where the radiation originates.

This thesis focuses on the ability of climate models in reproducing the interannual variability of the OLR using spectral satellite observations. The aim of the work is to further extend the use of spectral measurements to study the mechanisms behind the short-term variability of the EEB, potentially providing a better constraint for climate models projections. We focused on OLR variability driven by El-Niño Southern Oscil-

lations (ENSO), which is the dominant variability mode of the climate system on the interannual time scale. ENSO causes perturbations to sea surface temperatures (SSTs) across the tropical Pacific Ocean, coupled to changes in the above atmospheric circulation, with important implications for the Earth climate. ENSO effects are not limited to the tropical region but reach remote areas through teleconnections. Studying the OLR response to ENSO provides an important insight into the mechanisms underlying the relationship between the TOA EEB and the processes taking place at the planet surface and within the atmosphere.

The work is divided into three parts. The first step involves the assessment of OLR variability driven by ENSO as simulated by climate models participating to the Coupled Model Intercomparison Project - Phase 6 (CMIP6). To do so, lagged regressions of the tropical OLR with ENSO in models have been compared to broadband CERES observations, giving information on the magnitude and timing of that relationship. In a second phase, two datasets of OLR spectral fluxes derived from AIRS and IASI measurements are analyzed with the aid of spectral radiative kernels, obtaining the fingerprint due to water vapor, surface and atmospheric temperature and ozone on the OLR response. Finally, the additional information provided by the spectral dimension is used to disclose climate models biases that may compensate each other when the broadband fluxes are considered.

Chapter 2

Scientific background

2.1 The climate system

2.1.1 Radiation and the Earth energy budget

The Sun is the primary energy source of the Earth. In order to maintain the thermal equilibrium, the solar energy absorbed must be balanced by an equal amount of energy release. Solar energy is transmitted to the Earth in the form of radiation. The solar radiation that reaches the Earth is determined by the solar constant (S_0). It is defined as the density flux at the mean Sun-Earth distance. The solar radiation is considered as a parallel and uniform beam, since the diameter of the planet is small compared to the distance from the Sun. The actual energy amount absorbed by the planet is given by the solar constant times the area the planet sweeps out of the incident beam, called the shadow area, minus the planetary albedo (α_p). The latter accounts for the solar radiation reflected back to space by the Earth surface and clouds, which are characterized by high reflectivity values. The absorbed solar radiation is:

$$\text{absorbed solar radiation} = S_0(1 - \alpha_p)\pi r_p^2 \quad (2.1)$$

where r_p is the Earth's radius. The atmosphere can be ignored due to its very small thickness compared to the Earth's radius. Radiation emitted by the Earth can be approximated to that of a blackbody. Following the Stefan-Boltzmann law, the blackbody emission coming from an area equal to that of a sphere is:

$$\text{emitted terrestrial radiation} = \sigma T_e^4 4\pi r_p^2 \quad (2.2)$$

where, T_e is the equivalent blackbody emission temperature of the Earth and r_p is the Earth's radius. This simple energy balance model can be used to estimate the Earth's equivalent blackbody temperature required for its radiative emission to balance the ab-

sorbed solar radiation:

$$T_e = \sqrt[4]{\frac{(S_0/4)(1 - \alpha_p)}{\sigma}} \quad (2.3)$$

Substituting all the respective constants, an emission temperature of about -18°C is obtained, which is about 30°C lower than the observed global mean surface temperature (GMST) ($\sim 15^\circ\text{C}$). This model ignores the Earth’s atmosphere. Atmospheric constituents absorb radiation in the thermal infrared, the spectral region in which the Earth emits radiation, and re-emit it half downward and half upward. Absorption and emission processes repeat until OLR is ultimately emitted back to space at higher atmospheric levels characterised by lower temperatures. Consequently, more energy is trapped at the Earth’s surface, resulting in greater warming than would occur in the absence of an atmosphere. The equivalent blackbody emission temperature of -18°C corresponds to that of the middle troposphere, where most of the OLR emission actually occurs. This is the so-called *greenhouse effect* and the atmospheric gases that interact with terrestrial radiation are the *greenhouse gases* (GHGs).

The Earth energy budget

At the TOA the EEB can be considered purely radiative and it is driven by the balance between the incoming solar radiation in the SW, and the LW radiation emitted by the Earth. However, energy is also exchanged within the Earth’s climate system. Radiative and non-radiative energy fluxes described by the vertical EEB are depicted in Figure 2.1, along with the global mean estimate of the individual components referred to the 21st century included in the 6th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (K. Armour et al. 2021). Approximately half of the incident solar radiation (yellow arrows in Figure 2.1) reaching the planet is absorbed at the surface (160 Wm^{-2} out of 340 Wm^{-2}), while the rest is partly reflected into space by the surface (25 Wm^{-2}) and clouds (100 Wm^{-2}) (together constituting the planetary albedo) and partly absorbed by atmospheric constituents (185 Wm^{-2}) (e.g. water vapor, ozone, aerosols). The absorbed solar energy must be balance by an equal amount of energy emission to accomplish the EEB. Thermal radiation emitted by the Earth’s surface and atmosphere is the main mechanism involved in the cooling of the climate system (orange arrows in Figure 2.1). However, only a small amount of the LW radiation that is emitted by the surface (398 Wm^{-2}) is directly released back to space. As such, the latent heat flux (82 Wm^{-2}) due to water phase changes, and the sensible heat flux (21 Wm^{-2}) are the main contributions to the transfer of the energy from the surface to the atmosphere.

Within the atmosphere, the greatest fraction of LW radiation emitted at the surface is absorbed by GHGs (e.g. carbon dioxide, water vapor, ozone) and re-emitted back to the surface (342 Wm^{-2} out of 398 Wm^{-2}). Terrestrial radiation is also scattered by atmospheric clouds and aerosols. The resulting OLR emitted to space is estimated to be

239 Wm^{-2} .

Clouds have a very important role in shaping the variability of the EEB (Figure 2.1, top panel). They act to both reflect solar radiation, increasing the planetary albedo, and decrease the OLR emission, absorbing LW radiation and shifting the emission level above the colder cloud top. Figure 2.1 shows that when clouds are removed a radiative imbalance of 20 Wm^{-2} would result from 47 Wm^{-2} less of solar radiation reflected and 28 Wm^{-2} more of thermal radiation emitted to space.

Globally the net TOA EEB (i.e. net = absorbed - emitted) varies in space and time, according to the atmospheric and surface properties of geographical regions and to the amount of insulation. Planetary albedo is greater over polar regions, due to the presence of clouds and snow. At these latitudes the solar zenith angle is also large. Albedo is also high at the tropics where clouds are thick and over deserts, while ocean surface has intrinsically a small albedo. On the other side, the OLR is greatest over regions characterized by a high surface temperature and low cloud cover. As a result the net TOA EEB is positive at the equator while it is negative at the poles: this latitudinal gradient must be balanced by a poleward energy transport, which is accomplished by the movement of air and water masses constituting the atmospheric and ocean circulation.

Shortwave and longwave radiation

Solar and terrestrial radiation can be treated separately for energetic purposes. This is possible due to the different emission temperature of the emitters (the Sun and Earth). The emission temperature of the Sun is about 6000 K, the temperature of the photosphere, where the solar radiation mostly originates, and the peak of the blackbody curve is near $0.5 \mu\text{m}$. The wings extend to the UV ($\lambda < 0.3 \mu\text{m}$) and VIS ($\lambda > 0.7 \mu\text{m}$). Instead, the blackbody curve for the Earth, with an emission temperature of about 255 K, peaks near $10 \mu\text{m}$ and extends to wavelengths near $5 \mu\text{m}$ and $100 \mu\text{m}$. Around $4 \mu\text{m}$ the overlap between the two curves is negligible. In climate science, solar radiation is conventionally named *shortwave (SW)*, while terrestrial radiation is called *longwave (LW)*.

Spectra of SW and LW radiation are shaped by the transmission properties of the atmosphere, which depend on the composition. The Earth atmosphere is almost transparent to solar radiation, in the SW, while it efficiently emits and absorbs terrestrial radiation, in the LW. Depending on their physical and chemical properties there are some molecular gasses that can absorb radiation at different wavelengths. Figure 2.2 reports the solar spectrum, along with the main absorption processes at the different wavelengths. The most energetic part of the solar radiation (UV-A and UV-B) is absorbed at high levels through photodissociation and ionization of oxygen and ozone. As such only a small part of UVs reaches the troposphere. Within the troposphere, the near-infrared part of SW radiation is absorbed by carbon dioxide and water vapor. Radiation at visible wavelengths arrives at the surface. Indeed, atmosphere is almost transparent to these wavelengths.

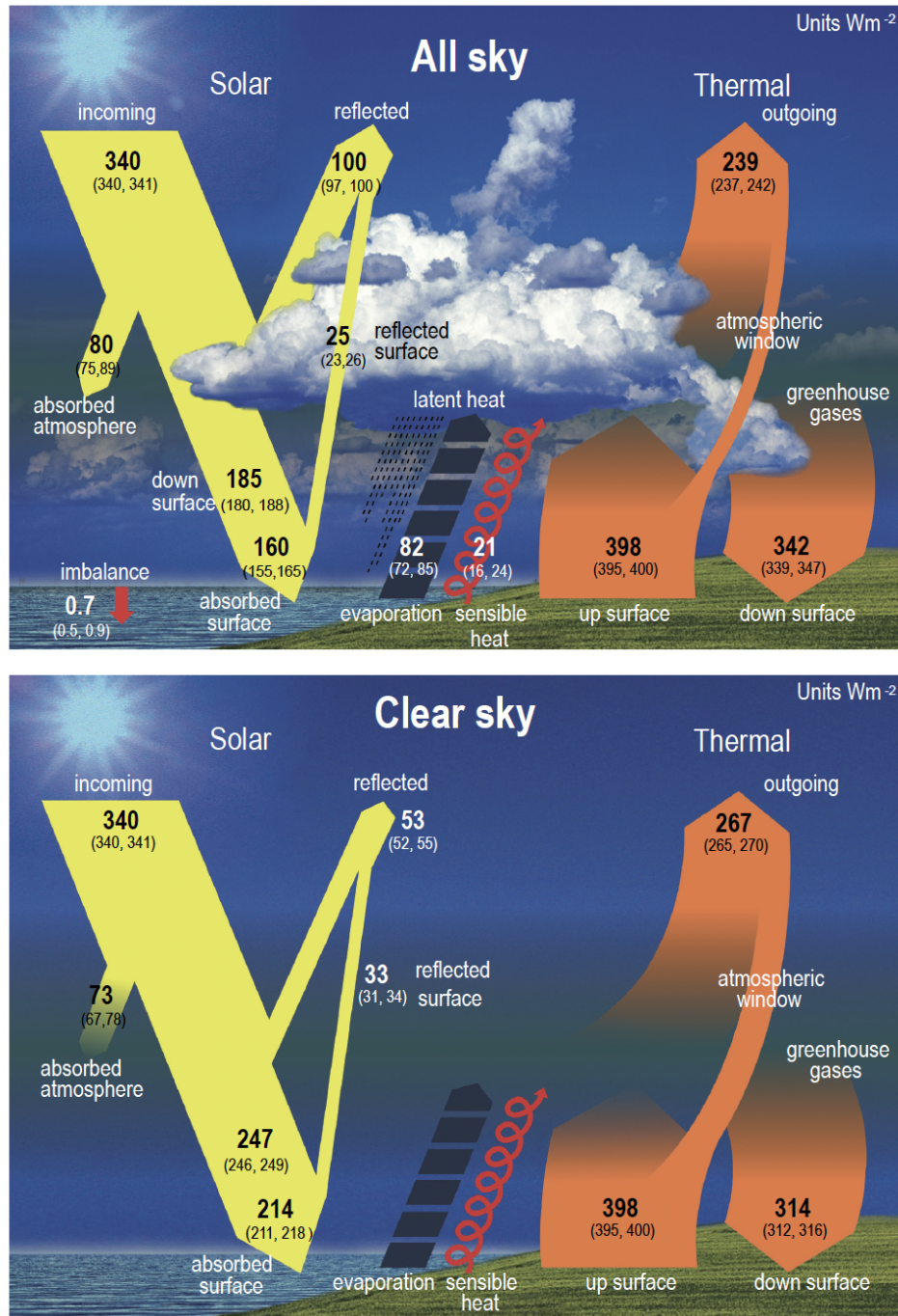


Figure 2.1: Components of the global mean energy budget and corresponding estimates, for all-sky (top panel) and clear-sky (bottom) conditions (K. Armour et al. 2021).

On the contrary, the Earth atmosphere efficiently absorbs and emits terrestrial radiation. Gasses that absorb radiation in the thermal and far-infrared spectral regions are the so-called greenhouse gasses (GHGs), the major GHGs are carbon dioxide (the most abundant), methane, ozone, nitrous oxide, water vapor. Figure 2.3 reports the Earth emission spectrum. LW radiation is almost completely absorbed by water vapor around $6.3\mu\text{m}$ and within the far-infrared spectral region (above $15\mu\text{m}$), and carbon dioxide, whose absorption band is centered at $15\mu\text{m}$. Other trace gases that absorb the OLR are ozone, methane and nitrous oxide. As a result most of the radiation is absorbed by the atmosphere. Only between 8 and $12\mu\text{m}$, the so-called atmospheric window, the LW radiation is directly emitted to space (except around $9.6\mu\text{m}$ where the ozone absorption band is centered). Two blackbody emission curves are also pictured. They correspond to the emission of a blackbody at a temperature of 295 and 210 K, which correspond to the temperature at the Earth surface and the stratosphere, where most of the radiation is emitted in the spectral region associated to carbon dioxide absorption and within the atmospheric windows, respectively.

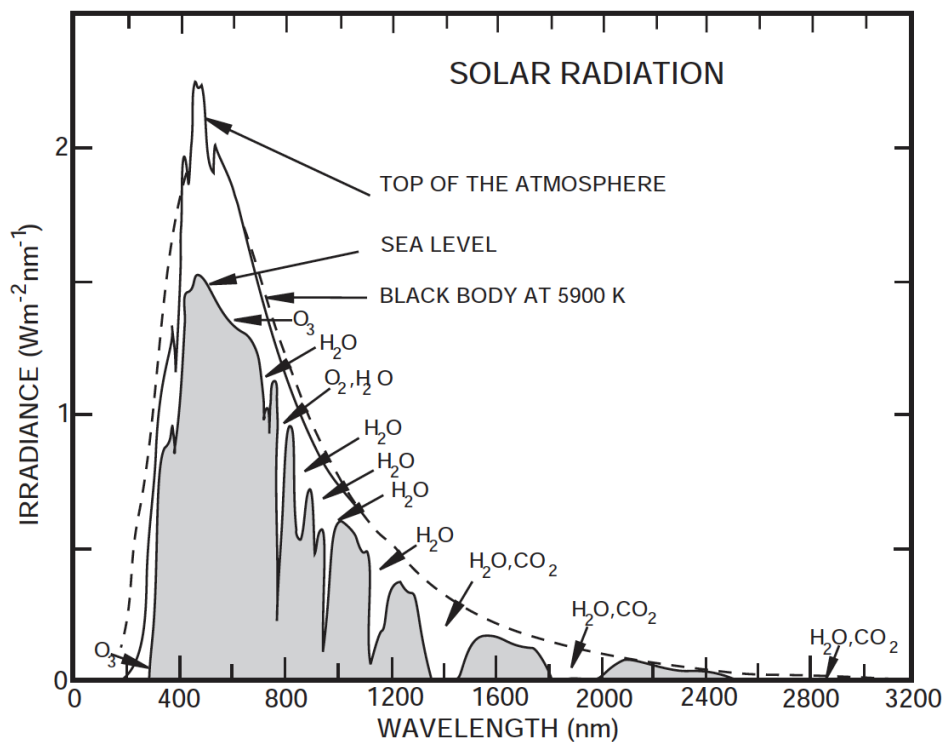


Figure 2.2: Spectrum of the solar radiation (Salby 2012).

2.1.2 Radiative forcing, feedbacks and equilibrium climate sensitivity

As long as the incoming and outgoing energy fluxes balance each other in the long-term global mean, the Earth's thermal equilibrium is maintained and the climate remains

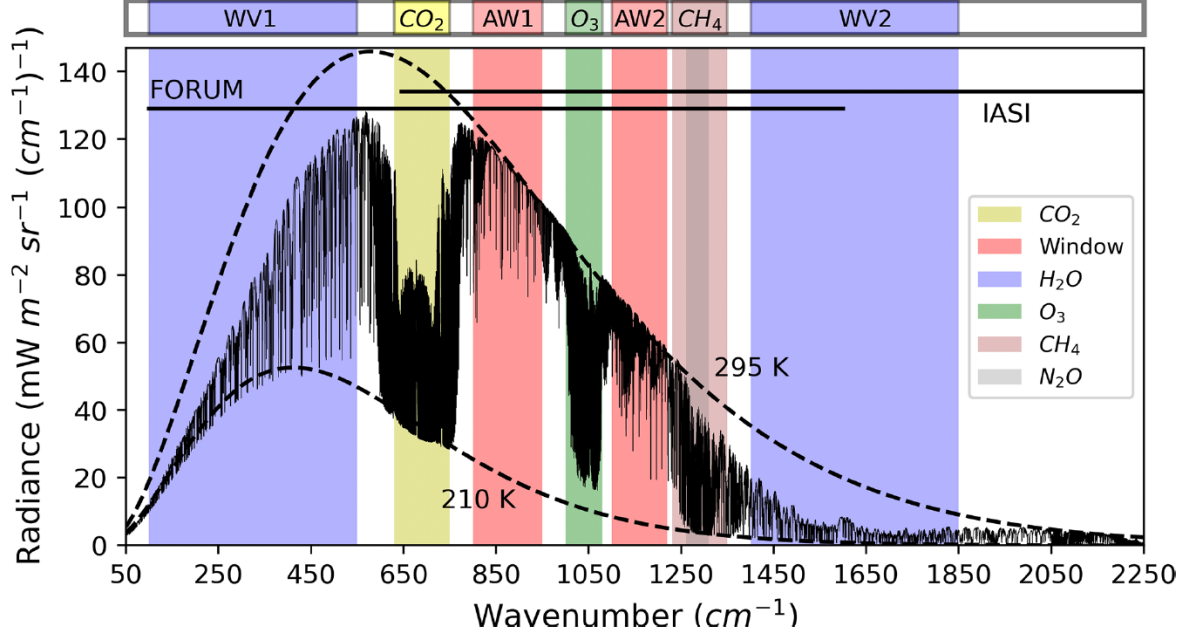


Figure 2.3: Spectrum of radiation emitted by the Earth surface and atmosphere (Della Fera, Fabiano, Raspollini, Ridolfi, Ugo Cortesi, et al. 2023) ($1 \text{ cm}^{-1} = 10 \times 10^4 \mu\text{m}$).

stable over time. However, this equilibrium can be perturbed by natural (internal) or anthropogenic (external) factors, collectively known as radiative forcings. An example of natural forcing can be a volcanic eruption or the change in solar variability; while anthropogenic forcings can be related to variations of the atmospheric composition or land surface. The increase in atmospheric concentration of carbon dioxide due to human activities is the largest external forcing that characterizes the modern era. Given the human ability to alter the climate, it is of paramount importance to quantify the effect of external perturbations, as well as the climate system response.

The GMST (T_s) is the main variable used to measure the state of the climate. In the context of the climate change, it is used to quantify the climate system response to an imposed external forcing, such as the increase in GHGs concentration, taking into consideration all the possible internal feedbacks. The GMST change in response to perturbations that give rise to an energy imbalance can be approximated by the following linear equation:

$$\Delta N = \Delta F + \lambda \Delta T_s \quad (2.4)$$

where, ΔN is the change in net radiative flux at TOA, ΔF is the perturbation driven by a radiative forcing, λ is the net feedback parameter and ΔT_s is the change in GMST.

The relationship between the magnitude of the perturbation and the climate system response expressed as a temperature change is quantified by the *climate sensitivity*. A common metric to assess the magnitude of the climate system response under the increase in GHGs concentration is the equilibrium climate sensitivity (ECS). Indeed, the ECS is

defined as the change in GMST required to restore the radiative equilibrium of the planet in response to a doubling of the carbon dioxide concentration (ΔF_{2xCO_2}).

$$ECS = -\frac{\Delta F_{2xCO_2}}{\lambda} \quad (2.5)$$

Estimating the ECS is important because it provides a measure of the sensitivity of the climate system to external perturbations (Stevens et al. 2016). This can be done in several ways, which include the use of paleoclimate records (from paleoclimatic proxies), reanalysis, observations and climate models. The ultimate response of the climate system to external perturbations is also affected by *radiative feedbacks*. Radiative feedbacks account for all those mechanisms that modify the system radiative response as a temperature change, and thus having an impact on the ECS. They can be positive, in which case their effect is to amplify the magnitude of the response, further destabilizing the Earth system, or negative if they reduce it and act to stabilize the system.

In equation 2.5, the net feedback parameter λ , can be approximated as the sum of different contributions from variables that have an effect on the net TOA radiative flux N :

$$\lambda = \sum_x \lambda_x \quad (2.6)$$

where,

$$\lambda_x = \frac{\partial N}{\partial x} \frac{dx}{dT} \quad (2.7)$$

The major physical feedbacks of the climate system that affect the TOA energy budget are:

- **Planck feedback**, in response to global warming the planet will emit more longwave radiation to space (negative feedback);
- **lapse-rate feedback**, the change in temperature profile induces change to the emission of longwave radiation;
- **water vapor feedback**, in a warmer climate the atmosphere gets moister leading to an enhanced water vapor greenhouse effect;
- **surface albedo feedback**, the planet shortwave absorptivity increase due to the decrease of areas covered by ice and snow;
- **cloud feedback**, change in clouds properties could affect both the shortwave absorptivity and longwave emissivity.

Feedback assessment in the context of the IPCC AR6 is reported by Figure 2.4 (in red) and compared against estimates of CMIP5 (in blue) and CMIP6 (in yellow). The feedbacks considered are the Planck, water vapor, lapse-rate, cloud, biogeochemical and

biogeophysical. The net feedback is negative, meaning that it stabilizes the system. The stabilization is due to the Planck temperature feedback. The cloud feedback is characterized by the greatest uncertainty in all the three estimates. The spread in ECS estimates using climate models reflect uncertainties in the quantification of climate feedbacks (Zelinka et al. 2020).

The feedback λ_x , associated to a particular variable x , can be calculated using the radiative kernel method (B. J. Soden et al. 2008). The kernel, $\frac{\partial N}{\partial x}$, obtained perturbing x within a radiative transfer code, is then multiplied by $\frac{dx}{dT}$ inferred from observations, reanalysis or climate models.

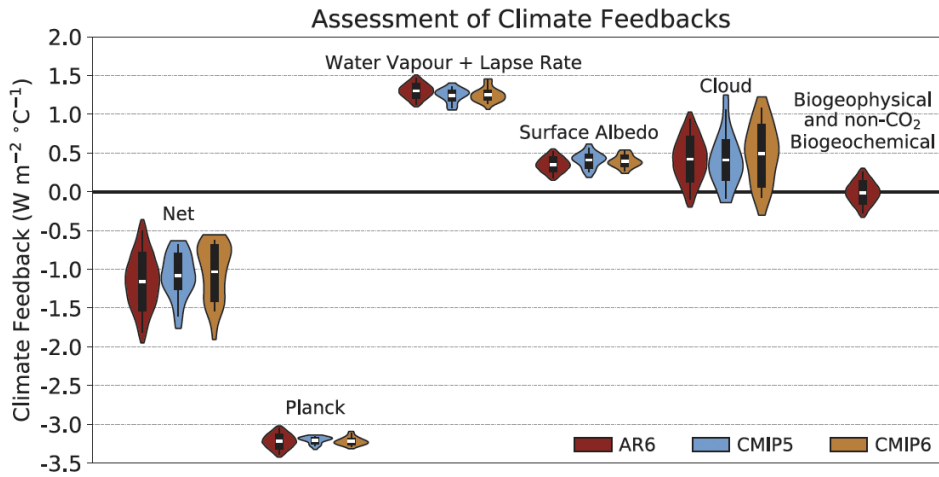


Figure 2.4: Global mean climate feedbacks estimated in the IPCC AR6 (red) compared to that calculated using CMIP6 (yellow) and CMIP5 (blue) abrupt4xCO2 (Figure taken from the IPCC AR6).

2.1.3 Internal variability of the climate system

In addition to external forcings, that drive the TOA EEB out of balance, fluctuations around the long-term global mean always occur as a result of internal climate variability arising from the continuous energy redistribution within the climate system. Over a variety of spatial and temporal scales, energy is exchanged between the different components of the climate system, involving positive and negative feedback mechanisms and strong interactions between them. Due to the wide range of space and time scales over which these processes occur, an even redistribution of energy is never reached and energy is exchanged perpetually.

The imprint of internal variability is superimposed on the signal of external forcings in climate records, so as separating forced from unforced variability is not an easy task (Frankcombe et al. 2015; Wills, Battisti, et al. 2020), further complicating the detection and the quantification of the climate change. Internal variability constitutes also a cause of uncertainty for future climate projections, comparable to other sources (Lehner and

Clara Deser 2023). It is therefore of crucial importance to assess how climate models reproduce related physical processes (Fasullo, Phillips, and Deser 2020; Jain et al. 2023).

Given the dominant effect of the inter-annual variability on the short term trend of the TOA EEB, it has been estimated that multi-decadal records are needed to accurately quantify the long-term response related to the climate change (Uribe, Bender, and Mauritsen 2022). Although caution has to be taken in predicting the future evolution of the EEB on the basis of its behaviour on short temporal scales (Uribe, Bender, and Mauritsen 2022), short-term unforced variability can provide much information on the processes on longer timescales, especially on the long-term feedback related to the climate change. In this context, there has been a rising interest in emergent constraints. Emergent constraints are based on the existence of a significant relationship between an observable and a future climate variable. If such a significant relationship exists, then internal variability feedbacks calculated using observations can be used to constrain long-term forced feedback in climate models (Andrew E Dessler 2013; Uribe, Bender, and Mauritsen 2022). Although, this may represent a promising way to improve climate models performances in anticipation to longer observational records, their robustness must be carefully tested.

An important relation that governs short-term climate variability is the coupling between the ocean and atmosphere (Kayano, Rao, and Andreoli 2005). This interaction is controlled by both dynamic and thermodynamic processes. Solar radiation absorbed by the ocean is returned back to the atmosphere through radiation, conduction and evaporation. This is particularly important at the tropics, where solar irradiance is highest. Energy transfer from the ocean to the atmosphere is also accomplished through latent and sensible heat release. The solar differential heating of the tropics and polar regions is the main driving force for the atmospheric general circulation, which act to reduce the heat gradient with the meridional transfer of energy from the tropics to extratropics. An important role is also played by oceanic currents, which contribute to the meridional transfer of sensible heat.

On the inter-annual time scale the Tropical Pacific Ocean is characterized by ENSO activity (McPhaden, Santoso, and Cai 2020). ENSO causes the change in the SST pattern of the Tropical Pacific Ocean coupled to changes in the above atmospheric circulation. Its impact on the SST and sea level pressure (SLP) across the Tropical Pacific Ocean, in turns affects the rainfall patterns in the near coasts of South America and Indonesia which experience anomalous droughts or extreme weather events. ENSO effects are not limited to the Pacific Ocean but are spread worldwide through teleconnections, reaching remote basins (Klein, B. J. Soden, and Lau 1999). With its important implications for society, there is a great interest in understanding ENSO dynamics and related physical mechanisms to improve both its predictability in weather forecasts and its simulations in GCMs. It is also important to understand how ENSO will evolve in a changing climate (Beobide-Arsuaga et al. 2021).

El-Niño Southern Oscillation

ENSO variability is characterized by two phases: El-Niño, also called the warm phase of ENSO, and La-Niña, referred to the cold phase. La-Niña and El-Niño are referred to the "oceanic part" of this variability mode, which involves changes in the SST pattern of the Tropical Pacific Ocean, while the term Southern Oscillation refers to the "atmospheric part", which involves perturbations to the sea level pressure (SLP). It has been recognized that these two different processes are correlated and that they are part of a single phenomenon, referred to as "El-Niño Southern Oscillation". During an El-Niño episode SLP are higher than normal in the southeastern Tropical Pacific, SST anomalies are positive in the eastern and central part of the Tropical Pacific Ocean and negative in the western part, an eastward shift of the Walker Circulation (WC) is also observed. The opposite phase, La-Niña, is accompanied by a reversed pattern: negative SST anomalies in the eastern and central part of the Tropical Pacific Ocean, positive in the western part of the basin, and a strengthening of the WC. The ocean-atmosphere system oscillates between warm and cool ENSO phase without a given periodicity. They alternate with a period that varies from 2 to 10 years. The peak is observed between 3 and 4 years. Normal conditions are between the positive (El-Niño) and negative (La-Niña) phase, resembling more this last. ENSO phases and their effects on the atmosphere and ocean components are shown in Figure 2.5.

In normal conditions there is a temperature gradients of about 8 degree Celsius between the eastern and western part of the Tropical Pacific Ocean, with the western part climatologically warmer than the eastern. This is associated with an eastward air movement which constitutes the Walker Circulation (WC). Air raises above Indonesia and sink near the coasts of South America. The cell of the WC is completed by western trade winds which induce upwelling of cold water near the Peruvian coast and accumulation of warm waters in the western part of the basin. In such way the sea level is from 50 cm to 1 m higher in the western part than in the eastern part, causing the thermocline to rise in the eastern Tropical Pacific and to deepen in the western. This in turn drives the surface temperature gradient. Any perturbation to the SST therefore will also affect the WC. The development of an El-Niño event is associated to the relaxation of the trade winds. The thermocline deepens in the eastern part of the tropical Pacific and rise in the western part. A warm pool forms at its the central and eastern, where a region of deep convection is settled. The WC is split into two cells with one descending branch over Indonesia and the other over the northern/northeastern South America. During La-Niña phase these atmospheric and surface conditions are almost reversed.

ENSO is usually classified by means of an index based on temperature or pressure anomalies which informs on its magnitude and phase. SST or SLP anomalies are calculated for an area-averaged value over a certain region of interest for ENSO activity within

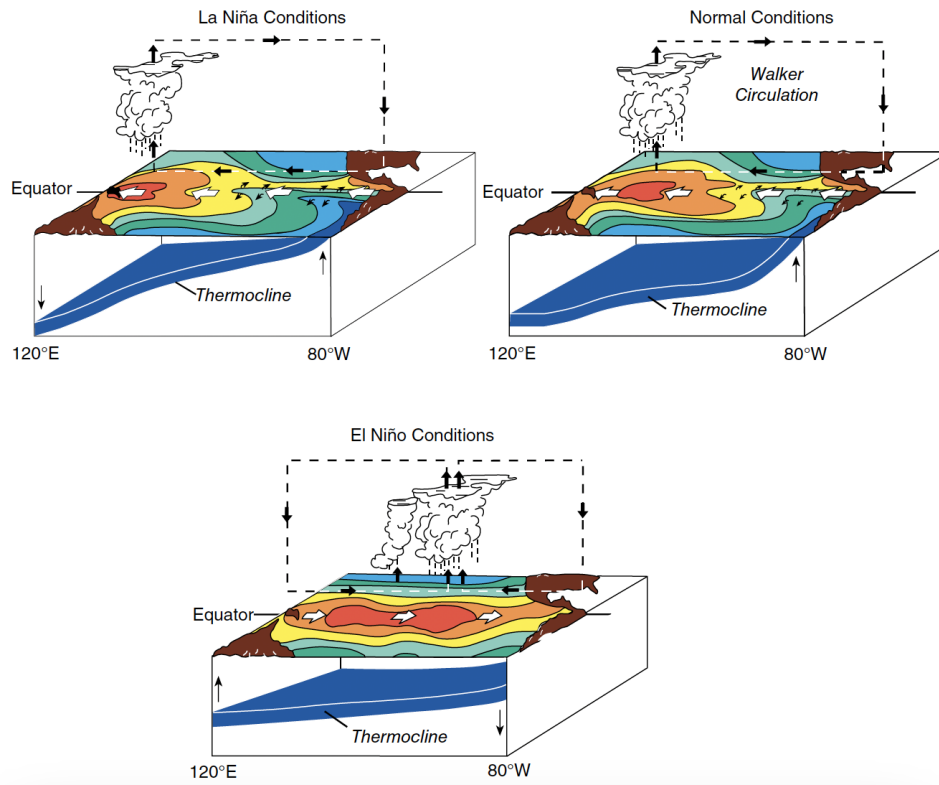


Figure 2.5: ENSO phases, La-Niña (top left), neutral (top right), El-Niño (bottom), and their implications for the SST, thermocline and atmospheric circulation. Credits: McPhaden, Santoso, and Cai [2020](#).

the tropical Pacific Ocean. During years different indexes have been proposed (Hanley et al. [2003](#)): Niño-1+2 (0-10S, 90W-80W), Niño-3 (5N-5S, 150W-90W), Niño-3.4 (5N-5S, 170W-120W), Niño-4 (5N-5S, 160W-150W) (Figure [2.6](#)). Historically, the indices were named after the ships that crossed these regions, which allowed El-Niño records to date back to 1949 (Rasmusson and Carpenter [1982](#)).

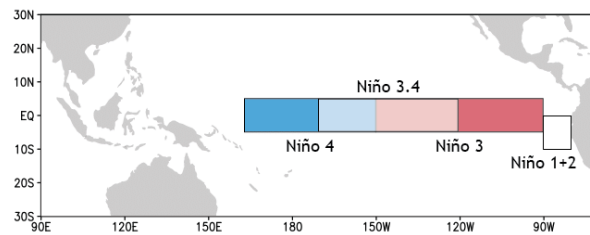


Figure 2.6: ENSO SST base indices and their respective region (credits: Quispe [2018](#)).

2.2 Understanding the climate system: observations and models

To study the physical processes behind the variability of the Earth climate we can rely on observations and climate models.

2.2.1 Satellites instruments

Satellite measurements of the OLR has strongly contributed to advance our understanding of the EEB and to investigate the atmospheric and surface properties that shape the OLR variability.

The OLR is defined as the flux of radiant energy emitted by the Earth and integrated over all the wavenumbers.

It can be directly measured by satellite-based radiometers or reconstructed from spectrally resolved radiances ($\text{Wm}^{-2} \text{sr}^{-1} (\text{cm}^{-1})^{-1}$) measured by spectrometers deployed on satellites, stratospheric balloons, or aircrafts.

A radiometer is an instrument designed to measures the radiant flux. Satellite radiometers can be classified in non-scanning or scanning instruments. Non-scanning instruments or wide-field-of-view (WFOV) directly measure the radiative flux (Wm^{-2}) at the satellite altitude from limb to limb, over a wide wavelength range. Instead, scanning instruments or narrow-field-of-view (NFOV) acquires measurements of the Earth radiance ($\text{Wm}^{-2} \text{sr}^{-1} (\text{cm}^{-1})^{-1}$) over a narrow spectral interval, scanning the position of that narrow spectral interval across the spectrum. They are called *spectroradiometers*. Spectroradiometers with an intentional wide spectral coverage are referred to as *broadband* radiometers. Broadband radiometers are for example the Earth Energy Budget Experiment (ERBE) (B. Barkstrom and Hall Jr 1982), SCAnner for RAdiation Budget (ScaRaB) (Kandel et al. 1998) or the Clouds and Earth Radiant Energy System (CERES) (Wielicki, Bruce R Barkstrom, et al. 1996). Spectroradiometers that measure the radiance over a narrow spectral range are hyperspectral sounders, which measure the spectrally resolved radiance. Examples of hyperspectral sounders are the Infrared Atmospheric Sounder Interferometer (IASI) (Simeoni et al. 2004), High Resolution Infrared Sounder (HRIS) (Dozier and Goetz 1989), Atmospheric InfraRed Sounder (AIRS) (Aumann et al. 2003) or Cross-Track Infrared Sounder (CrIS) (Stumpf and Overbeck 2002).

For NFOV instruments, which measure the Earth emitted radiance ($\text{Wm}^{-2} \text{sr}^{-1} (\text{cm}^{-1})^{-1}$) and not the flux, the radiance is then used to reconstruct the corresponding flux (Su et al. 2015; Simon Whitburn, Clarisse, Bauduin, et al. 2020; X. Huang, JPL, et al. 2019).

In addition, instruments can fly on board satellites with a sun-synchronous or geostationary orbit. In the first case the instrument samples each pixel always at the same time, and it is characterized by a crossing time of the equator. If the satellite orbit is

geostationary, the satellite follows the Earth motion and crosses always the same location during the entire revolution of the planet. A sun-synchronous orbits around Earth at 600-800 km, while a geostationary orbits at a higher distance (approximately 36000 km from the Earth surface).

OLR variability from satellite observations

Thanks to satellite observations we can study OLR variability both in space and time. The first satellite observations date back to the 1960s, meaning that combining data from multiple instruments about 60 years of observations can be gathered. However, combining measurements from different instruments is not straightforward, presenting several issues which affect the accuracy of the calculation of the OLR long-term trend. Data from different instruments show differences of a few Wm^{-2} due to absolute calibration (Loeb, Kato, et al. 2012). If there is an overlap in their observational records it is possible to place the records on a common radiometric scale. In G. L. Smith et al. 2006 they derive a set of standard deviations to properly connect measurements from different radiometers, particularly ERBE, ScaRaB I and II and CERES instruments are considered. Exploiting overlapping periods between ERBE and CERES, Wielicki, Wong, et al. 2002 analysed OLR changes over the 22-years period from 1979 to 2002. Remarkably large anomalies, of the order of 5 Wm^{-2} are obtained, highlighting the high variability of the climate system. Peaks of about 3 Wm^{-2} are observed in correspondence of the major volcanic eruptions. Positive (negative) peaks are also associated to El-Niño (La-Niña) phases related to ENSO activity. OLR changes during these decades evidence a strengthening of the Tropical General Circulation, as further confirmed by the analysis of other physical variables: upper tropospheric humidity, cloud amount, surface air temperature, vertical velocity (J. Chen, Carlson, and Del Genio 2002). Dewitte and N. Clerbaux 2018 analysed OLR variability from 1985 to 2017 using observations from the High-resolution Infrared Radiation Sounder (HIRS), CERES and ERBE, providing an empirical estimate of the longwave climate feedback parameter of $2.93 \pm 0.3 \text{ Wm}^{-2}\text{K}$, that show the climate system response to the rising of GMST: the emission of OLR to space is enhanced in order to restore thermal equilibrium. Regional patterns show strong OLR variations associated to surface warming in the Arctic and cloud changes in the Tropical Pacific Ocean associated to ENSO. Interannual variability of the EEB is investigated by Kato 2009, which analyses both SW and LW outgoing fluxes over the 2000-2004 period of CERES measurements. Tropical western and central Pacific are the regions associated to the higher standard deviations due to ENSO activity. Loeb, Kato, et al. 2012 and Susskind et al. 2012 analyse OLR variability on the interannual time scale, using the first ten years of CERES observations, which show mainly changes driven by ENSO, the dominant variability model of climate system on this time scale.

2.2.2 Simulating the Earth climate

Climate models are the main tool to study how the Earth climate system works and evolves, allowing to conduct experiments across multiple time and spatial scales. This comprises also the possibility to look ahead into future climate scenarios, which plays a fundamental role in the context of the present-day climate change, to ultimately develop strategies to cope with it.

Climate models simulate the Earth climate based on the knowledge of the physical processes that drive the evolution of the various components of the climate system such as the atmosphere, ocean, cryosphere, land and biosphere, and the carbon cycle, in most sophisticated models (i.e. Earth System Models, ESMs). Fundamental laws of nature (e.g. mass, momentum and energy conservations) describing the evolution of a specific climate variable are expressed in mathematical terms and the corresponding equations are implemented in large numerical models to be solved. Given the complexity of these equations, their solution is obtained using numerical integration techniques, which allow the solution for a discretized mathematical expression over a finite grid and specific time-steps, which determine the model resolution. Models of high complexity use 3-dimensional grids defined over latitude, longitude and a vertical coordinate. The size of the time steps and the horizontal grid over which the integration is implemented affects the models accuracy as well as the computational cost of the calculation.

Some physical processes are not explicitly represented in CMs, because of high level complexity or limits in the spatial/temporal resolution (i.e. sub-grid processes). To cope with that parametrization schemes are introduced. This implies the choice of a set of parameters for each of them. The choice is based on different factors that may involve mathematical convergence and physical considerations, observations or their combination. Climate models are tuned on observations. One of the most important global tuning targets for the CMIP6 is the TOA heat flux and its radiative components. In addition, simplifications involving the physical processes to be included are necessary to contain the computational costs.

The field of climate modelling developed from numerical weather predictions. Their evolution has followed advances in computational resources. Starting from simple models accounting only for fluid dynamics and with a limited spatial and vertical resolution, the availability of super computers allows state of the art CMs to provide a global coverage and account for complex interactions between different compartments and composition changes, with increased spatial resolution of the order of km as well as simulation length.

Trade-offs among previous considerations lead to CMs of different complexity (Figure 2.7). Based on the processes that are included there are energy balance models (EBMs), Earth models of intermediate complexity (EMICs) and general circulation models (GCMs). Global Earth system models (ESMs) are the most advanced kind of CMs

simulating interactions between the ocean and the atmosphere and other components, such as the global biogeochemical cycles (e.g. carbon cycle), interactive vegetation and ice sheets. At the core of an ESM there is a GCM representing the coupled dynamics of the atmosphere and ocean.

The basic dynamical framework of a GCM involves the solution of equations that describe the conservation of momentum, mass and energy for a fluid. An equation to account for water conservation is also included to predict the amount of water vapor within the atmosphere. Equations of the motion for the atmospheric component can be written in a simplified form thanks to some approximations. The vertical momentum balance is approximated with the hydrostatic balance, since the atmosphere is thin compared to its horizontal dimension, and the Earth is assumed to be spherical. These, along with some other small terms in the momentum equation that can be neglected, form the so-called primitive equations. The sigma coordinate is used as vertical coordinate:

$$\sigma = \frac{p}{p_s} \quad (2.8)$$

it is pressure (p) normalized by surface pressure (p_s). For a numerical model of the atmosphere the primitive equations expressed in vector notation are the following:

- Momentum conservation

$$\frac{D\vec{V}}{Dt} + f\vec{k} \times \vec{V} + \vec{\nabla}\Phi + RT\vec{\nabla}\ln p_s = \vec{P}_V \quad (2.9)$$

- Energy conservation

$$\frac{DT}{Dt} - \frac{RT\omega}{c_p p_s \sigma} = P_T \quad (2.10)$$

- Water vapor conservation

$$\frac{Dq}{Dt} = P_q \quad (2.11)$$

- Mass conservation

$$\frac{Dp_s}{Dt} - p_s \vec{\nabla} \cdot \vec{V} + \dot{\sigma} \frac{\partial}{\partial \sigma} \quad (2.12)$$

- Hydrostatic balance

$$\frac{\partial \phi}{\partial \sigma} = -\frac{RT}{\sigma} \quad (2.13)$$

Where D/Dt represents the time derivative following the motion of a fluid, in sigma coordinates it becomes:

$$\frac{D}{Dt} = \frac{\partial}{\partial t} + \vec{V} \cdot \vec{\nabla} + \dot{\sigma} \frac{\partial}{\partial \sigma} \quad (2.14)$$

$\vec{V}$ is the horizontal vector wind, $\dot{\sigma}$ is the sigma component of velocity, f is the Coriolis parameter, $\vec{k}$ is the vertical unit vector, $\vec{\nabla}$ is the two-dimensional gradient operator on

a surface of constant sigma, Φ is the geopotential field, R is the gas constant, c_p is the specific heat of dry air, and P_x denotes the rate of change of a variable x as a result of parametrized processes.

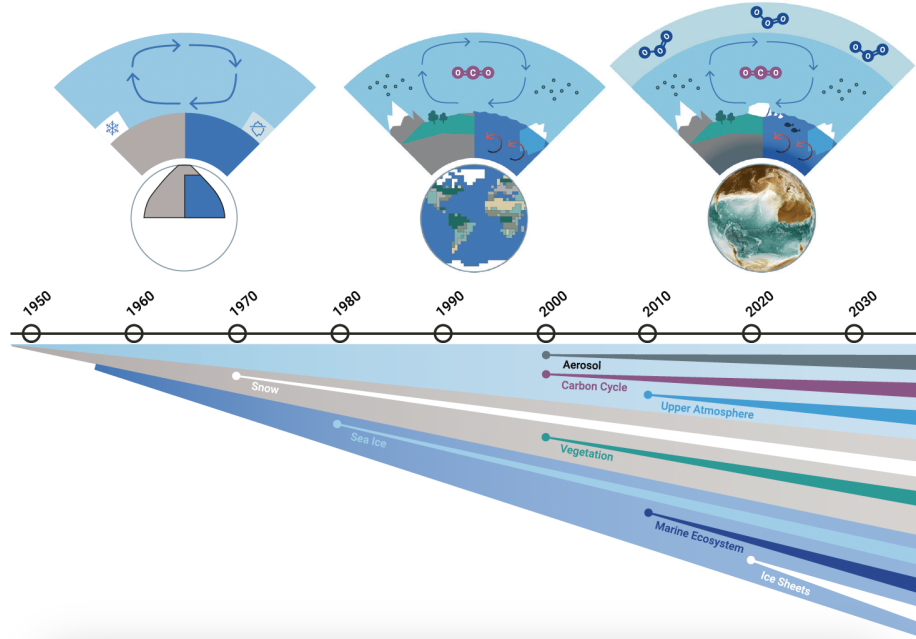


Figure 2.7: Evolution of climate models complexity (Bordoni et al. 2025)

The model resolution, parametrization schemes as well as the formulation of the CM itself all contribute to determine its performance. Climate models need to be validated to assess the reliability of their simulations. Validation is performed comparing climate models outputs against the respective observations.

The Coupled Model Intercomparison Project (CMIP)

The Coupled Model Intercomparison Project (CMIP) is an international multi-model research activity promoted by the World Climate Research Programme (WCRP) which collects climate models simulations developed by research centers around the world. One of its main objectives is to make multi-model outputs publicly available in a standardize format to facilitate analysis by the climate models community and users. The CMIP project provides outputs from different kind of simulations to address a wide range of scientific questions. The CMIP phase 6 provides baseline experiments, which are grouped under the so-called Diagnostic, Evaluation and Characterization of Klima (DECK) experiments and the CMIP6 historical simulations. Additional experiments are designed to address specific scientific questions that were chosen during the sixth phase (Eyring et al. 2016). The DECK experiments comprise the atmosphere model intercomparison project (AMIP) simulation, the multi-century pre-industrial control simulation, the abruptly quadrupling CO_2 and the 1% CO_2 increase simulation. AMIP simulations are run with SSTs

and sea ice concentration (SICs) prescribed to observed values, as such they are primarily designed to evaluate the atmospheric component of a climate model, in addition to climate variability. Besides ocean conditions, realistic forcings are imposed: volcanic aerosols, solar variability, GHGs concentrations and anthropogenic aerosols. They span the time from 1979 to 2014. Pre-industrial control simulations reproduce a stable quasi-equilibrium climate state under 1850 conditions. This mean that no secular changes in forcings (nor natural or human) are applied. This kind of experiment is conceived to study unforced climate variability. The two last DECK experiments are designed to study the climate system response to GHG forcing. For the abruptly quadrupled CO₂, the system is forced to undergo an immediate increase in CO₂ concentration of four times the global annual mean concentration relative to 1850. While in 1% CO₂ increase simulation the CO₂ concentration is increased of 1% per year. Finally, the CMIP experiments simulate the climate over the historical period defined as the time from 1850 to the present days. They are forced with the same natural and anthropogenic forcings based on observations as the AMIP simulations. CMIP models enable us to evaluate the ability of climate models to simulate the climate and its variability over centuries.

Experiment short name	CMIP6 label	Experiment description	Forcing methods	Start year	End year	Minimum no. years per simulation	Major purpose
DECK experiments							
AMIP	<i>amip</i>	Observed SSTs and SICs prescribed	All; CO ₂ concentration prescribed	1979	2014	36	Evaluation, variability
Pre-industrial control	<i>piControl</i> or <i>esm-piControl</i>	Coupled atmosphere–ocean pre-industrial control	CO ₂ concentration prescribed or calculated	n/a	n/a	500	Evaluation, unforced variability
Abrupt quadrupling of CO ₂ concentration	<i>abrupt-4×CO2</i>	CO ₂ abruptly quadrupled and then held constant	CO ₂ concentration prescribed	n/a	n/a	150	Climate sensitivity, feedback, fast responses
1 % yr ^{−1} CO ₂ concentration increase	<i>1pctCO2</i>	CO ₂ prescribed to increase at 1 % yr ^{−1}	CO ₂ concentration prescribed	n/a	n/a	150	Climate sensitivity, feedback, idealized benchmark
CMIP6 historical simulation							
Past ∼ 1.5 centuries	<i>historical</i> or <i>esm-hist</i>	Simulation of the recent past	All; CO ₂ concentration prescribed or calculated	1850	2014	165	Evaluation

Figure 2.8: Experiments included in the CMIP phase 6 and their main features.

Chapter 3

ENSO-driven OLR variability in CMIP6 models

The ability of climate models to correctly reproduce OLR variability is a strict test of their reliability (MD Palmer and McNeall 2014). On the inter-annual timescale, OLR variations are mostly affected by ENSO variability (Susskind et al. 2012; Loeb, Kato, et al. 2012). Understanding whether the current generation of GCMs is able to reproduce ENSO variability brings along important issues such as those related to the future evolution of ENSO (Beobide-Arsuaga et al. 2021; Wills, Dong, et al. 2022; Seager, Henderson, and Cane 2022). Uncertainties in ENSO simulations also affect estimates in ECS and other parameters that are used to quantify the climate system response to the climate change. (Rugenstein, Dhame, et al. 2023; Andrews, Bodas-Salcedo, et al. 2022; K. C. Armour et al. 2024; Dong et al. 2021).

ENSO is a complex phenomenon, featuring different flavours, which characterize each single El-Niño/La-Niña event, such as the amplitude and the periodicity, or the phase locking, whereby the La-Niña and El-Niño typically peak in intensity during the boreal winter, or the teleconnections, through which ENSO perturbations are spread globally. Although there has been a great improvement in ENSO simulation by coupled general circulation models (CGCMs) - physical processes parametrization, higher vertical and horizontal resolution ... -, which has led to a better representation of the SST pattern in the Eastern Tropical Pacific, as well as a better simulation of ENSO periodicity, there are still biases in the multi-model mean climate - mean state, annual cycle and interannual variability of the Tropical Pacific - that in turn affect the simulation of other ENSO features, such as the amplitude, periodicity, asymmetry and the spatial pattern (É. Guilyardi et al. 2004; Bayr et al. 2018). As they are all correlated, it is difficult to identify the sources of errors in CGCMs. Therefore, it is important to understand whether improvements to the atmospheric or oceanic components are needed to achieve the most accurate ENSO simulation (E. Guilyardi et al. 2009).

The ability of a subset of CMIP6 models in reproducing the inter-annual variability of

the EEB has been assessed by Loeb, H. Wang, et al. 2020 using CERES satellite observations. A surprisingly agreement has been found between simulations and observations. Instead, Vijayeta and Dommenges 2018 showed that CMIP3 and 5 generation of models underestimate the negative and positive atmospheric feedbacks, and errors in the oceanic and atmospheric components compensate each other. Atmospheric and oceanic feedbacks play an important role in shaping ENSO dynamic, such as the thermocline depth and the east-west SST gradient in the tropical Pacific. Recently, Planton et al. 2021 presented a package providing a set of diagnostics to allow for a systematic evaluation of several ENSO features in climate models, which has been used to test CMIP5 and 6 simulations.

In support to previous studies cited above, this chapter presents an evaluation of the ability of CMIP6 models in reproducing the inter-annual variability of the EEB driven by ENSO. Specifically, our focus is the evaluation of the OLR component, performing an extensive assessment of the biases that characterize the historical CMIP and AMIP simulations of the CMIP6 generation. To evaluate whether climate models are able to correctly reproduce the radiative response to ENSO, OLR derived from CERES observations are used as reference against which simulated fluxes are compared to. The bias respect to observations and the inter-model spread in OLR response to ENSO is investigated. The comparison is performed over the years from 2000 to 2014, over which models simulations and satellites observations overlap. Although clouds play an important role in mediating the TOA radiative response to ENSO atmospheric and surface perturbations, the analysis has been focused on clear-sky conditions. The main reason is that clouds introduce a high level of variability. Therefore, we decided to first analyse the clear-sky conditions, and leave the all-sky scenario for a future analysis. Secondly, not all observational datasets provide fluxes under all-sky conditions. Since our aim was to compare the outputs of climate models with spectral satellite observations, the analysis was limited to clear-sky scenario, for which both AIRS and IASI data products provide fluxes.

Initially, it was evaluated how CMIP6 models reproduce the correlation between radiative anomalies and ENSO activity, in both space and time dimension. Then, the analysis focused on a particular aspect of ENSO induced variability, which is the time relationship between radiative and SSTs anomalies. This is carried out performing a lagged regression analysis between radiative and SSTs anomalies driven by ENSO. The lag between the TOA OLR response and ENSO set the context for the rest of the work, which involves the investigation of the physical processes driving the peak of the radiative response (Chapter 4) using spectral OLR measurements, and their assessment in CMIP6 models (Chapter 5).

3.1 Data

3.1.1 CMIP6 outputs

Among the available CMIP6 experiments we used clear-sky OLR outputs from AMIP and CMIP simulations, which corresponds to the *'rlutcs'* CMIP6 variable table. As far as AMIP simulations have been concerned they allow to investigate the role of the atmospheric component of CMIP6 models. Indeed, in addition to external radiative forcings (i.e. carbon dioxide, longed and short-lived greenhouse gases, solar variability and land use), AMIP simulations are forced with monthly time-varying fields of SSTs and SICs prescribed to observed values. This means that the model atmosphere responds to the oceanic SSTs forcing, but there is not such a corresponding response of SSTs to atmospheric driven perturbations. According to the CMIP6 protocol (Eyring et al. 2016), AMIP simulations cover the period from 1979 to 2014. In addition to CMIP6 AMIP experiments, we chose to evaluate also CMIP historical simulations, which simulate the observed climate and associated changes over the historical period from 1850 to 2014. These are atmosphere-ocean coupled simulations, meaning they are run with interactive oceanic and atmospheric components. As such, these simulations include a two-way ocean-atmosphere coupling, allowing to assess how models reproduce this interaction. They are forced with the same time dependent external forcing as AMIP (except for the SSTs and SICs).

A total of 38 models for which OLR outputs were available for both AMIP and CMIP historical runs have been chosen. The models considered are reported in the Appendix B. Only the first ensemble member (*'r1i1pif1'* CMIP6 output) is taken into account. Since climate models have different horizontal resolution and grid, they have all been regridded by means of a bilinear interpolation, to a common grid of 2.5° latitude per 2.5° longitude.

3.1.2 CERES satellite observations

Climate models outputs are evaluated against OLR fluxes derived from observations of the Clouds and Earth Radiant Energy System (CERES), which represents the reference for the evaluation of radiative fluxes in climate models. CERES is a broadband radiometer (Wielicki, Bruce R Barkstrom, et al. 1996). It is provided with three channels that measure radiances across the whole spectrum ($0.3\text{--}200\text{ }\mu\text{m}$), the shortwave (SW, $0.3\text{--}5\text{ }\mu\text{m}$) and the atmospheric window ($8\text{--}12\text{ }\mu\text{m}$) regions. Multiple CERES instruments have been deployed on several platforms. CERES has flown on board Terra and Aqua platforms since 2000 and 2002, respectively, and on the Suomi National Polar-Orbiting Partnership (SNPP) since 2011, and most recently on NOAA-20 since 2017. The instrument has a 20 km nadir-viewing footprint and provide a daily global coverage. OLR fluxes are calculated from CERES radiances exploiting a set of angular distribution models (ADMs) (Su et al.

2015).

Here the CERES energy balanced and filled (EBAF) edition 4.1 data product is used (Loeb, Rose, et al. 2020). It is built on data collected by different CERES instruments on board Terra and Aqua platforms since 2000 to present days (data collection is still ongoing). This dataset provides monthly mean OLR fluxes in clear and all-sky conditions, for the period 03/2000 - 03/2022, with a grid resolution of $1^\circ \times 1^\circ$. Two clear-sky products are available: EBAF Ed4.1 clear-sky fluxes estimated following the approach used for climate models, so that the comparison between models and observations is as consistent as possible, and clear-sky fluxes calculated using observations corresponding to clear-sky pixels only (named "total region"). The first product has been selected for this part of the analysis, since it is more appropriate to compare with climate models. Indeed, climate models clear-sky fluxes are calculated using the same atmospheric and surface properties as all-sky fluxes but removing clouds from the atmospheric column. As a result, the corresponding top of atmosphere LW fluxes are systematically lower than observations, due to an higher moisture in the atmospheric column. To avoid this bias, an adjustment factor estimated from the difference between clear-sky fluxes calculated in the same way as climate models and the sampling approach used for observations, is added to the clear-sky fluxes. Following this approach the overall regional uncertainty in CERES EBAF Ed4.1 TOA LW clear-sky fluxes is estimated to be approximately 4.6 Wm^{-2} . The same horizontal grid has been applied to the CERES data as to the climate models, to enable a pointwise comparison.

3.1.3 Niño 3.4 index

Among the different ENSO indices that are commonly used to account for ENSO magnitude and phase (Chapter 2), the Niño 3.4 index has been chosen for the analysis. This is a common choice to study ENSO, since SST variability within this region is strongly related to the global climate (Goddard and Dilley 2005). Although other indices may be recommended for a better description of a single ENSO event, the Niño 3.4 index allows to capture basin scale variability (Barnston, Chelliah, and Goldenberg 1997), being a good indicator of the central tropical Pacific El-Niño conditions. Furthermore, using the Niño 3.4 index allows an easier comparison to the results of other studies.

Following Trenberth 1997, the Niño 3.4 index is defined as the area averaged SST anomalies within the Niño 3.4 region (5°N - 5°S , 190° - 240°E), smoothed with a 5-months running mean. An ENSO index has been calculated for each CMIP6 historical simulation, using its SST output ("tos" CMIP6 variable table). The analysis also relied on the Niño 3.4 index calculated using SSTs area averaged provided by the NOAA database (<https://www.cpc.ncep.noaa.gov/data/indices/ersst5.nino.mth.91-20.ascii>).

Figure 3.1 shows the Niño 3.4 index calculated using SSTs simulated by historical

simulations (colored lines), and the index calculated using SSTs provided by the NCAR database (black thick line). The red horizontal line is set at 0.4°C , above which an ENSO event is classified as El-Niño; the blue horizontal line is set at -0.4°C , below which an ENSO event is classified as La-Niña (Trenberth 1997).

The Niño 3.4 indices calculated using SSTs outputs of CMIP6 historical simulations (Figure 3.1, coloured thinner lines) show a different variability respect to the index calculated using observed SSTs. This is due to the fact that the coupled models are free to evolve and thus do not reproduce the same phase of the observed internal variability. A straightforward comparison between simulated and observed SSTs can be done using power spectra (AchutaRao and Sperber 2006), which allow to evaluate the ability of climate models in matching the realistic ENSO periodicity. The Welch's power spectra of the simulated and observed Niño 3.4 index are reported in Figure 3.2. Models capture the observed ENSO periodicity (black thick line) quite well, being almost all between two and seven years. However, the power is quite different to that of observations. For most of the models, a more intense peak is obtained around four years.

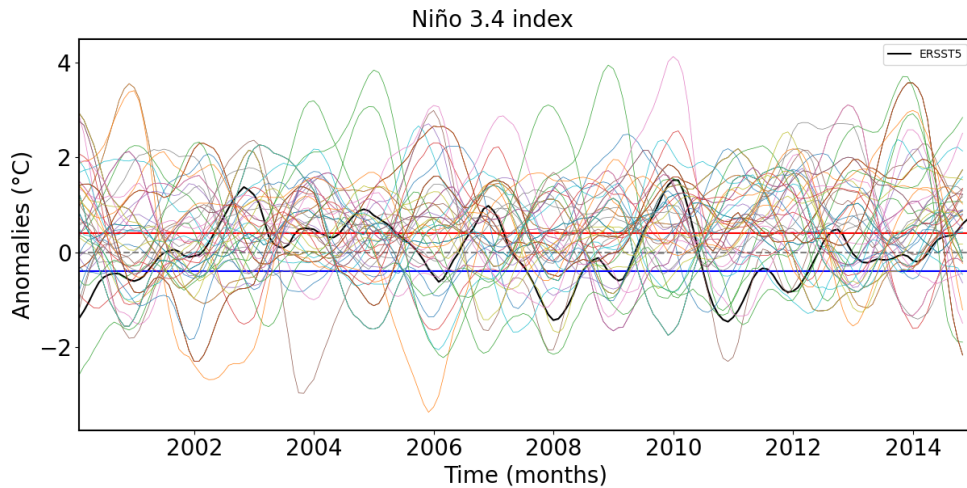


Figure 3.1: The Niño 3.4 index from 2000 to 2014 calculated using SSTs outputs of CMIP6 historical experiments (coloured thin lines) and area averaged SSTs provided by the NOAA database (black thick line).

3.2 Correlations between TOA OLR anomalies and the Niño 3.4 index

The first step of climate models evaluation has involved the assessment of the temporal correlation between OLR anomalies and the Niño 3.4 index, which provides a measure of the strength of how these two variables vary together (e.g. if they are in phase or not).

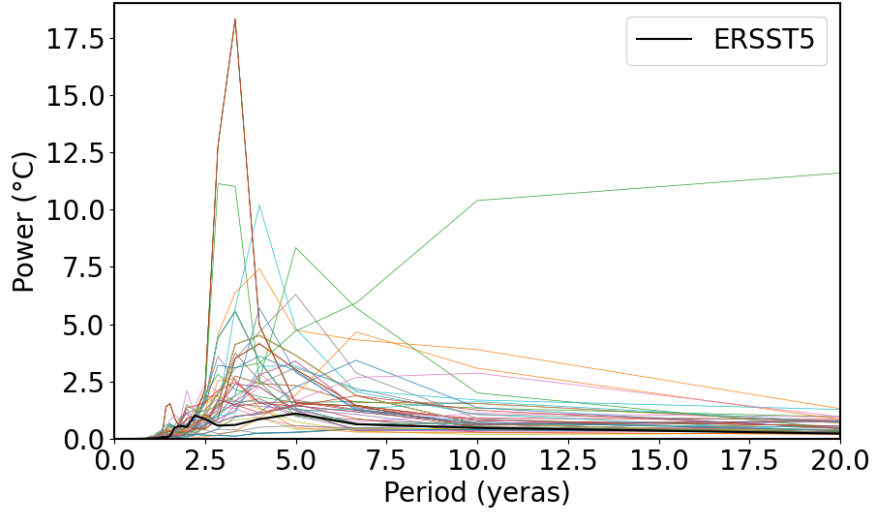


Figure 3.2: The power spectra of the SST anomalies used to calculate the Niño 3.4 index (from 1950 to 2014). SSTs outputs of CMIP6 historical experiments (coloured thin lines); area averaged SSTs provided by the NOAA database (black thick line).

The Pearson's correlation reported below has been used:

$$r = \frac{\sum (x - m_x)(y - m_y)}{\sqrt{\sum (x - m_x)^2 (y - m_y)^2}} \quad (3.1)$$

where, r is the correlation coefficient, x and y are the elements of the observed and simulated OLR anomaly time series, and m_x and m_y are their time averages. The analysis has been carried out over the 178-months period from March 2000 to December 2014, common to AMIP and historical CMIP6 models and CERES observations. OLR anomalies have been calculated by subtracting the monthly climatology to the monthly mean time series to remove the seasonal cycle. The monthly climatologies were calculated by averaging the OLR for a given month over all the same months from 2000 to 2014. The linear trend of the OLR anomalies relative to the considered period has also been removed. This approach enables the removal of OLR variations related to increased GHGs concentration and better isolation of internal system variability. The Niño 3.4 index, as obtained from the respective SST outputs, was used to calculate the correlations for CMIP6 historical models. For CERES observations and AMIP models, the Niño 3.4 index based on the NOAA SST averages was employed.

3.2.1 ENSO and the tropical mean OLR anomaly

The Niño 3.4 index suggests that during the period from March 2000 to December 2014 two major El-Niño events took place (Figure 3.3, black line). The first began in June 2002 and concluded in March 2003, peaking in January 2003. The second began in August 2009

and continued until June 2010, peaking in December 2009. In addition, two major La-Niña events also occurred between March 2007 and August 2008, and between July 2010 and March 2011, which peaked in January 2008 and January 2011, respectively.

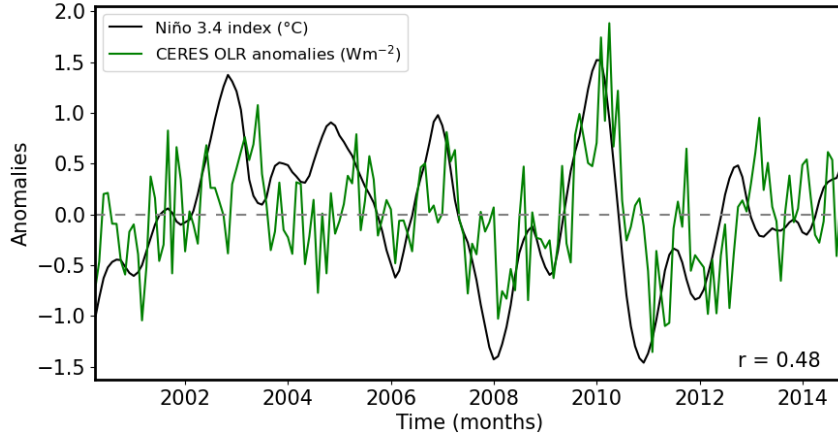


Figure 3.3: The Niño 3.4 index calculated using SSTs averages of the NOAA database (black line) and OLR anomaly calculated using CERES fluxes (green line). r is the correlation coefficient between the two time series calculated over the period from March 2000 to December 2014.

In Figure 3.3 the tropical mean OLR anomaly calculated using CERES observations is superimposed on the Niño 3.4 index. As in Ceppi and Fueglistaler 2021, OLR anomaly have been averaged over the tropical zone ($30^{\circ}\text{N} - 30^{\circ}\text{S}$), where the radiative perturbations induced by ENSO are strongest, using only values above ocean, to avoid variability from land induced by surface temperature variations.

The OLR anomaly closely tracks ENSO phases, with positive values observed in correspondence with El-Niño events, and vice versa for La-Niña conditions. For example, in correspondence with the strong El-Niño event of 2010, when the SST anomaly reached 1.5°C , consistent OLR anomalies of about 1.5 Wm^{-2} are observed. Instead, negative peak of OLR anomalies characterize the two La-Niña episodes in 2008 and 2009, when SST anomalies are lower than -1°C . We obtain a correlation between CERES OLR anomalies and the Niño 3.4 index of 0.48. This is in line with Loeb, Kato, et al. 2012, which reports an even stronger relationship between CERES all-sky tropical OLR anomalies and ENSO (quantified by the Multivariate ENSO Index (MEI)), with correlation values of 0.56 for the months from July 2002 to February 2010, and Susskind et al. 2012, who finds a correlation of 0.81 between CERES clear-sky tropical OLR anomaly and the Niño 4 index from September 2002 to June 2011.

The same correlation between the tropical mean OLR anomaly and the Niño 3.4 index are performed for AMIP and historical CMIP6 simulations. Their respective time series are reported by Figure 3.4 and 3.5, along with the correlation coefficient (r). A summary of the correlation results is showed by the last plot of Figure 3.4 and 3.5. While correlation

values of CMIP6 historical models are distributed around the 0.48 value of CERES, with few exceptions, there is a tendency for AMIP models to underestimate the magnitude of the correlation. Indeed, as showed by the last plot of Figure 3.4, for more than a half of the AMIP models considered the r value is below 0.48. If the performance of AMIP and historical experiments relative to the same model is compared there is not a clear tendency: some AMIP experiments show an higher agreement with CERES with respect to the historical ones, and vice versa (Figure 3.4 and 3.5, last bottom plots).

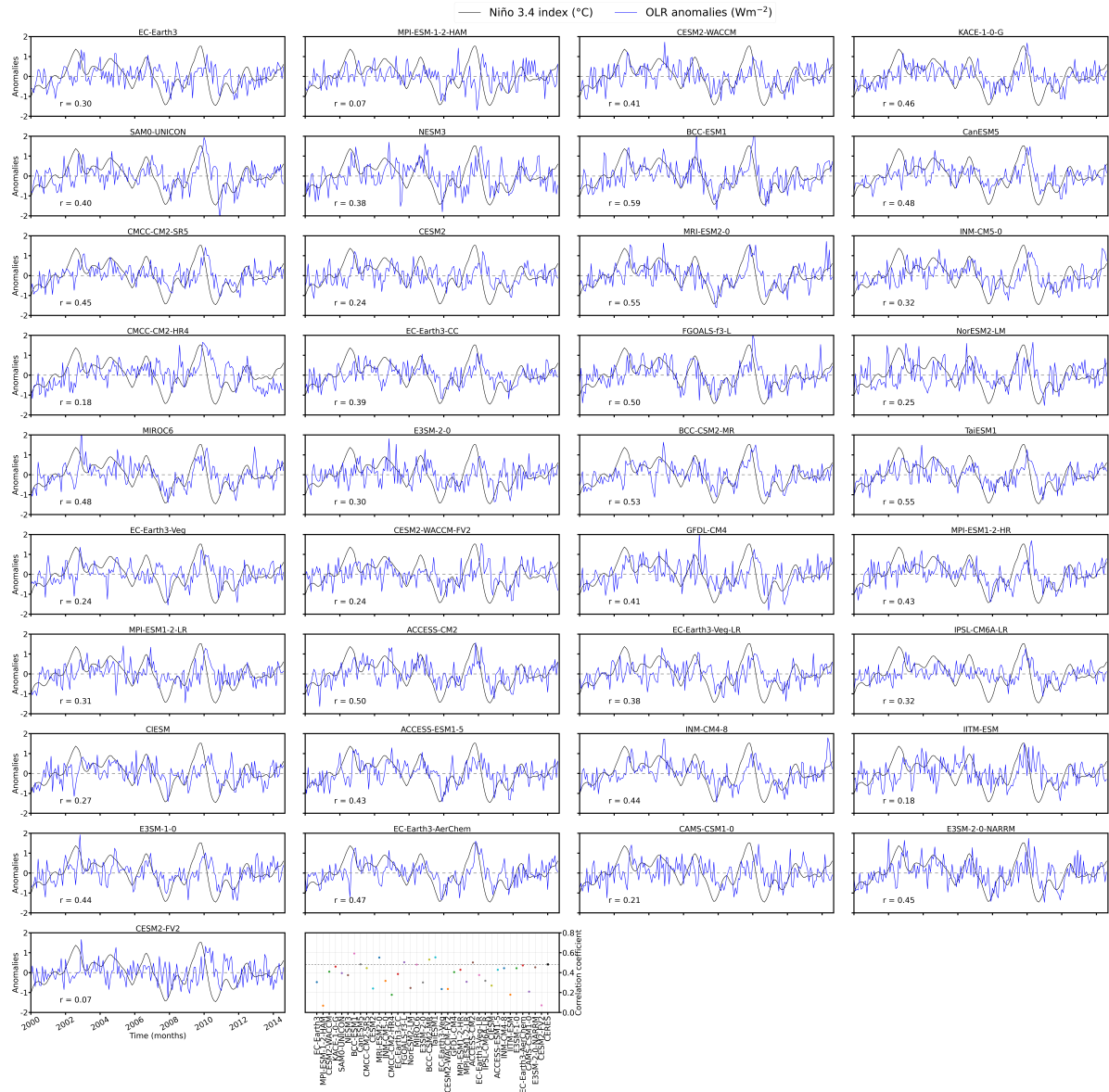


Figure 3.4: The Niño 3.4 index calculated using SST averages of the NOAA database (black line) and OLR anomalies calculated using CMIP6 AMIP OLR fluxes (blue line). r is the correlation coefficient between the two time series calculated over the period from March 2000 to December 2014. The r values of every model considered are reported together in the last plot, along with the one of CERES.

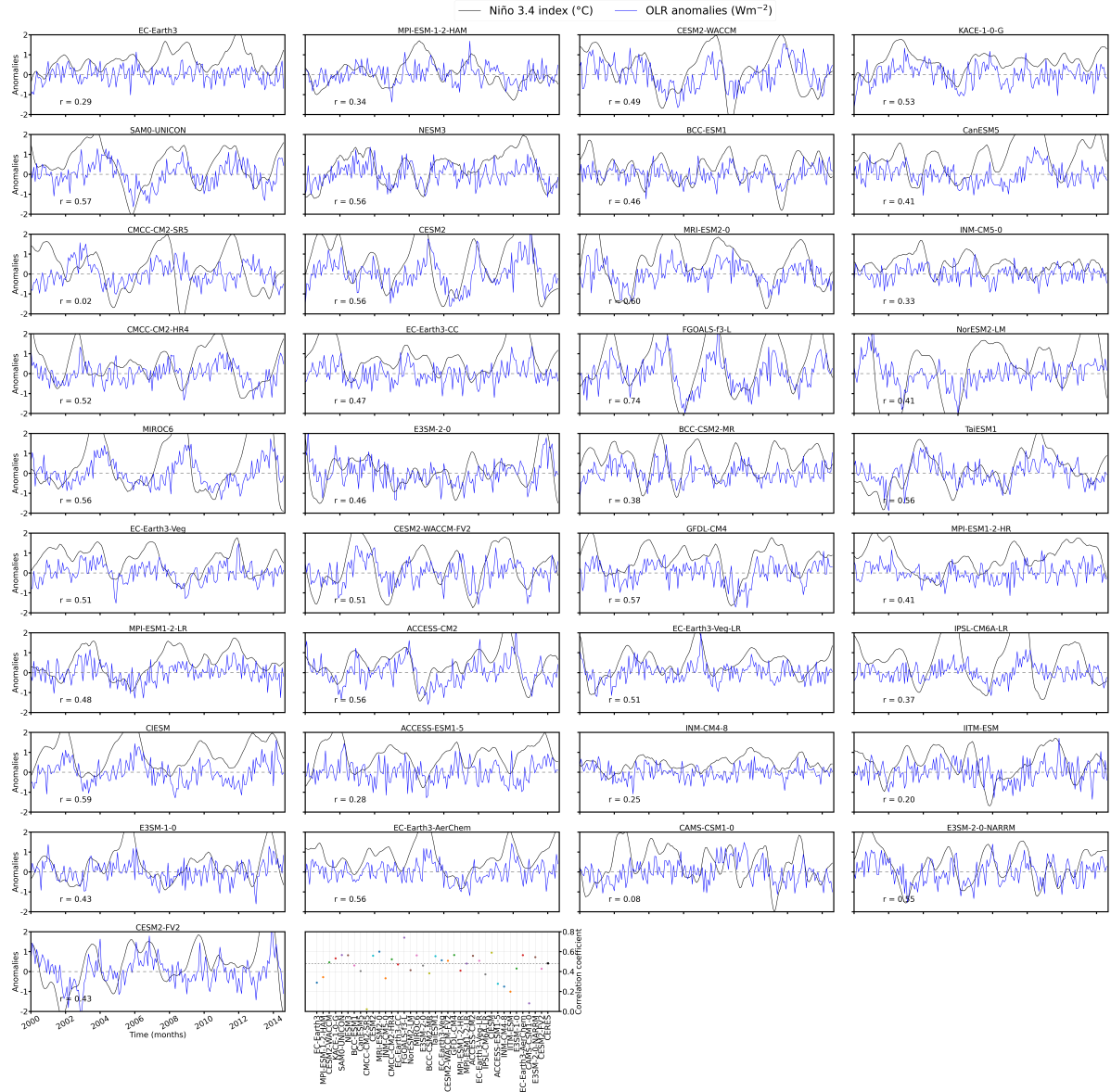


Figure 3.5: Same as Figure 3.4 but for CMIP6 historical simulations. In this case, the Niño 3.4 index has been calculated using SST outputs from historical models.

3.2.2 The spatial pattern of the OLR response to ENSO

We now wish to examine the spatial structure of the correlations between the OLR and ENSO in order to identify the regions that mostly contribute to this relationship. These can be appreciated in Figure 3.6, which reports the correlation between OLR anomalies and the Niño 3.4 index at each grid box for CERES observations.

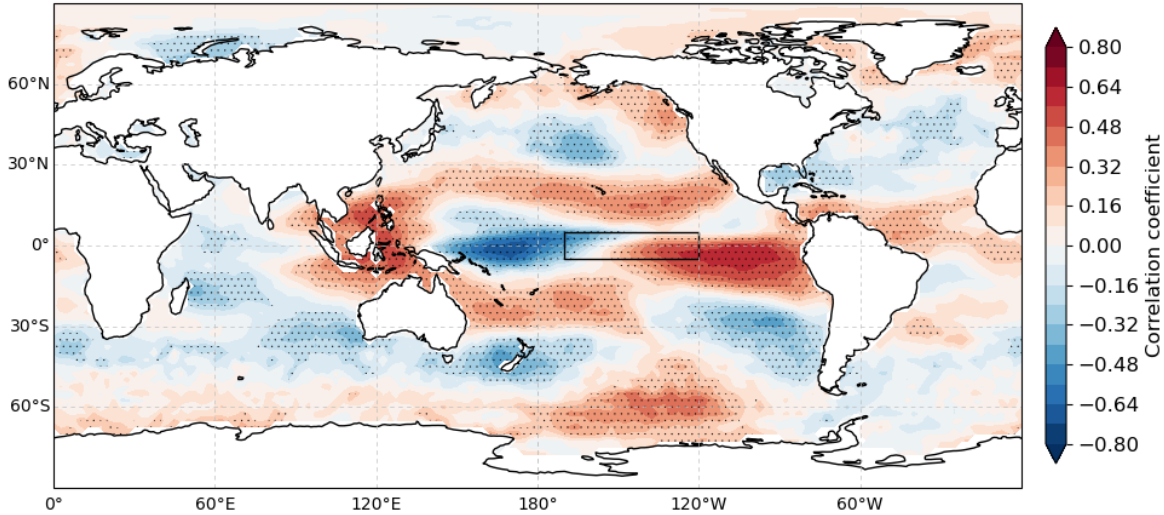


Figure 3.6: Correlations spatial pattern between CERES OLR anomalies and the Niño 3.4 index over the period from March 2000 to December 2014. Black dots mark statistically significant correlations at the 95% confidence level. The black rectangle marks the Niño 3.4 region.

The correlation spatial pattern is strongly polarised across the tropical Pacific Ocean. According to CERES observations (Figure 3.6), OLR is positively correlated to ENSO over the central and eastern part of the basin, while negative values characterize the western part. This pattern follows the SST anomalies induced by El-Niño phase, which are positive in the central and eastern part of the Tropical Pacific Ocean and negative in the western part of the basin. It is important to remark that the Niño 3.4 index is defined over the Niño 3.4 region (marked by a black rectangle in Figure 3.6), which is located in the central Pacific and thus it experiences positive SST anomalies during El-Niño phase and negative SST anomalies during La-Niña phase. Other statistically significant features involve regions far off the equator. This last is flanked by moderate positive correlations to the north and south. A marked positive correlation is also observed over the Maritime Continent, the southern Pacific and near the coast of North America. Furthermore, negative and positive correlations over remote basins, such as the Indian

Ocean and equatorial Atlantic Ocean, respectively, show ENSO teleconnections (Klein, B. J. Soden, and Lau 1999).

The spatial structure of the correlations presented above agrees with the one of Figure 4b in Susskind et al. 2012, where three main regions are highlighted: the Maritime Continent (MC), the West Pacific (WP) and the Center/East Pacific (C/EP). According to Susskind et al. 2012, they are all important for the tropical mean OLR response to ENSO. Specifically, the behaviour observed over the MC and the C/EP is in phase: over these regions OLR is positively correlated with the Niño 3.4 index. Instead, a negative correlation is observed over the WP. Both the MC and the C/EP significantly contributes to the tropical mean response and each of them counteracts the opposite response associated to the WP region.

The observed OLR response can be explained by changes in climate variables to which it is sensitive and how these are affected by El-Niño/La-Niña phases. Three main variables that are strongly affected by ENSO activity are surface temperature, water vapor and cloud cover. In general, with everything else being equal, OLR decreases for increasing humidity, while it increases for warmer surface temperatures. Therefore, in regions of increased convective activity, where the air is rich in water vapor and high clouds are abundant, OLR decreases, while the opposite is observed over subsidence regions.

Susskind et al. 2012 observes that changes in specific humidity (at 500 hPa) and cloud fraction are strongly negatively correlated to the Niño 3.4 index in the MC and E/CP regions, while the opposite is observed over the WP. The SST shows negative correlation over the MC as well, but positive correlation that extends from the WP to the CP region. The strong negative correlation values observed over the MC for specific humidity would be the evidence for the westward shift of the ascending branch of the WC during La-Niña phase. OLR shows positive correlation with the Niño 3.4 index over the MC, as it increases with dry, sinking air during El-Niño and decreases with moist air during La-Niña. Within the WP region, we found negative correlation between OLR and the Niño 3.4 index. Here, the OLR is out of phase with respect to specific humidity, surface temperature and cloud fraction (Susskind et al. 2012). During El-Niño phase the SST within this region is cooler than the average, which corresponds to period of decreased convection. The low moisture leads to an enhanced OLR emission with respect to the opposite conditions that are observed during La-Niña. According to Susskind et al. 2012, specific humidity and cloud cover are both negatively correlated to ENSO in the EP region, while the opposite is observed for surface temperature, although correlation values are lower with respect to the other regions identified across the tropical Pacific. An hypothesis can be that the warmer SSTs observed during El-Niño phase, enhance emission of OLR which absorbs atmospheric water vapor. As such, the ultimate OLR emission to space would be achieved through tropospheric cooling.

The map of the correlation spatial pattern of each single CMIP6 model out of the

37 considered is reported in Figure 3.7 and 3.9 for AMIP and historical simulations, respectively. All AMIP models capture the main correlation features across the tropical Pacific Ocean, which were previously observed from CERES observations: the negative correlations over the WP, the positive correlations over the eastern part of the basin and the MC, as well as the positive correlations extending to the north and south of the equator. This is further demonstrated by the multi-model mean (Figure 3.8, panel a), which is the average of the correlation spatial pattern of the 37 models considered and allows to capture systematic errors shared by different models. The standard deviation of the multi-model mean shows that within the EP the models responses agree very well, the same is true for part of the WP region, although the greatest variability among AMIP models is observed near the New Guinea coasts. The difference between CERES correlation spatial pattern and the multi-model mean highlights some biases in the magnitude of the correlation which involve the EP region near the coast of South America and the area near the coasts of central America, where AMIP models underestimate the magnitude of the correlation with respect to CERES observations (Figure 3.8, panel c). The agreement between CERES and AMIP multi-model mean is very good in the WP region and over the MC.

As for regard historical simulations, they generally show a negative correlation over the WP region that extends too eastward than CERES and the corresponding AMIP ones (Figure 3.9), as it appears also from the multi-model mean (Figure 3.10, panel a). The difference between CERES and this last shows that this constitutes the main bias shared by most of the models with respect to the observations and give origin to a consistent underestimation of the correlation magnitude in CP and EP regions (Figure 3.10, panel c). The standard deviation of the multi-model mean shows a high inter-model spread over the WP region, but the greatest variability among historical simulations is concentrated within the Niño 3.4 area (Figure 3.10, panel b). In addition, such as for AMIP models, a high spread is observed near the New Guinea coasts. With respect to the AMIP multi-model mean, CMIP6 historical simulations seem to better capture the positive correlations to the north of the equator near the coasts of central America (Figure 3.10, panel d). However, it can be observed that the multi-model mean difference between AMIP and historical simulations is very similar to that between CERES and the historical multi-model mean. It is interesting to note that both AMIP and historical simulations underestimate the magnitude of the correlations in the EP, but in two slightly different regions: the positive correlation near the coast of Peru is better caught by the historical multi-model mean than AMIP, while the opposite is observed around the equatorial EP, where the multi-model mean suggests an overall better performance of AMIP simulations.

The agreement between each model and CERES spatial pattern has been quantitatively evaluated by means of the Taylor’s diagram (Figure 3.11), in which three statistics are reported: the standard deviation, the correlation and the centered root mean square

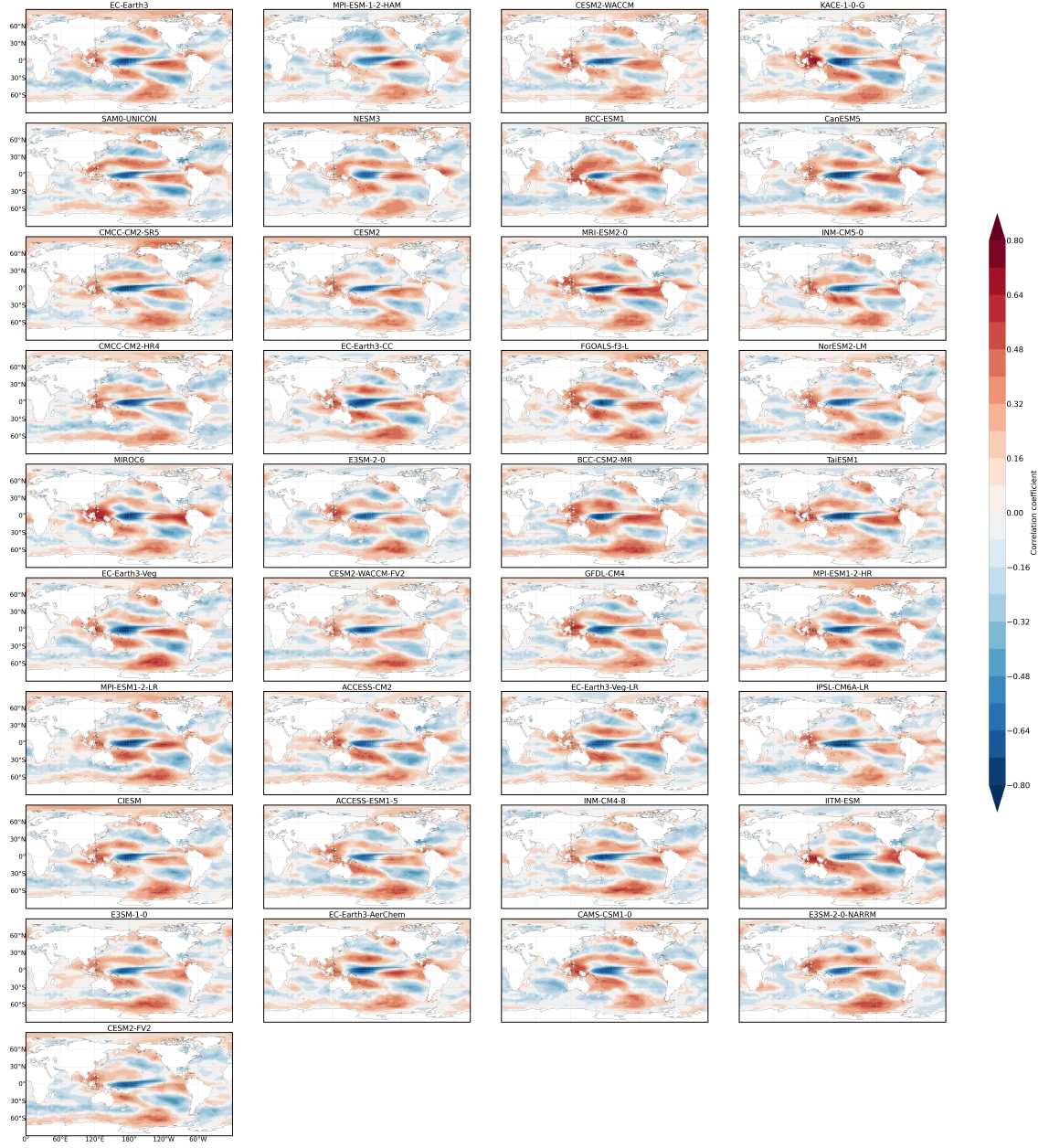


Figure 3.7: Same as Figure 3.6, but for each of the 37 CMIP6 AMIP models considered.

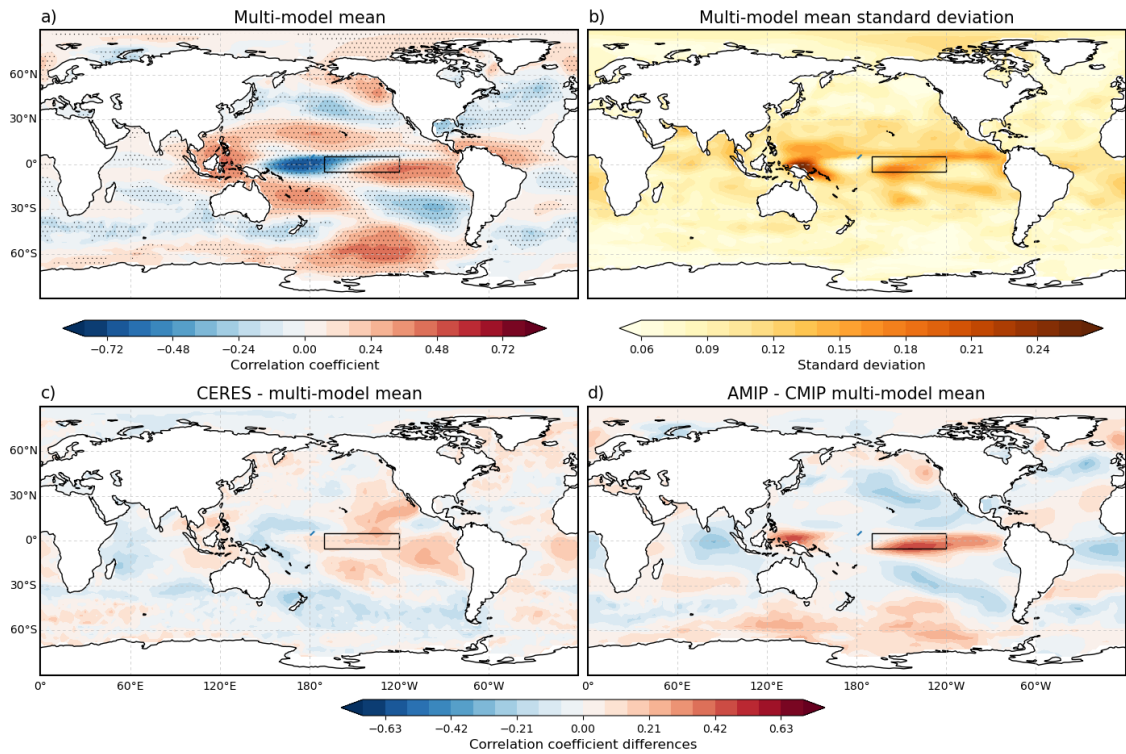


Figure 3.8: Panel a: AMIP multi-model mean of the spatial pattern relative to Figure 3.7; panel b: standard deviation of the multi-model mean of panel a; panel c: spatial pattern of the correlation of CERES observations minus the one of historical multi-model mean reported in panel a; panel d: same as panel c but for AMIP minus historical multi-model mean.

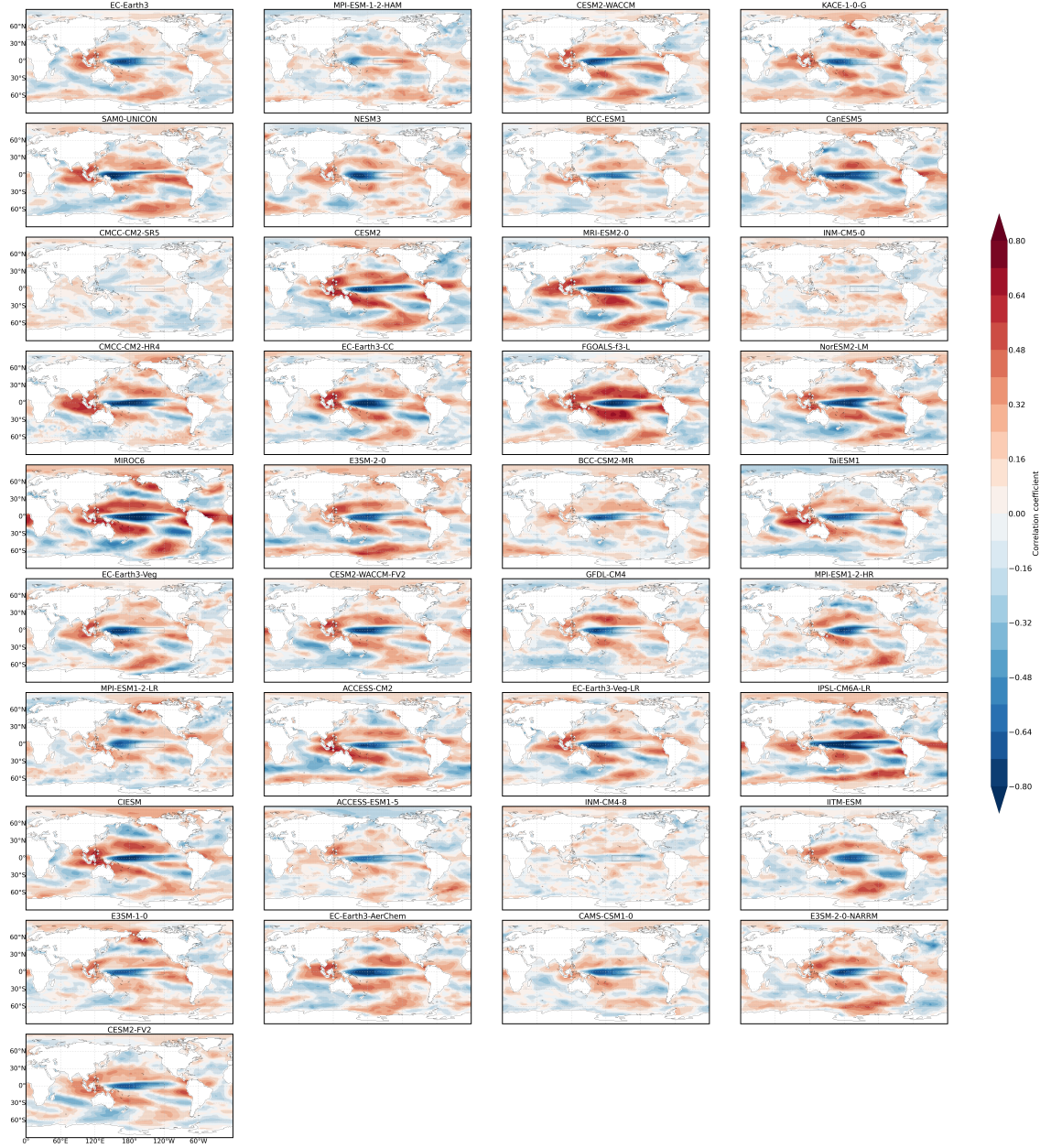


Figure 3.9: Same as Figure 3.6, but for each of the 37 CMIP6 historical models considered.

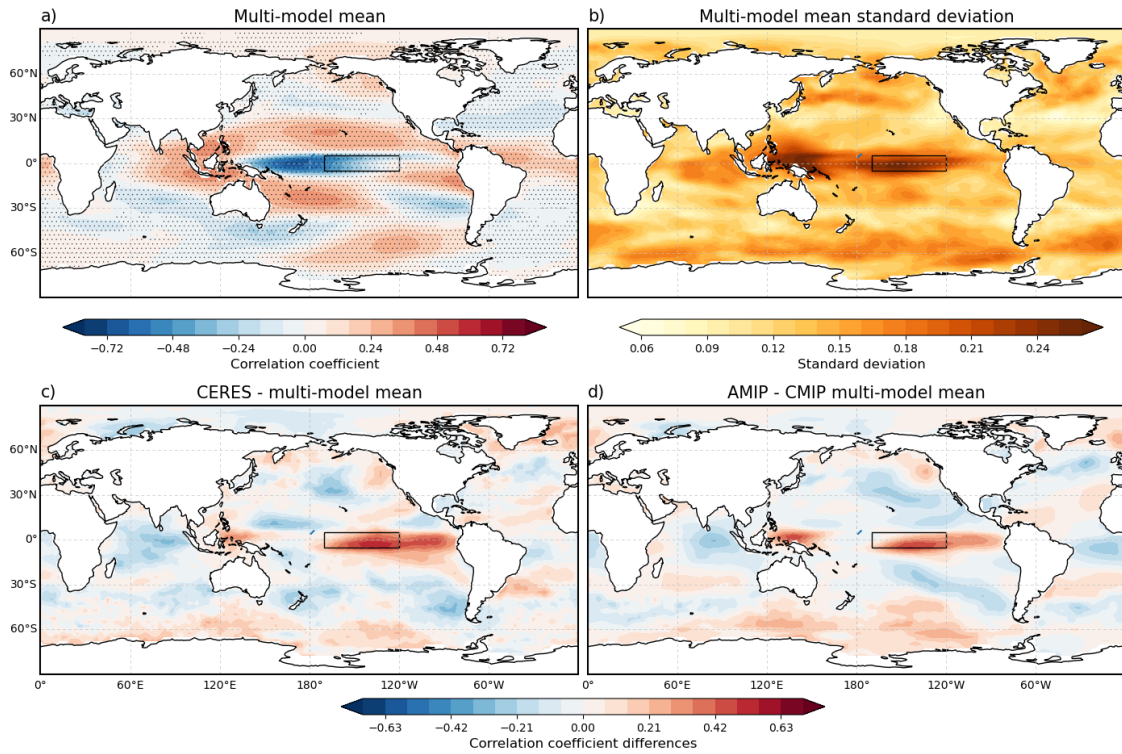


Figure 3.10: Same as Figure 3.8, but for CMIP6 historical simulations.

error. These are evaluated for each model considered. The standard deviation of the spatial pattern of the variable examined is reported in the x axis; the correlation between the spatial pattern of the variable examined as reproduced by the climate model respect to that of CERES observations is reported in the polar axis; and the centered root mean square error - expressed as one standard deviation of CERES - is marked by the dotted circle (centered on CERES standard deviation).

AMIP simulations capture the variability of the spatial pattern of the correlations, which are located mainly between 0.15 and 0.17. The correlation of their spatial pattern with that of CERES is also good, being located between 0.7 and 0.8 for most of the models (Figure 3.11, left plot). Furthermore all the models are grouped around the same values of the statistics considered, suggesting a similar behaviour. Instead, CMIP6 historical simulations show a great inter model variability as for regard the standard deviation, being distributed between 0.1 to 0.25. The correlation with CERES spatial pattern is poorer than AMIP, being around 0.6 for almost all the models (Figure 3.11, right plot).

Correlations between OLR anomalies and ENSO showed that ENSO variability contributes to shape the OLR at the TOA. Different responses are observed across the tropical Pacific Ocean which follow the change of the SST pattern driven by ENSO. The analysis showed that CMIP6 AMIP and historical simulations capture the main variability features of the OLR. However, a discrepancy between the multi-model mean and observations is found in the central and eastern Tropical Pacific Ocean, where models underestimate the

strength of the relationship. Historical simulations show the greatest bias located at the equator. Despite some exceptions, coupled models tend to simulate either a negative response that extends too eastward or a positive response in the east Pacific that is very low respect to that observed by CERES.

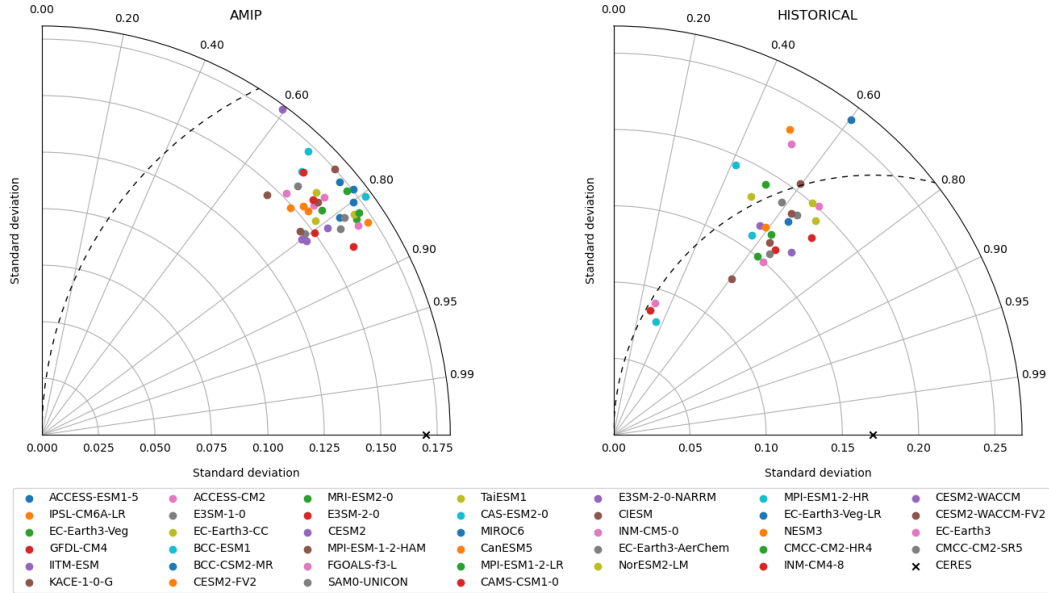


Figure 3.11: Taylor's diagram of the correlations spatial pattern obtained for each AMIP (left) and CMIP6 historical (right) simulation considered relative to CERES.

3.3 Time relationship between TOA OLR and ENSO

The relationship between the oceanic and atmospheric components has been the subject of debate within the ENSO dynamical framework. Historically, this debate has been dominated by two theories (C. Wang and Picaut 2004): (i) ENSO is a natural self-sustained variability mode of the ocean-atmosphere system; (ii) ENSO is a damping mode sustained by an external atmospheric stochastic forcing (random noise). There are works in support of both theories and others suggesting that these two different "regimes" have alternated over the multidecadal time scale.

More recently, Ceppi and Fueglistaler 2021 showed that net EEB is out of phase respect to ENSO activity. Their findings suggested a two way relationship between radiative and SST anomalies, in which the role of the atmospheric component is not explained only by a stochastic forcing. This is supported by the fact that the leading role of the atmosphere is also reproduced by CMIP6 AMIP simulations which do not include stochastic atmospheric forcing onto the oceanic component due to prescribed SST. This behaviour has been attributed to the ENSO-driven SST pattern effect. The SST pattern effect is defined as the change observed in the TOA radiative flux due to the existence of a SST pattern that

would not be observed with a uniform SST distribution (Stevens et al. 2016). The SST pattern effect is of particular importance for the response of the climate system, since feedback mechanisms show a dependency to the spatial pattern of the SST (Stevens et al. 2016; Andrews, Gregory, and Webb 2015; Proistosescu et al. 2018; Andrews, Bodas-Salcedo, et al. 2022; Wills, Battisti, et al. 2020; K. C. Armour et al. 2024; Rugenstein, Van Loon, and Barnes 2025).

We decided to assess the ability of CMIP6 AMIP and historical simulations in reproducing the TOA OLR response to ENSO, which is an important feature to be correctly reproduced by models since it entails the relationship between the atmospheric and oceanic components. Following Ceppi and Fueglistaler 2021 and Kolly and Y. Huang 2018, the time relationship is investigated through a lagged regression analysis.

3.3.1 Lagged regression analysis

Lagged regression consists in performing linear regressions between two variables at different time lags, where the linear regression is calculated as follow:

$$y = mx + q \quad (3.2)$$

In this case, y is the TOA OLR anomaly time series and x is the Niño 3.4 index. The Niño 3.4 index time series has been shifted by one month at a time respect to the OLR anomaly (from -12 to +12 months), thus obtaining 25 regression coefficients, m . The regression coefficient (units of $\text{Wm}^{-2}\text{K}^{-1}$) is the quantity used to measure the radiative perturbations driven by ENSO induced SST anomalies. Calculated at different lags it provides information on the role of the atmospheric component during the life-cycle of an ENSO event (Kolly and Y. Huang 2018; H. Huang, Y. Huang, and Hu 2021). Positive lags indicate that SST leads the OLR response, while for negative lags radiation leads.

3.3.2 Tropical mean response

As for correlations, the linear relationship between the OLR and ENSO has been firstly investigated at the tropical mean level. As before, OLR has been averaged over the tropical zone (30°N - 30°S) considering only values above ocean. The regression coefficients (m) are plotted on the left side of Figure 3.12 ("slope" in the y axis) as a function of the time-lag, for CMIP6 historical (top) and AMIP (bottom) simulations. The plots on the right side of Figure 3.12 report the peak of the radiative response quantified by the maximum value of the slope plotted as a function of the corresponding lag. The reference value obtained using CERES observations is marked by the black solid line (left side plots) and the black dot (right side plots). OLR is considered positive upward, therefore positive values of m indicate an increase in the TOA OLR emission, and vice versa.

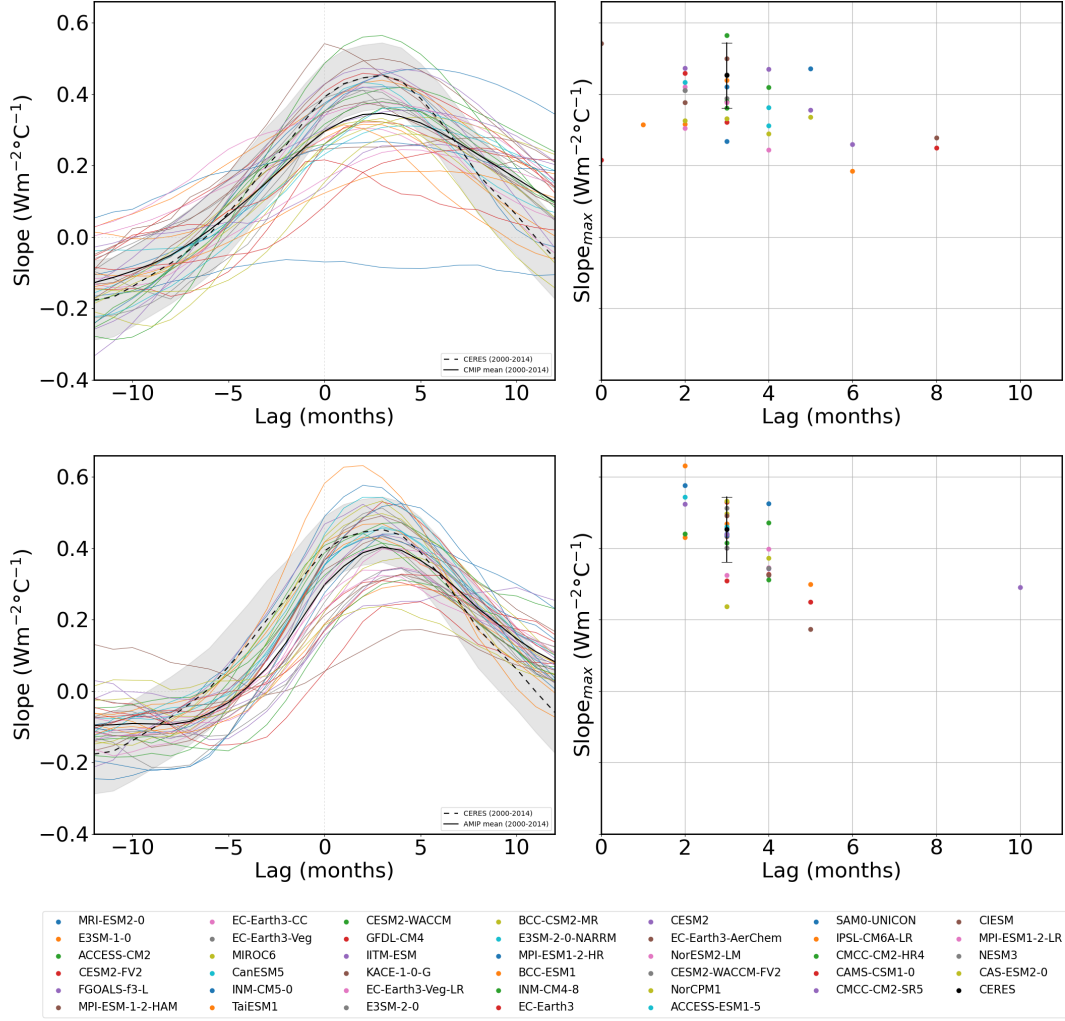


Figure 3.12: Left side: lagged regressions between the Nino 3.4 index and top-of-atmosphere outgoing longwave radiation anomalies from CERES (dashed black line), CMIP6 models (coloured lines) and the multi-models mean (solid black line), for the period 2000 - 2014. Gray shade is the 95% confidence interval of CERES slopes. Right side: the lag associated with the maximum slope, for CERES (black dot) and CMIP6 models (coloured dots).

The magnitude of the linear regressions increases from -12 to a couple of months after lag 0, when it peaks, to smoothly decrease thereafter. According to CERES, the maximum slope is of about $0.4 \text{ Wm}^{-2}\text{K}^{-1}$ and it is reached with a lag of 3 months, when ENSO leads the OLR response (Figure 3.12, left plot, dashed black line, and right plot, black dot). As in Ceppi and Fueglistaler 2021, results are indicative of an increase in OLR emission to space at the TOA during and right after ENSO, which peaks 3 months after it. The authors argue that the OLR response to ENSO in clear-sky conditions is very similar to that of the SST, thus suggesting that the Planck surface effect is the main driver.

The majority of CMIP6 historical simulations are able to correctly reproduce the magnitude of the response within the 95% confidence interval of CERES (Figure 3.12, upper right plot, coloured dots). A fairly good agreement is also observed for the timing of the response, whose peak matches the 3-months lag of CERES for several models, while it is anticipated or postponed of one month for more than a half, with only few exceptions. The agreement between CERES and AMIP simulations seems even better (Figure 3.12, lower right plot, coloured dots). Indeed, most of the models match both the peak of the slope and the corresponding lag. As for historical simulations, the rest of the models that do not reproduce the CERES peak and lag, anticipate or postpone the lag of one month, with very few exceptions. However, AMIP simulations shows a tendency for models that postpone the response peak to also underestimate its magnitude. On the contrary, models that anticipate it seem to overestimate it. This is not the case for historical simulations, where the magnitude of the response peak is distributed around that of CERES with no clear pattern. As expected, CMIP6 historical simulations show a greater inter model variability than AMIP, as was also the case for the correlations spatial pattern (Figure 3.11, right panel). Both AMIP and historical multi-model mean underestimates the OLR response respect to CERES (Figure 3.12, left plots, dashed black lines). Although, the difference is lower for the AMIP multi model mean.

3.3.3 Spatial pattern of the lagged regressions

We now examine the spatial pattern of the linear regressions between the OLR anomaly and the Niño 3.4 index, since it provides additional information on the variability of the radiative response across the Pacific Ocean - and the tropical region - that may shed light on the biases observed in the lagged regression at the tropical mean level. We focus on the spatial pattern at a specific lag of 3 months, where the tropical mean regression peaks.

Results for CERES observations are reported in Figure 3.13. According to CERES fluxes a pattern similar to the correlation one is obtained. Indeed, positive regression coefficients characterize the eastern part of the tropical Pacific, while negative regression coefficients are found in the western part. In addition to the west-east dipole, which,

as already mentioned, reflects the El-Niño SST pattern, other relevant relationships are found over the Maritime Continent, to the north and south of the Equator and in the southern part of the basin: over these regions the sign of regression coefficients is positive. Negative regression coefficients are instead observed near the coast of Peru.

The spatial pattern of correlation and linear regression is consistent across the regions of the Pacific Ocean: over the E/CP OLR anomaly is in phase with El-Niño, while in the WP region the opposite relationship exists. However, it is interesting to note that the magnitude of the linear regression slightly differs from that of the correlation coefficients. Indeed, the strongest positive linear relationship is found north of the equator and over the Maritime Continent, while the strongest positive correlation values are located above the eastern Pacific region. The strongest out-of-phase relationship between OLR and SST anomalies is found in the western pacific.

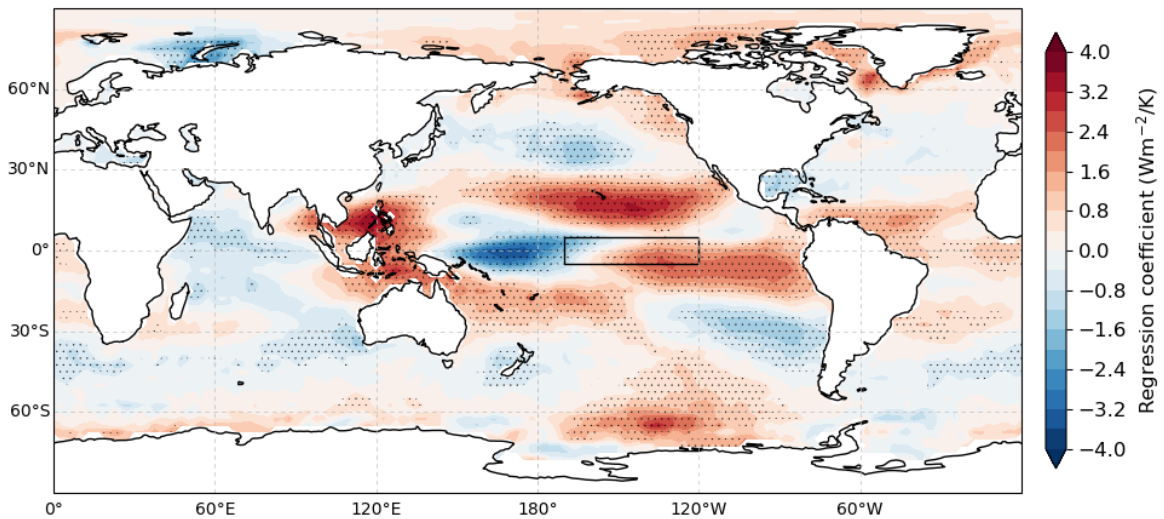


Figure 3.13: Spatial distribution of the linear regressions between CERES OLR anomalies and the Niño 3.4 index shifted ahead of 3 months over the period from March 2000 to December 2014. Black dots mark statistically significant regression coefficients at the 95% confidence level. The black rectangle marks the Niño 3.4 region.

The same linear regressions at a lag of 3 months have been performed for each of the CMIP6 historical and AMIP models considered. Results are showed by Figure 3.16 and 3.14, for AMIP and historical simulations, respectively. The bias between CERES observations and the multi-model mean is also showed (panels a of Figure 3.16 and 3.14), along with the standard deviations of the multi-model means (panels b of Figure 3.16 and 3.14).

As for the correlation spatial patterns the most evident bias is observed for CMIP6 his-

torical simulations, which underestimate the regression coefficients in the eastern Tropical Pacific with respect to CERES observations (Figure 3.15, panel c). On the other hand, the multi-model standard deviation over this region is characterized by the smallest values across the Pacific Ocean (Figure 3.15, panel b). This suggests a systematic error in reproducing OLR response to ENSO in the eastern part of the Pacific Ocean, since all the models considered show the same behaviour. The OLR response to ENSO in the western part of the basin agrees more with observations (Figure 3.15, panel c), but it shows a greater inter-model spread. It can be seen from Figure 3.14 that, while the radiative response in the eastern part of the Tropical Pacific is the same among the 37 models - smaller in magnitude than CERES observations - the western part of the basin is characterized by responses of both stronger and weaker magnitude, which may compensate each other in the multi-model mean (Figure 3.15, panel a). This is supported by the Taylor's diagram (Figure 3.18, left plot). The spatial pattern of the regression coefficients of CMIP6 historical simulations is for almost all the models correlated around 0.6 to the one of CERES. The standard deviations of the spatial pattern show a higher spread, being distributed from 0.2 to 1.0 $\text{Wm}^{-2}/^{\circ}\text{C}$.

The AMIP multi-model mean agrees with the CERES spatial pattern (Figure 3.17, panel a) and its standard deviation (Figure 3.17, panel b) is quite homogenous across the tropical Pacific Ocean, even if slightly higher values are obtained over the western Pacific Ocean. The CERES - multi-model mean difference (Figure 3.17, panel c) shows that the magnitude of the linear regressions is slightly overestimated by AMIP models in the west Pacific at the equator, characterized by negative correlation coefficients, and to the north of it, where regression coefficients are positive. Instead, regression coefficients are underestimated over the east Pacific, near the coast of South America. This spatial pattern could explain the two behaviours of the tropical mean response: a group of models overestimated and anticipated the response peak, and another that underestimated and postponed it. An hypothesis could be an issue with the compensation of the response between different regions. For example, the model BCC-ESM1 shows a strong positive response to the north of the equator in the western part of the Pacific Ocean, while the remaining regions are characterized by weak responses. The IPSL-CM6A-LR model is instead characterized by a strong negative response in the western part of the tropics and a weak response in the remaining regions.

3.4 Discussion

Interannual variability of the OLR driven by ENSO has been examined for 37 climate models participating in the CMIP6 project. OLR outputs of AMIP and historical experiments of each of the models considered were compared to OLR derived from CERES observations, over the period from March 2000 to December 2014, during which mod-

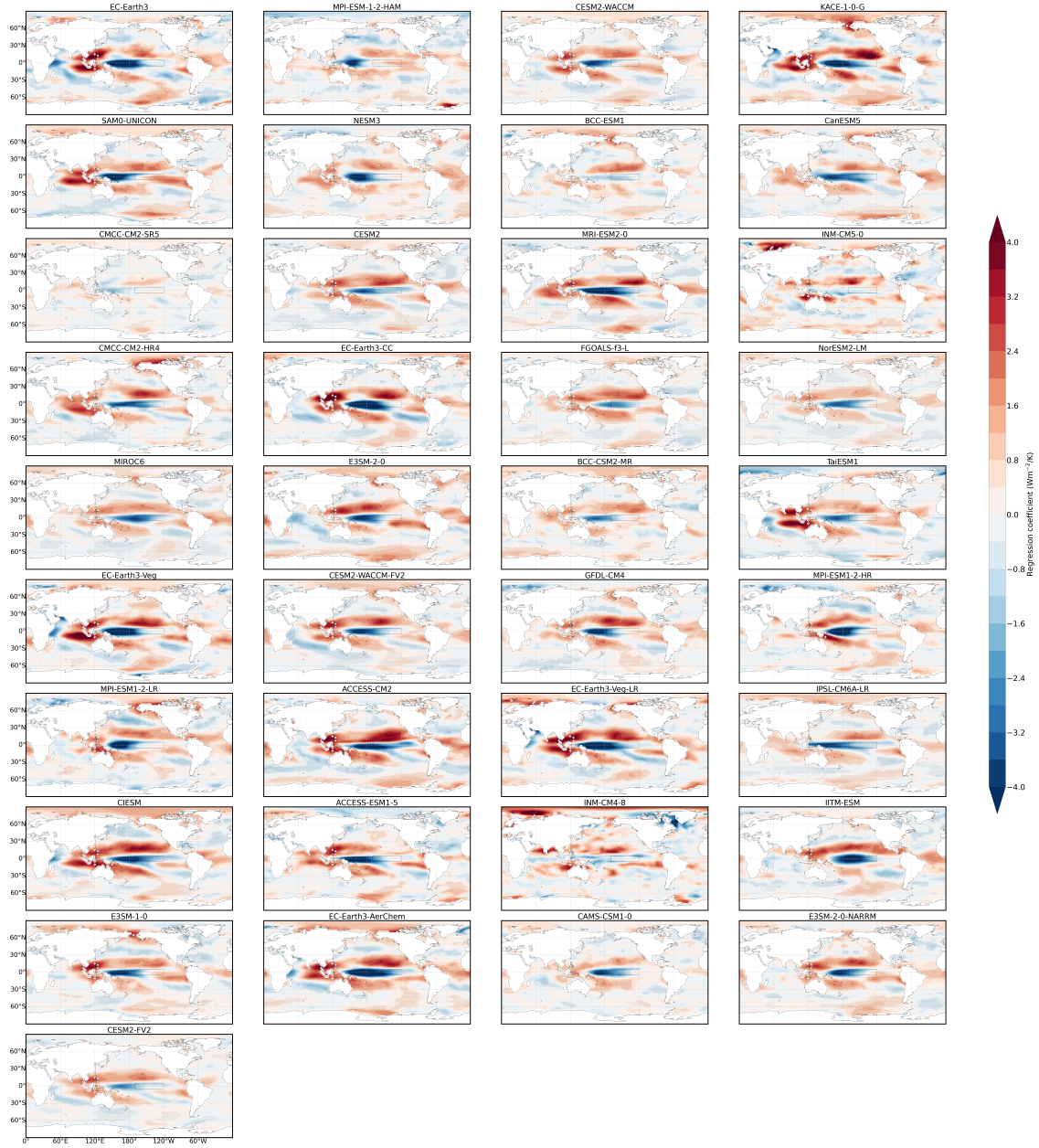


Figure 3.14: Same as Figure 3.13, but for each of the 37 historical models considered.

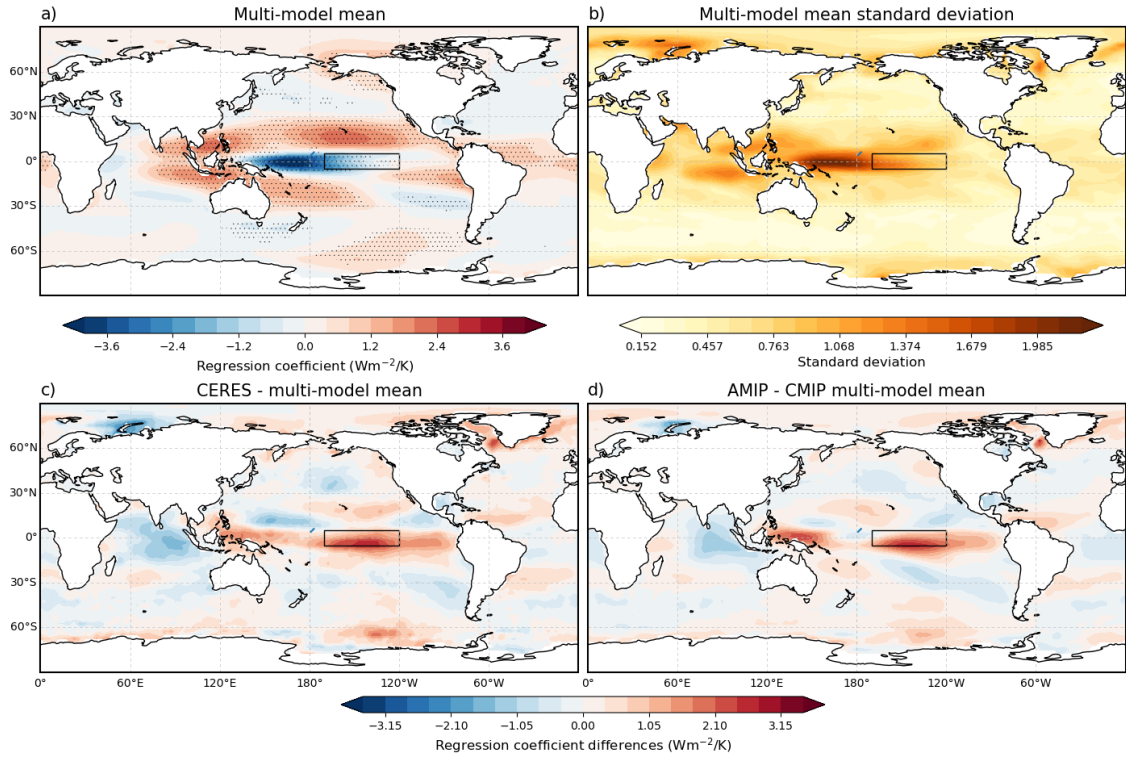


Figure 3.15: Panel a: historical multi-model mean of the spatial pattern relative to Figure 3.14; panel b: standard deviation of the multi-model mean of panel a; panel c: spatial pattern of the linear regressions at lag 3 of CERES observations minus the one of historical multi-model mean reported in panel a; panel d: same as panel c but for AMIP minus historical multi-model mean.

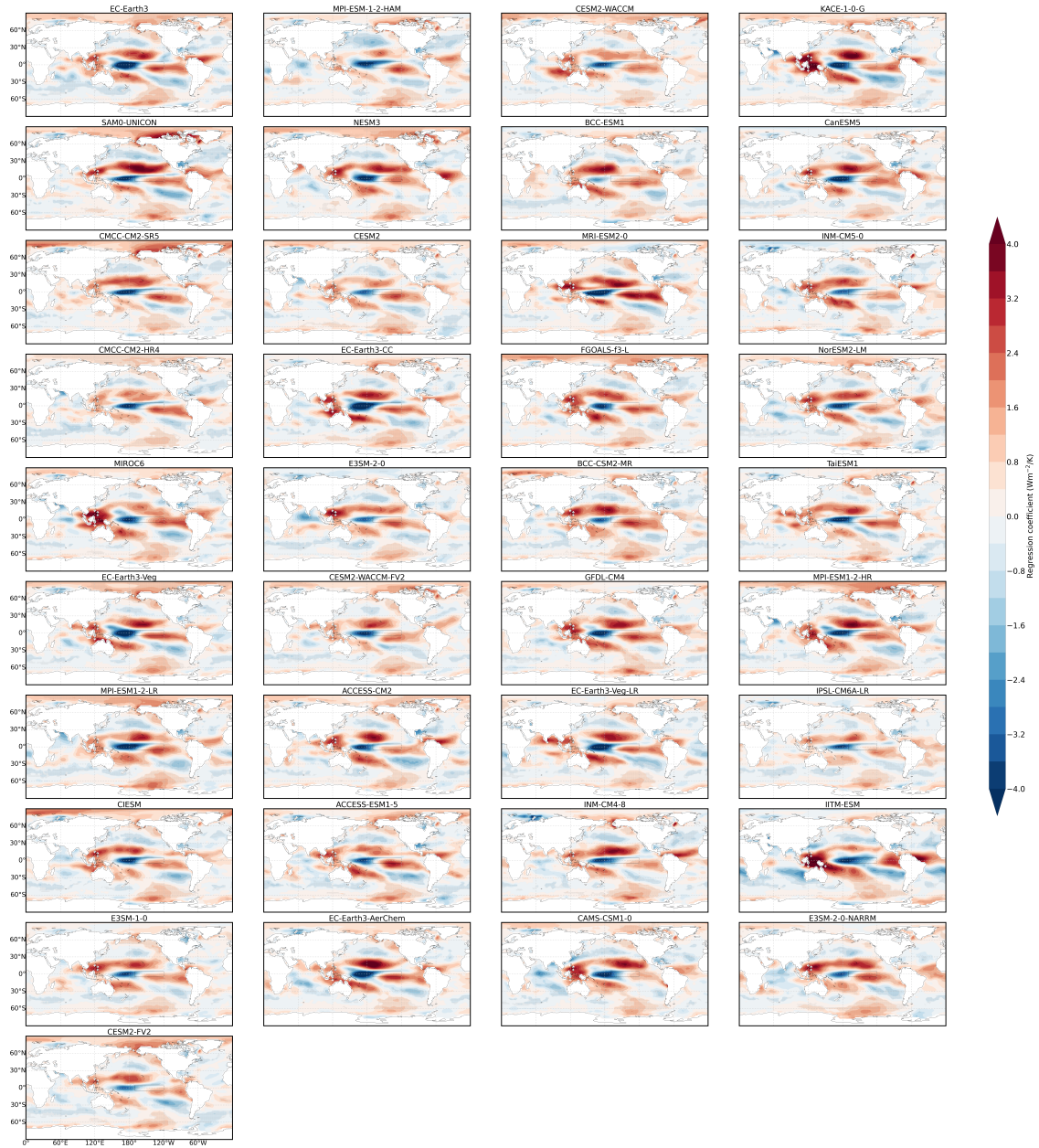


Figure 3.16: Same as Figure 3.14, but for each of the 37 AMIP models considered.

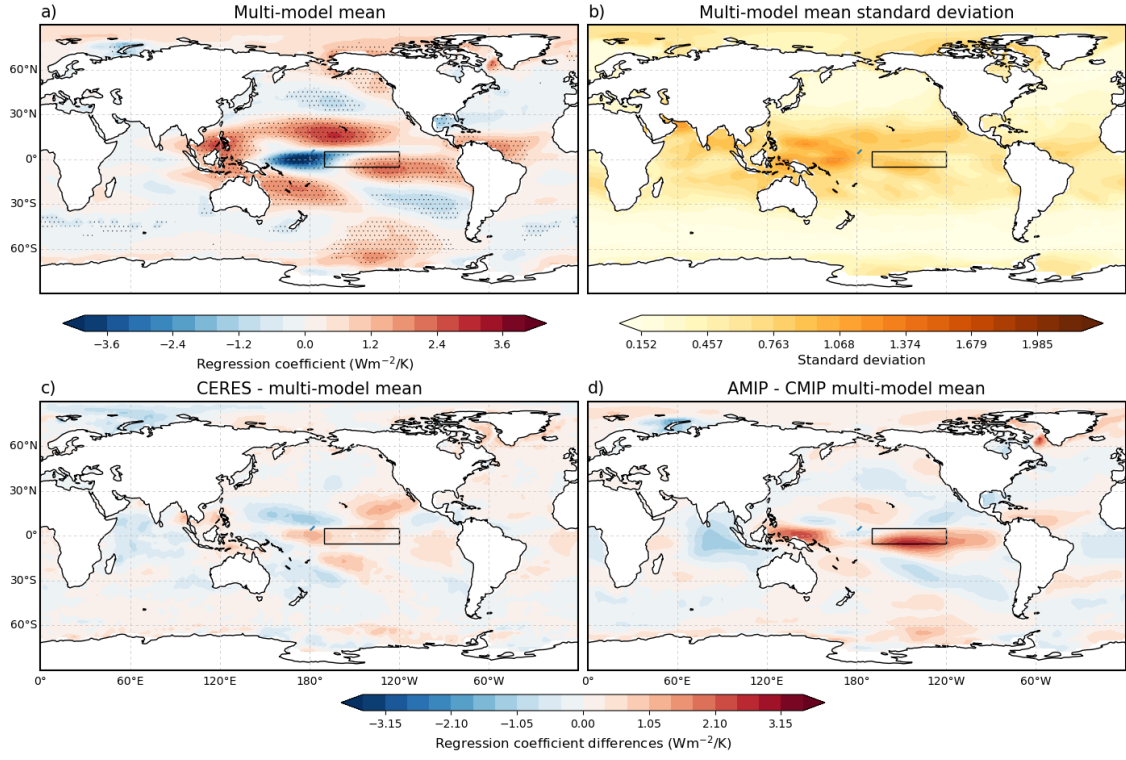


Figure 3.17: Same as Figure 3.15, but for each of the 37 AMIP models considered.

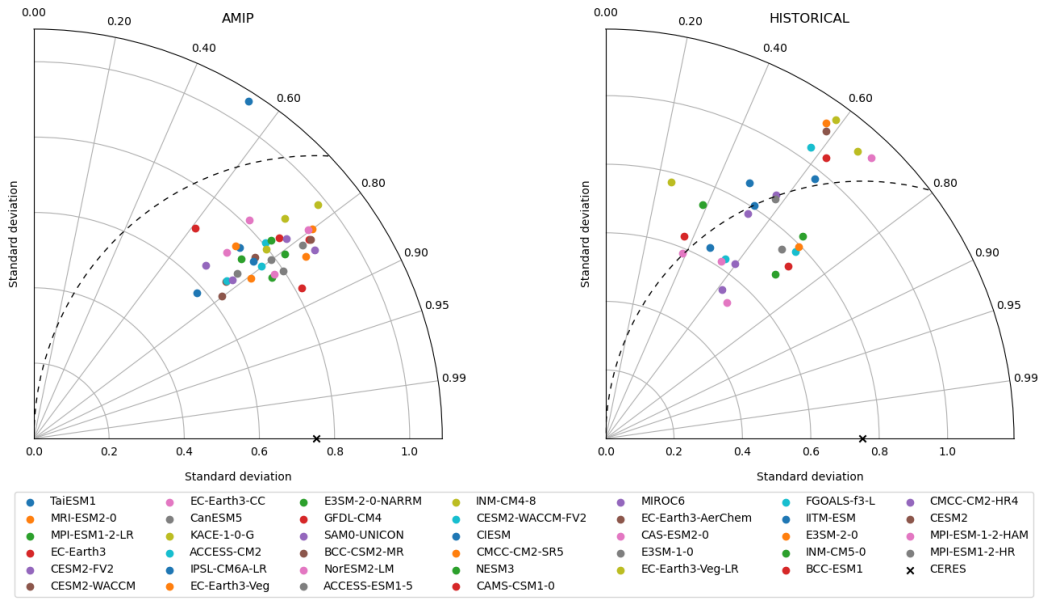


Figure 3.18: Taylor diagram of the spatial pattern of the linear regressions obtained for each AMIP (left) and CMIP6 historical (right) simulations considered relative to CERES.

els simulations and the observational data overlapped. Only the clear-sky scenario was considered.

Several studies that investigated OLR variations using CERES observations show how tropical mean OLR anomalies closely track ENSO phase, with positive (negative) anomalies in correspondence to El-Niño (La-Niña) phase (Loeb, Kato, et al. 2012; Susskind et al. 2012), which give an overall positive correlation at the tropical mean level. Beyond the tropical mean, OLR response to ENSO gives rise to an interesting pattern, that can be related to changes in atmospheric and surface variables resulting from the transition between El-Niño and La-Niña phases (Loeb, Kato, et al. 2012; Susskind et al. 2012). Specifically, three main regions of the tropical Pacific Ocean emerge to be important for the above mentioned relationship: the Maritime Continent, the western and central/eastern parts. Correlations reveal an in-phase relationship between El-Niño and the OLR anomaly over the Maritime Continent and the central/eastern regions, while the opposite is observed for the western tropical Pacific. The relationship over the MC can be mostly explained by changes in specific humidity driven by the shift of the WC. OLR variability above the WP and C/EP regions is suggested to be strongly related also to surface and atmospheric temperature changes, respectively. The compensation between these regions plays a crucial role in determining the tropical mean response (Susskind et al. 2012).

We find a good agreement between AMIP simulations and CERES observations regarding the tropical average and the spatial pattern of the OLR response to ENSO. A similar result was also obtained by Loeb, H. Wang, et al. 2020, which investigated the ability of a subset of atmosphere-only global CMs in reproducing inter-annual variability of the OLR during the first two decades of the 21st century. The most critical region for AMIP simulations is the eastern Pacific, where the magnitude of the correlations is underestimated. On the contrary, AMIP simulations overestimate the magnitude of the linear regressions in the western part of the basin. According to Loeb, Ham, et al. 2024, this region was characterized by the greatest variability over the period considered. For these kind of models a very low inter models spread is obtained.

CMIP6 historical simulations generally overestimate the correlations at the tropical mean level respect to the corresponding AMIP ones. They show the greatest bias in reproducing the correlations magnitude within the central and eastern Tropical Pacific. This region is affected by the so called "cold tongue" bias, due to which SSTs in the east Pacific are too cold and extend too westward in models (Planton et al. 2021). In our case, this leads to an underestimation of both the linear regressions and the correlations over that region. Such as the corresponding AMIP models, they show a bias in reproducing the linear regressions in the western part of the basin. CMIP6 historical simulations are also affected by a larger inter-model spread than the corresponding AMIP ones, which is mainly associated with the western Pacific.

The lag of the regression peak depends on the overall tropical behaviour. In general agreement with Ceppi and Fueglistaler 2021, the clear-sky broadband OLR response suggests that ENSO activity during the time period considered resulted in an enhanced OLR emission at the TOA, whose peak lags ENSO by 3 months. The observed lag of the radiative response can be explained by the fact that ENSO-induced SST anomalies are not constrained to the Niño 3.4 region, but migrate across the tropical Pacific ocean from the east, at the beginning of an El-Niño event, to the west, where positive anomalies persist up to five months after ENSO peak (Ceppi and Fueglistaler 2021).

Previous considerations lead to two main questions:

- *In which way the different climate variables affected by ENSO shape the OLR response peak?*
- *What are the factors behind the spread in the tropical mean response of CMIP6 AMIP and historical simulations?*

Understanding the physical processes that control the response peak and its time lag relative to the peak of SSTs anomalies driven by ENSO can help, firstly, to improve our knowledge of ENSO itself (e.g. its features and dynamics) and, secondly, to reduce systematic biases of climate models or, at least, to understand the reasons behind them. This motivated the analysis presented in Chapter 4.

Chapter 4

ENSO-driven inter-annual variability of the OLR from satellite observations

Chapter 3 presented the analysis of the OLR response to ENSO as simulated by CMIP6 AMIP and historical experiments. Comparison against OLR variability observed by CERES instrument, showed that the majority of climate models considered is able to qualitatively reproduce the observed peak in OLR emission that follows the peak of ENSO of a couple of months. However, not all the models agree on the 3-months lag and magnitude suggested by observations, showing a peak that is anticipated or postponed.

In this Chapter, the OLR response to ENSO is investigated using spectral fluxes derived from IASI and AIRS measurements. The aim is to improve the understanding of the physical processes beyond this relationship with a particular focus on the factors that drive the peak of the radiative response, in order to better explain the source of the biases in CMIP6 models. In addition to spectral observations, the analysis has been integrated calculating the individual radiative perturbation caused by water vapor, ozone, surface and air temperature using spectral radiative kernels. This enabled the spectral ENSO signal to be further decomposed into contributions from the surface and atmospheric Planck, water vapour and ozone feedbacks. Consistent with the previous analysis, only clear-sky conditions are considered.

The content of this chapter is presented in Taddia et al. [2025](#), that is currently under peer review in the Atmospheric Chemistry and Physics (ACP) journal.

4.1 The spectral dimension of the OLR

So far the OLR response to ENSO has been examined using its broadband value - from either satellite measurements or climate models simulations - which is the spectral flux

density integrated over all the wavenumbers. However, the spectral dimension intrinsically brings along more information than its integrated value. The main advantages are the possibility to isolate single contributions by examining different spectral regions and to identify the atmospheric layers where radiation originates.

Even if the development of hyperspectral sounders have followed the use of broadband instruments, there is now a well-established heritage that document the great contribution given by the spectral dimension (Brindley and RJ Bantges 2016). Spectrally resolved radiance simulations (Y. Huang and Venkatachalam Ramaswamy 2009; Y. Huang and Ramaswamy 2008) and observations (Pan et al. 2017; Helen Brindley et al. 2015; RJ Bantges et al. 2016; Griggs and JE Harries 2007; X. Huang and Yung 2005) have been used to study signals related to internal variability and climate change, specifically trends in GHGs, and to test the sensitivity of radiance to changes in atmospheric properties such as temperature and humidity (Helen E Brindley and Richard P Allan 2003; Y. Huang, Ramaswamy, and B. Soden 2007; Y. Huang 2013; Richard Philip Allan et al. 1999). The trend of the first ten years of observations acquired by IASI, shows the spectral signature related to both the increase in GHGs concentration, such as carbon dioxide and methane, and the signal related to ENSO variability across channels sensitive to water vapor and temperature (Simon Whitburn, Clarisse, Bouillon, et al. 2021). Using IASI observations, Roemer et al. 2023 calculated the LW spectral feedback parameter and directly observed the spectral fingerprint due to changes in relative humidity for an increasing value of global mean surface temperature. The trend of clear-sky radiances measured by AIRS from 2003 to 2020 have been investigated by X. Huang, X. Chen, Fan, et al. 2022.

There are several hyperspectral sounders which measure the spectrally resolved Earth’s emitted radiance. The choice was to use OLR values derived from IASI and AIRS observations, since for these two a product of spectral flux was already available. While for CERES observations the radiance-to-flux conversion is an operational task (Loeb, Rose, et al. 2020; Su et al. 2015), for spectral sounders it is not so common. AIRS measurements have been one of the first to provide a publicly available flux product (X. Huang, W. Yang, et al. 2008; X. Huang, JPL, et al. 2019). More recently OLR spectral fluxes from IASI observations became available (Simon Whitburn, Clarisse, Bauduin, et al. 2020). The algorithm used to derived IASI and AIRS fluxes is not the same, which can be a reason for discrepancies, along with the different overpass time of the two instruments (Simon Whitburn, Clarisse, Bauduin, et al. 2020). A description of the two datasets is provided below.

4.2 AIRS

AIRS is a grating array spectrometer that has flown on board Aqua satellite since 2002 (Aumann et al. 2003). It covers three different bands, 3.74–4.61 μm (650–1136 cm^{-1}),

6.20–8.22 μm (1216–1613 cm^{-1}), 8.8–15.4 μm (2170–2674 cm^{-1}), with a resolving power of $(\frac{\lambda}{\Delta\lambda})$ 1200. The instrument FOV corresponds to a nadir-viewing footprint of 13.5 km on the surface and the global coverage is obtained within two days. AIRS overpasses time over the equator are 1:30 and 13:30 local time.

Monthly-mean OLR spectral fluxes have been derived by (X. Huang, W. Yang, et al. 2008; X. Huang, JPL, et al. 2019) for both clear and all-sky conditions. AIRS fluxes are calculated exploiting the same scene type information from the CERES footprint and auxiliary information. This approach is based on a collocation strategy. Only data from AIRS pixels that overlap with the CERES footprint up to a certain threshold are retained for the radiance-to-flux conversion. In the clear-sky scenario only clear-sky CERES observations are considered affecting the final spatial sampling of AIRS. The original spectral range has been filled with simulations and extended to the FIR spectral region, so that the final product consists of monthly mean spectral fluxes computed every 10 cm^{-1} from 15 to 1995 cm^{-1} . AIRS data range from November 2002 to December 2021, with a horizontal resolution of $2^\circ \times 2^\circ$.

4.3 IASI

IASI instrument has been part of the MetOp-A (10/2007-12/2021) payload, and it is currently operating on board the MetOp-B (2012-) and C (2018-) satellites. It is a Fourier Transform Infrared spectrometer (FTIR) which measures radiances across the 645–2760 cm^{-1} spectral range with a resolution of 0.5 cm^{-1} and a spectral sampling of 0.25 cm^{-1} (Simeoni et al. 2004). The instrument has an instantaneous FOV at nadir corresponding to a spatial resolution of about 50 km x 50 km, composed of 2 x 2 circular pixels with a nadir footprint of 12 km of diameter each. It provides nearly global coverage twice a day. The overpass time at the equator is 9:30 a.m. and p.m local time. Here the monthly climatology of IASI spectral fluxes developed by Simon Whitburn, Clarisse, Bauduin, et al. 2020; S. Whitburn 2021 is used. Spectral fluxes are provided from 645 up to 2300 cm^{-1} (to avoid contamination of SW radiances) keeping the original resolution of 0.25 cm^{-1} and for only clear-sky scenario. They have an horizontal resolution of 2° per 2° latitude.

4.4 ENSO spectral footprint

The same lagged regression analysis that was performed on the broadband OLR outputs of the CMIP6 models and CERES observations (Section 3.3) has been applied to the spectral OLR data products derived from IASI and AIRS measurements. Similarly, the AIRS and IASI datasets have been regridded to a horizontal resolution of 2.5° latitude by 2.5° longitude through bilinear interpolation and only values above the ocean are selected

to calculate the tropical mean OLR anomaly. When observations are considered this is of particular importance to avoid introducing biases in the comparison of non-simultaneous measurements, which can arise from the rapid temperature variability typical of land surfaces (X. Huang and Yung 2005; Simon Whitburn, Clarisse, Bouillon, et al. 2021). We recall that the tropical mean OLR anomaly is calculated by averaging the OLR over the tropical zone (30°S – 30°N), and by removing both the monthly climatology, and the linear trend, relative to period considered. For this part of the analysis this covers the years from January 2008 to December 2020. This period was selected since it is common to both the IASI and AIRS data products. In line with the analysis presented in Section 3.3, the OLR anomaly has been regressed onto the Niño 3.4 index (see Section 3.1.3), which account for ENSO phase and magnitude, shifted of one month at a time from -12 to +12 months. When the analysis is extended to the spectral dimension, lagged regressions are performed on the OLR anomaly associated with each spectral channel within the wavenumber interval covered by the IASI and AIRS datasets. In this regard, IASI has been resampled at the same resolution of AIRS (10 cm^{-1}) to allow for a direct comparison between the two products. Results of the lagged regression analysis are reported by Figure 4.1, where the slope of the linear regression is plotted as a function of wavenumber and lag. As with the broadband response, the sign of the OLR is defined as positive upward. This means that positive slopes correspond to an increase in OLR emission at the TOA, while negative slopes indicate a decrease.

New features are revealed by the spectral dimension. The first thing to note is that the radiative response changes sign and magnitude in correspondence to different spectral regions. Specifically, wavenumbers between $1000 - 1065\text{ cm}^{-1}$, where the ozone absorption band is located, show a strong variation, which is the highest throughout the whole spectrum. Other interesting features are observed between about 600 and 750 cm^{-1} , in correspondence of the carbon dioxide absorption band. There are two regions showing a positive response, which corresponds to the band wings, between $\sim 600\text{--}645\text{ cm}^{-1}$ and $\sim 700\text{--}800\text{ cm}^{-1}$, while the center of the band ($\sim 645\text{--}700\text{ cm}^{-1}$) shows a negative response. The atmospheric windows, at $\sim 800\text{--}1000\text{ cm}^{-1}$ and $\sim 1100\text{--}1200\text{ cm}^{-1}$, show both a positive response. Most interesting a change in the time lag of the radiative response peak is also observed. The atmospheric windows show the earliest response, which peaks at lag equal to 2 months. It is followed by the response within the O_3 absorption band, which peaks at 3-months lag. The same is also obtained for the wings of the carbon dioxide band. While the center shows the latest response at a lag of 5 months. Below 600 cm^{-1} we can rely only on AIRS simulated spectral fluxes. These wavenumbers exhibit positive slopes, too, of higher magnitude between $\sim 400\text{--}600\text{ cm}^{-1}$, than between $\sim 100\text{--}400\text{ cm}^{-1}$. These two spectral regions also differ in the time of the response, centered at 3-month lag for the first and at 2-month lag for the second.

To aid interpretation of the lagged regressions performed as a function of wavenumber,

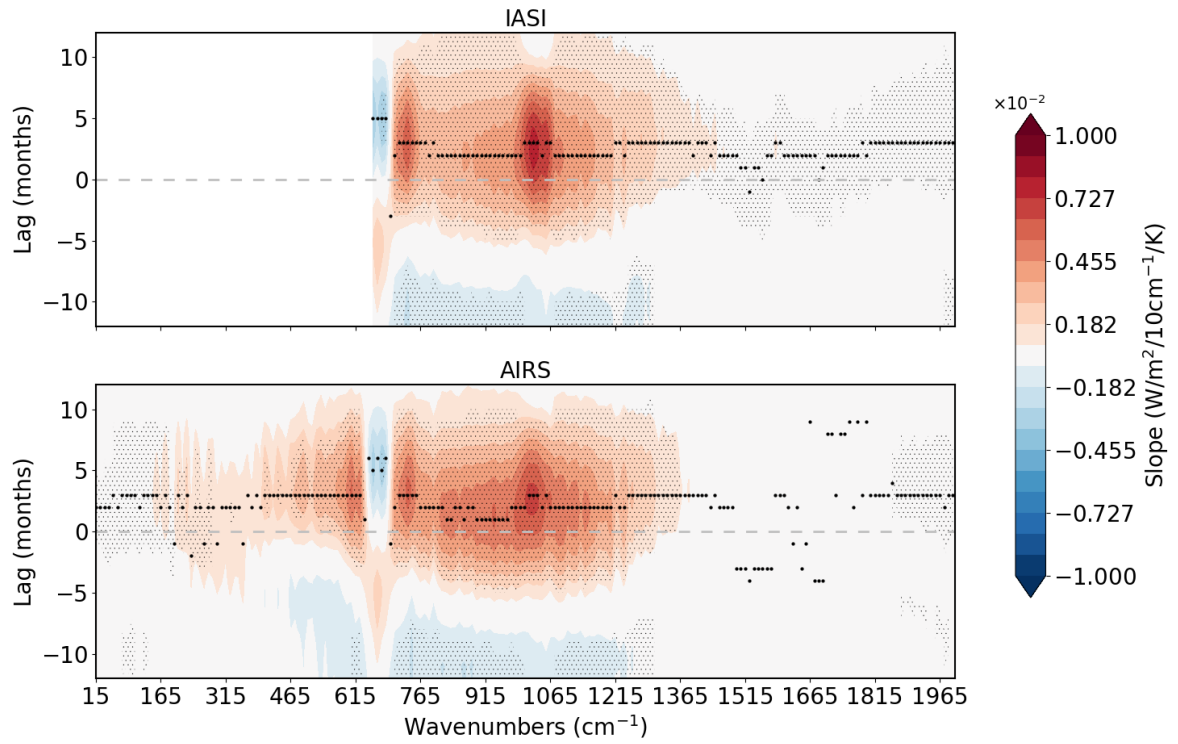


Figure 4.1: Slopes of the lagged regressions between OLR anomalies and the Niño 3.4 index as a function of wavenumber and lag for IASI (top panel) and AIRS (bottom panel). Thinner black dots mark 95% significance of the slopes, while thicker black dots mark the lag where the slope peaks at each wavenumber.

IASI and AIRS spectral OLR fluxes have been integrated along the spectral dimension to calculate their respective broadband response. In the case of AIRS, two broadband fluxes have been calculated: one using spectral channels from 50-1995 cm^{-1} (dashed line), to be as consistent as possible with CERES (encompassed range from 50 to 2000 cm^{-1}), and a second limited to the IASI spectral range (645-1995 cm^{-1}). The slopes of the linear regressions obtained from IASI and AIRS integrated fluxes are reported in Figure 4.2 as a function of time-lag, along with results obtained from CERES broadband flux. For this last the EBAF Ed 4.1 dataset that only considers cloud-free observations has been used (see Chapter 3, Section 3.1.2).

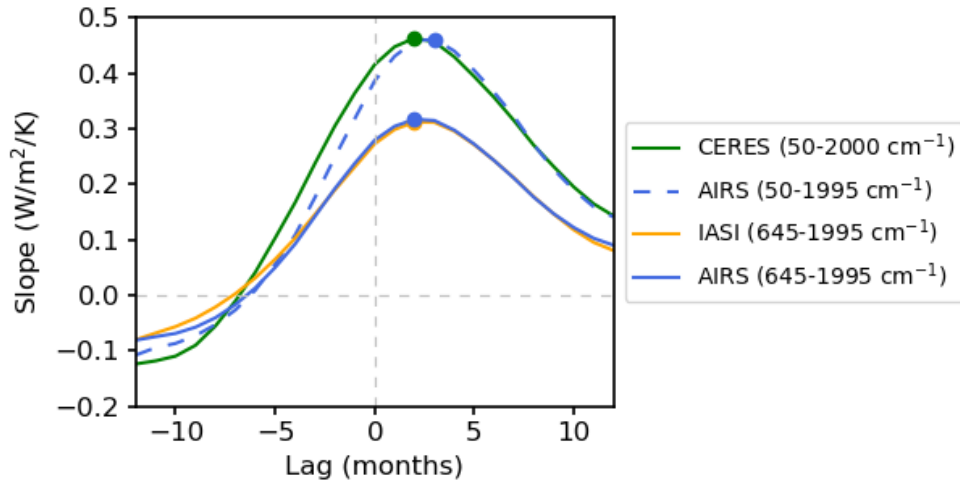


Figure 4.2: Lagged regressions of the tropical mean integrated OLR anomalies from CERES (green), AIRS (blue) and IASI (orange), respect to the Niño 3.4 index, from lag -12 to +12 months.

In line with Figure 3.12, the magnitude of the slopes increases when moving from negative to positive lags, peaking a few months after ENSO, showing an overall increase in the TOA OLR emission. In this case, the OLR response reaches its maximum with a lag of 2 months with respect to ENSO peak, instead of 3 months after. This difference suggests that the relationship depends on the period considered. The 3-month lag is obtained for the period from March 2000 to December 2014, while the 2-month lag is obtained for the period from January 2008 to December 2020. They do not share the same El-Niño/La-Niña events.

Another features which emerges from the comparison of IASI and AIRS integrated fluxes is the contribution of the FIR spectral region. Indeed, when both the Middle- (MIR, 650–2300 cm^{-1}) and Far-Infrared (FIR) (100–650 cm^{-1}) spectral regions are accounted for, the maximum slope is of $0.46 \pm 0.11 \text{ Wm}^{-2}\text{K}^{-1}$ for AIRS and $0.46 \pm 0.12 \text{ Wm}^{-2}\text{K}^{-1}$ for CERES, while its value is of $0.31 \pm 0.05 \text{ Wm}^{-2}\text{K}^{-1}$ for AIRS and $0.31 \pm 0.05 \text{ Wm}^{-2}\text{K}^{-1}$ for IASI, when only the MIR is considered. This denotes that an important part of OLR emission during ENSO is achieved across the FIR, confirming its importance for the TOA ERB (John Harries et al. 2008, Palchetti et al. 2020).

Although we find an excellent agreement in the value of the maximum slope between CERES and AIRS, there is a slight delay in the AIRS signal, with the peak delayed by 1 month (at 3-month lag) and a smaller slope at negative lags. The agreement between AIRS and IASI is excellent, with minor differences at negative lags. Figure 4.3 reports the slopes as a function of wavenumber for a lag of 2-months, where the broadband lagged regressions peak. Spectral footprints for AIRS and IASI are generally in a good agreement, showing the same main features. Nevertheless, there are some differences in the magnitude of the slopes in the atmospheric window between $\sim 800\text{-}1000\text{ cm}^{-1}$ and within the O_3 absorption band. AIRS slopes within the atmospheric window are higher than IASI, while they are lower within the O_3 absorption band. One factor to consider is the different overpass time of AIRS and IASI. This could partly explain the observed bias within the atmospheric window, where radiance is more sensitive to surface temperature (Simon Whitburn, Clarisse, Bauduin, et al. 2020). However, the different clear-sky scene selection could also play a role. Specifically, AIRS clear-sky fluxes are based on the collocated CERES measurements considered as clear-sky by the scene type information provided by the Moderate Resolution Imaging Spectroradiometer (MODIS), as described in X. Huang, W. Yang, et al. 2008. We found that this strategy produced a more conservative cloud screening than that of IASI (not shown). This aspect will be more evident in Section 4.6, when we will examine the spatial pattern of the ENSO feedbacks.

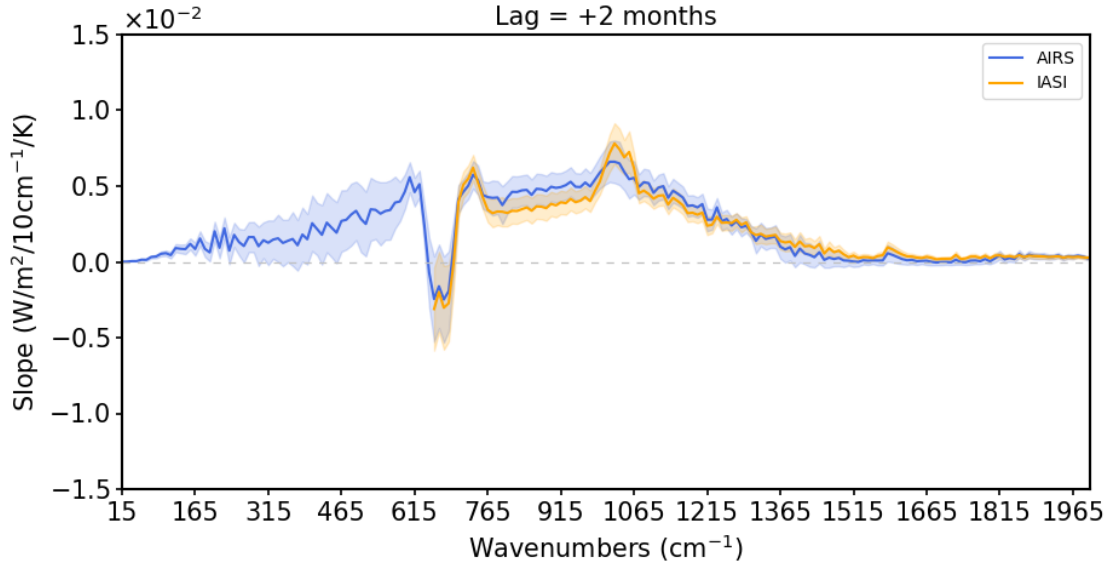


Figure 4.3: Slopes of the lagged regressions between OLR anomalies and the Niño 3.4 index as a function of wavenumber at a fixed lag of 2 months for IASI (orange) and AIRS (blue). Shades envelope the 95% confidence interval.

4.5 Radiative kernel analysis

We have first investigated the total LW response to ENSO using spectral observations. However, it contains the signal associated to different climate feedbacks, that contribute in different ways to the total response. Therefore, to better understand the role of each climate feedback we calculated their individual contribution applying a spectral kernel analysis. Radiative kernels allow to calculate the radiative change at TOA driven by the incremental change in feedback variables (B. J. Soden et al. 2008). Radiative kernels (or Jacobians) represent the partial derivative of spectral flux with respect to specific climate variables (temperature, surface temperature, water vapor and ozone), evaluated across the atmospheric levels in clear-sky conditions. Different sets of radiative kernels have been developed during years. In this work the same set of spectral radiative kernel used by Della Fera, Fabiano, Raspollini, Ridolfi, Hardenberg, et al. 2025 are employed.

4.5.1 Spectral radiative kernels

Radiative kernels used for this study have been computed using the RTTOV model (Radiative Transfer model for the TIROS-N Operational Vertical Sounder) (Matricardi 2009) and monthly mean profiles from the European Center for Medium-Range Weather Forecast (ECMWF) Reanalysis v5 (ERA5) dataset as the input for meteorological fields. The derivatives have been computed for three different years 2008, 2009, and 2010, and then averaged to obtain representative monthly kernels of surface and atmospheric temperature, water vapor and ozone. More details regarding the construction of the spectral kernels can be found in Della Fera, Fabiano, Raspollini, Ridolfi, Hardenberg, et al. 2025.

Furthermore, in order to obtain the derivatives of the spectral flux ($\text{W}/\text{m}^2/\text{cm}^{-1}$), radiance derivatives ($\text{W}/\text{m}^2/\text{cm}^{-1}/\text{sr}$) were computed at three distinct viewing angles (24.29° , 53.80° , 77.74°). The resulting values were then integrated using Gaussian quadrature, which has been shown to yield accurate results for clear-sky radiative transfer calculations (Clough, Iacono, and Moncet 1992).

The resulting product consists of radiative kernels, averaged over 10 cm^{-1} intervals, from 100 to 2300 cm^{-1} , spanning 17 pressure levels (hPa): 1000, 925, 850, 700, 600, 500, 400, 300, 250, 200, 150, 100, 70, 50, 30, 20, 10, on a horizontal grid of 2.5° longitude per 2.5° latitude.

Finally, the change in the radiative flux associated to the change in each climate variable is obtained multiplying the respective radiative kernel by the anomaly of that variable and then, for 3D fields, summing over the pressure levels to obtain the total atmospheric response. Surface and atmospheric temperature, water vapor and ozone fields are taken from the monthly ECMWF ERA5 reanalysis (Hersbach et al. 2023). Atmospheric variables are selected on the same 17 pressure levels used for the radiative kernels computation. Detrended anomalies of meteorological fields are computed relative

to the monthly mean from January 2008 to December 2020, the period selected for the analysis.

4.5.2 Atmospheric drivers of the radiative response

Radiative perturbations caused by surface and atmospheric temperature, water vapor and ozone underwent to the same lagged regressions as of IASI and AIRS OLR anomalies. In this way the ENSO feedback associated to the surface and atmospheric Planck effect, water vapor and ozone has been obtained. Results are reported by Figure 4.4. Starting from the top panel of Figure 4.4 there are the ENSO feedbacks as a function of lags and wavenumbers. The role of each feedback is discussed below.

The Planck surface feedback contributes to the total OLR only within the atmospheric windows, where the OLR is sensitive to the surface. The associated slopes are positive and their maximum is centered at lag equal to 2 months.

The Planck atmospheric feedback causes a positive response throughout all the spectral regions that peaks on average at a lag of 3 months, except between $645\text{--}700\text{ cm}^{-1}$, where the slopes are negative and peak at 5-month lag, explaining the negative slopes observed in the two plots of Figure 4.1. The positive peak associated to the Planck atmospheric feedback is located in the FIR spectral region, between $\sim 400\text{--}600\text{ cm}^{-1}$. Here the lag is of +4 months. When the Planck atmospheric feedback is separated in a tropospheric and stratospheric contribution, setting the tropical tropopause layer at 100 hPa, it is clear that the negative slopes come from the stratospheric temperature change (Figure 4.6) and that the strong positive slopes in the FIR spectral region are from the troposphere (Figure 4.5), particularly from the upper troposphere (600-150 hPa) (Figure 4.7).

The Planck surface and atmospheric feedback are both negative, enhancing the OLR emission. Water vapor, instead, constitutes the main positive feedback. Indeed, humidity changes cause negative regression slopes throughout the spectrum, meaning that a reduction in emission of OLR takes place. As for the Planck atmosphere, the FIR is associated to the highest slopes, with most of the signal coming from the upper troposphere (Figure 4.7). The water vapor feedback peaks with a lag of +3 months at all wavenumbers where the regression slopes are significant. Given the strong signal in correspondence of the ozone absorption band, we isolated the ozone contribution as well.

The ozone feedback is a small negative feedback, peaking in the stratosphere (Figure 4.6). It is found around 1025 cm^{-1} . It enhances the OLR emission from 2 until 6 months lag. At the same wavenumbers and lags there is also a smaller positive feedback associated to the stratospheric temperature (Figure 4.6), which, opposed to ozone, acts to reduce the OLR emission.

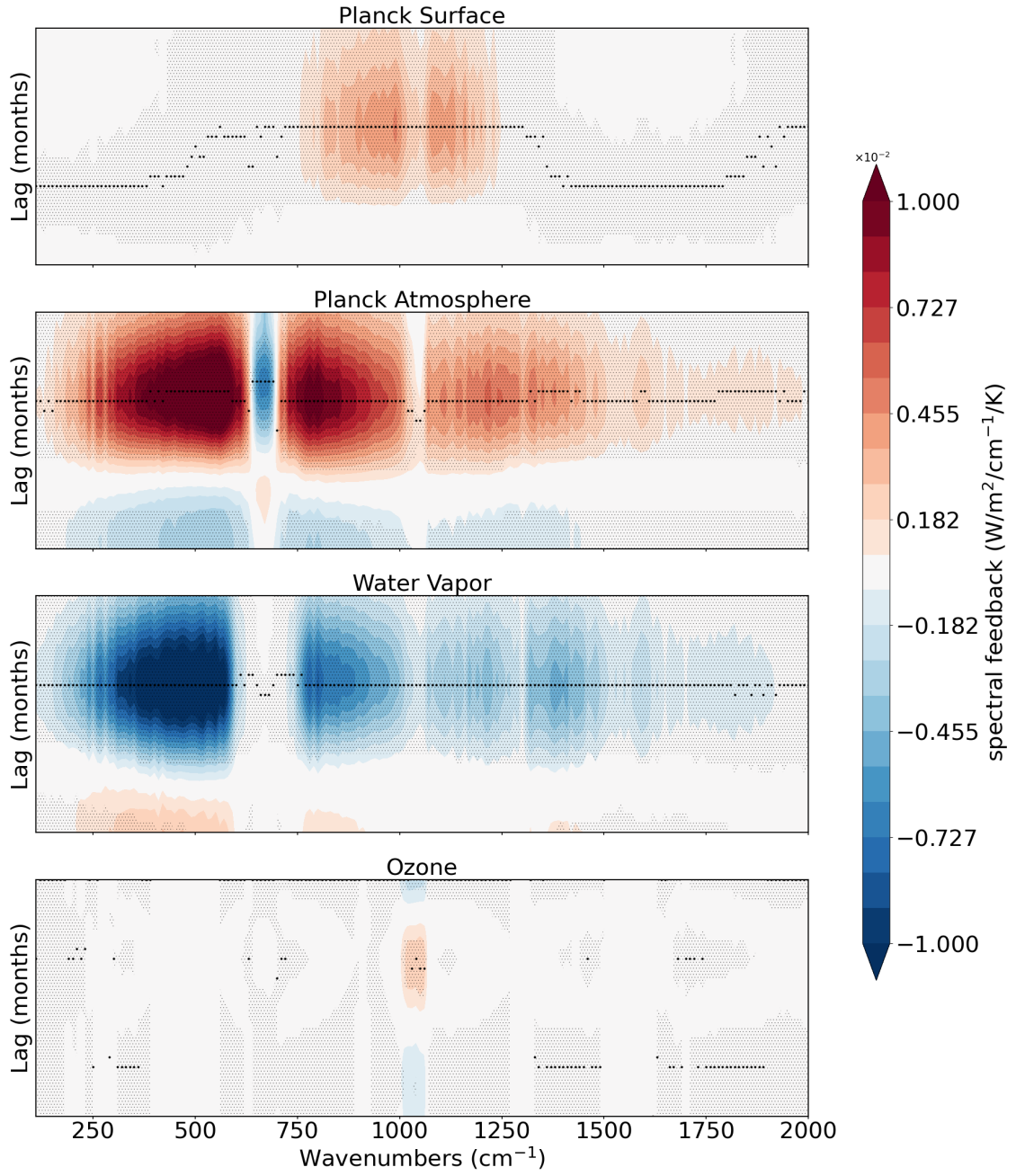


Figure 4.4: Slopes of the lagged regressions between OLR anomalies and the Niño 3.4 index, but for radiative changes decomposed into Planck surface and atmospheric, water vapor and ozone ENSO feedback. Slopes are reported as a function wavenumber and lags. Thinner black dots mark 95% significance of the slopes, while thicker black dots mark the lag where the slope peaks at each wavenumber.

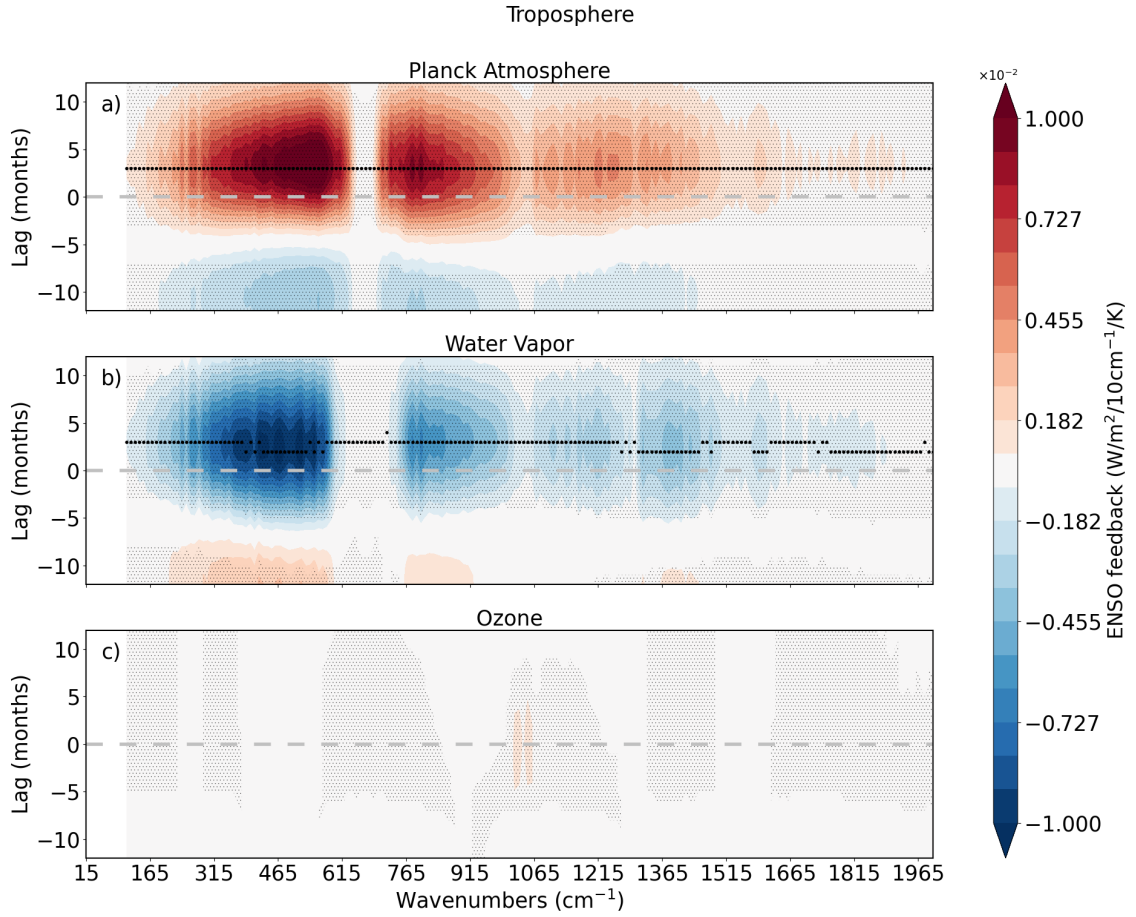


Figure 4.5: Slopes of the lagged regressions between OLR anomalies and the Niño 3.4 index, but for tropospheric radiative changes decomposed into atmospheric, water vapor and ozone ENSO feedback. The tropical tropopause is set at 100 hPa. Thinner black dots mark 95% significance of the slopes, while thicker black dots mark the lag where the slope peaks at each wavenumber.

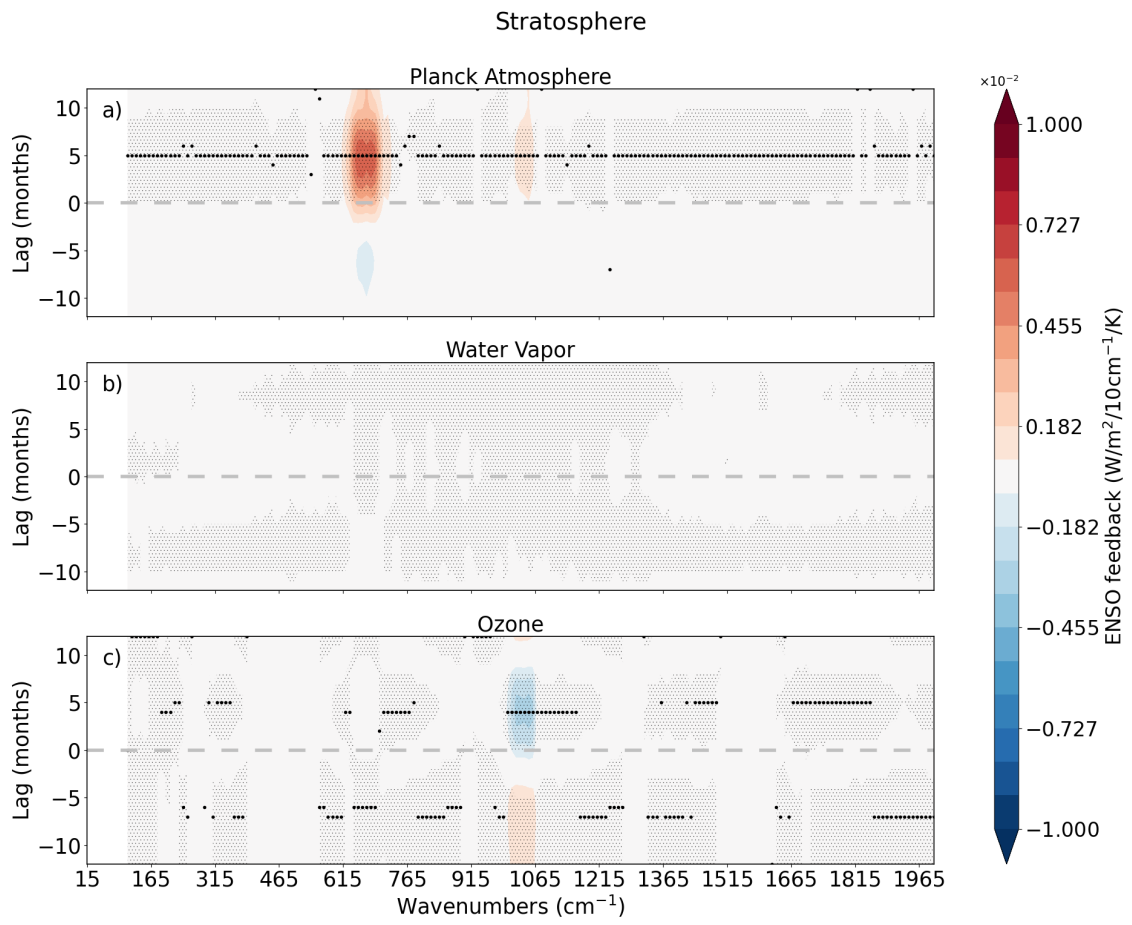


Figure 4.6: Same as Figure 4.5, but for radiative changes within the stratosphere.

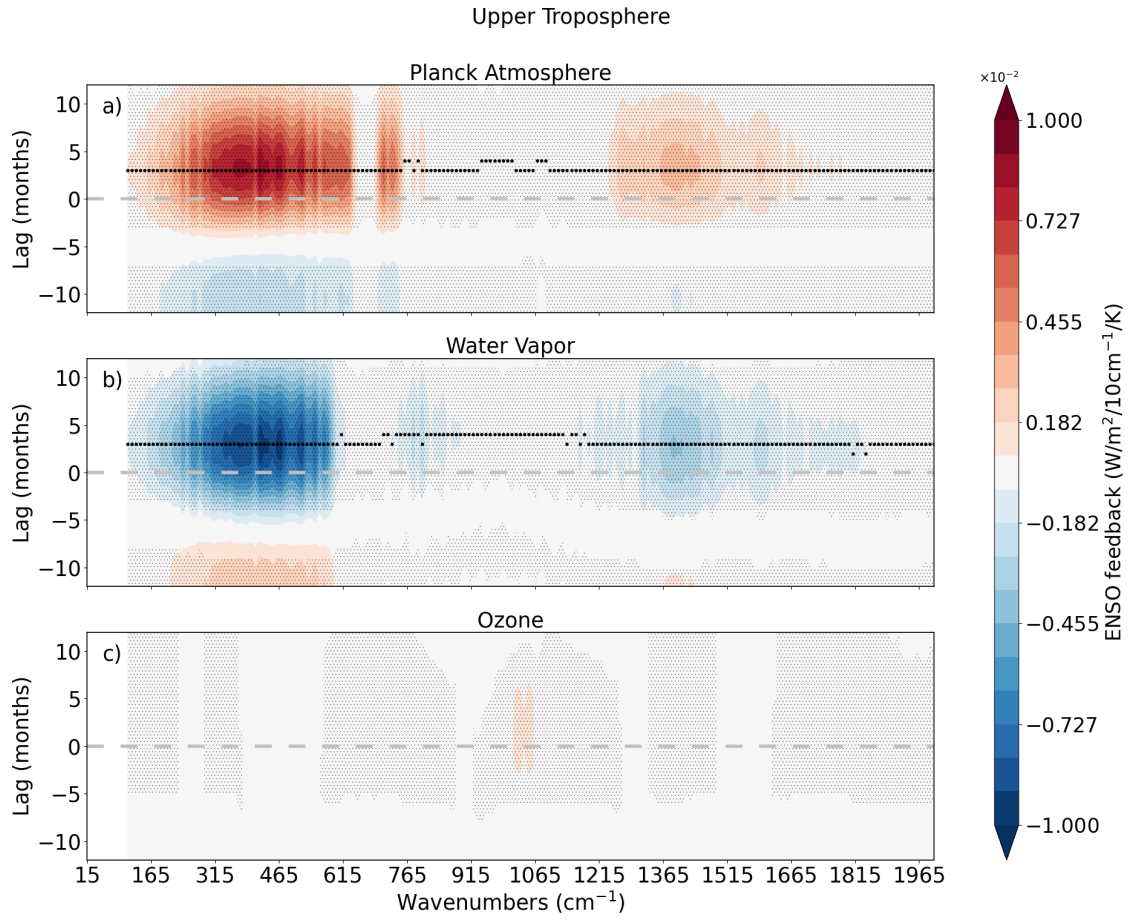


Figure 4.7: Same as Figure 4.5, but for radiative changes within the lower troposphere (1000-600 hPa).

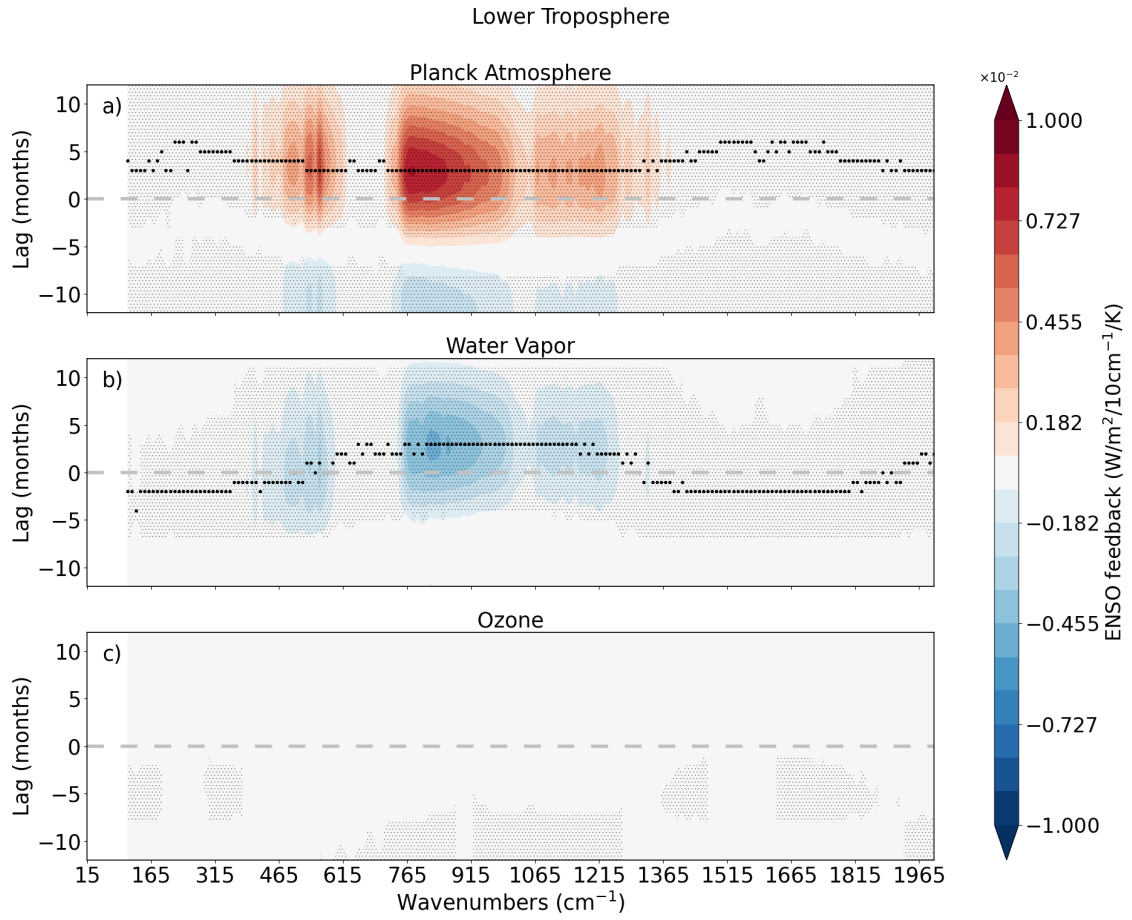


Figure 4.8: Same as Figure 4.5, but for radiative changes within the upper troposphere (600-150 hPa).

4.5.3 Reconstructed total LW response

Finally, we reconstructed the total observed LW response summing the individual feedbacks calculated with kernels. The feedback sum is shown in Figure 4.9, as a function of wavenumber and lag. It is also reported in Figure 4.10 together with each spectral feedback, as a function of wavenumbers only for the 2-month lag, where the broadband response peaks.

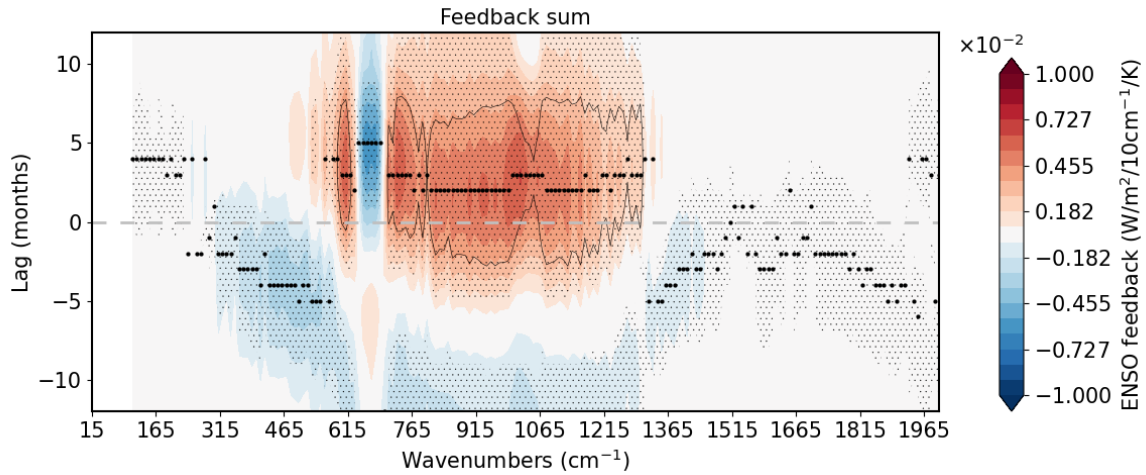


Figure 4.9: Same as Figure 4.4, but for the sum of water vapor, ozone, surface and air temperature feedback.

The major features of the observed clear-sky OLR response (Figure 4.1) are present. The kernel regression analysis correctly reproduces the positive slopes within the two atmospheric windows and at the wings of carbon dioxide absorption band, and the negative slopes at the center of it. Their magnitude and time-lag is also well reproduced. However, there are two notable exceptions: the peak found in correspondence with the ozone absorption band, which is underestimated by the kernel analysis, and the net signal in the FIR and MIR spectral region, which is positive and follows ENSO according to observations, while the opposite is suggested by the kernels sum. A possible explanation could be the fact that ERA5 profiles are referred to all-sky properties, that in the case of water vapor results in an higher humidity content than a clear-sky profile causing an over-estimation of the respective feedback, which masks the ozone signal and overcompensate the atmospheric temperature signal within the FIR and MIR regions.

Within the next section the spatial pattern of the OLR response to ENSO is examined, this will help to identify the regions associated to the previous biases.

4.6 Spatial pattern of the LW response to ENSO

We now examine the spatial pattern of the OLR response to ENSO across the tropics (30° S - 30° N), to find the regions associated to the strong O_3 response, and to the suspected

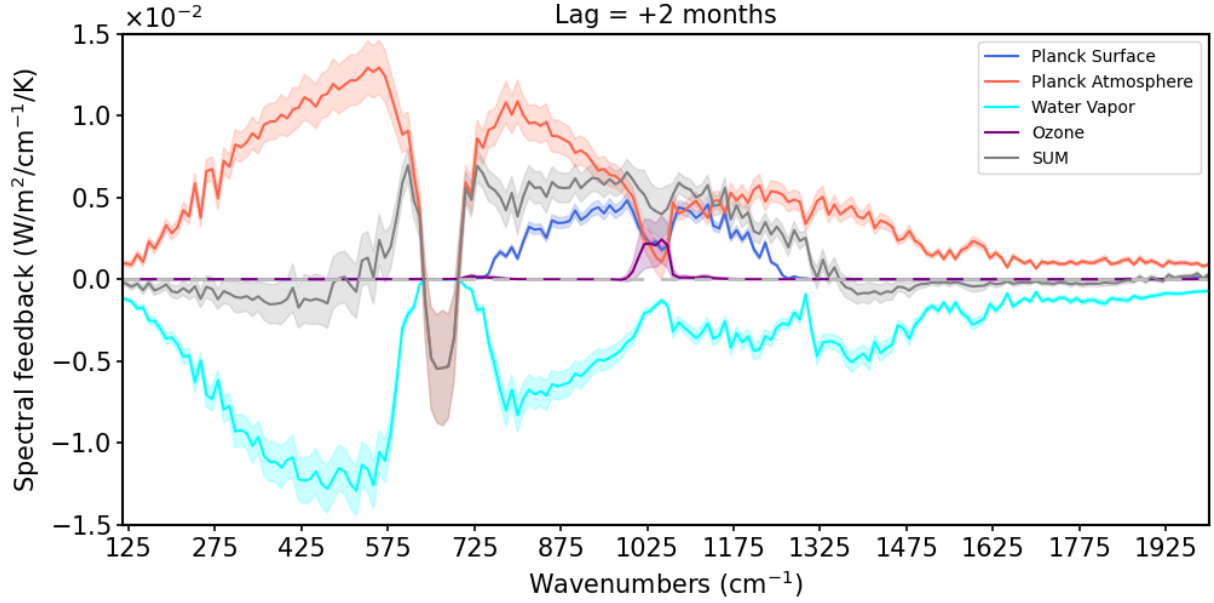


Figure 4.10: Slopes are reported as a function of wavenumber at a fixed lag of 2 months in the top panel (feedback sum in gray, Planck atmospheric feedback in red, Planck surface feedback in blue, water vapor feedback in cyan and ozone feedback in purple). Shades envelope the 95% confidence interval.

bias due to the overestimation of the water vapor contribution.

Figure 4.11 shows the spatial pattern of the linear regressions between OLR anomalies and the Niño 3.4 index at 2-month lag for two individual spectral channels. Starting from the top of Figure 4.11, the maps obtained for IASI (top), AIRS (mid) and the kernel reconstructed signal (bottom) are shown. The left column refers to the channel at 905 cm^{-1} , within the atmospheric window, providing information on the surface temperature, but also on the effect of water vapor, that we want to assess and compare among IASI, AIRS and the response reconstructed using spectral radiative kernels. The right column corresponds to the channel at 1025 cm^{-1} , within the O_3 absorption band, sensitive mainly to the atmospheric temperature profile and O_3 . Here is where the highest positive response within the ozone absorption band - and the whole wavenumber range - is observed.

At 905 cm^{-1} , a dipole is observed within the tropical Pacific Ocean, in phase with the SST pattern typical of El-Niño conditions. Indeed, negative slopes characterize the western part of the basin, while positive values are found in the central and eastern regions. Significant positive contributions are also found over the north-east subtropical region and over the Maritime Continent. The LW response at 1025 cm^{-1} is characterized by positive slopes coming from the central and eastern Pacific Ocean. Their magnitude is highest within the Niño 3.4 region (marked by a black box), and decreases moving off the equator.

Overall, there is a good agreement in the pattern obtained using IASI and AIRS products, although some minor differences can be observed. As mention before, the

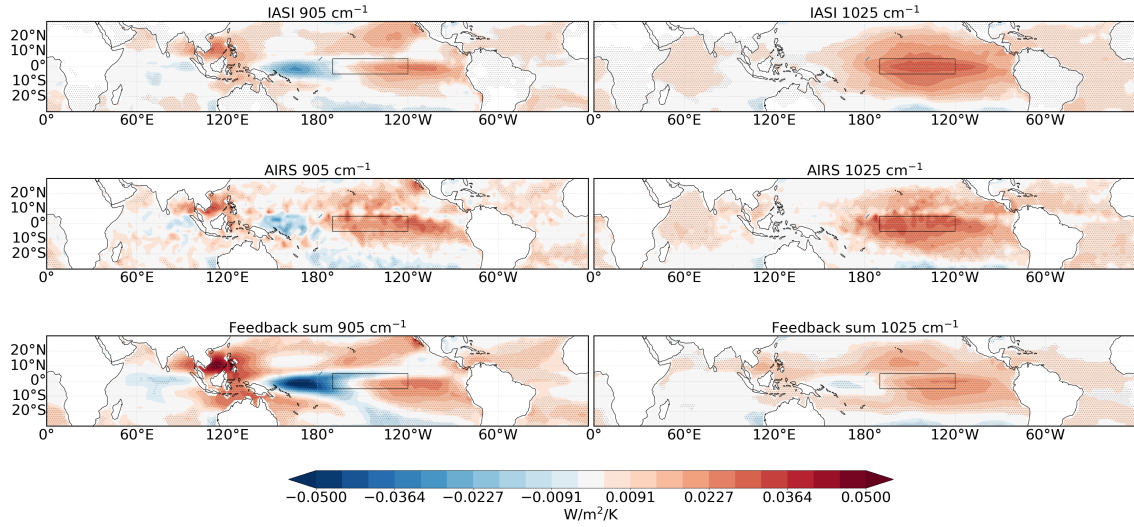


Figure 4.11: Slopes of the linear regressions at lag equal to 2 months between the tropical mean OLR anomalies, at two selected spectral channels, and the Niño 3.4 index, calculated at every grid box within the tropical zone (30°S - 30°N). Starting from the top, results for IASI, AIRS OLR and the feedbacks sum. On the left results at 905 cm^{-1} , on the right at 1025 cm^{-1} . Dots mark regions where the regressions reach the 95% significance level.

impact of the clear-sky scene selection of AIRS observations is evident here. Specifically, AIRS shows a more scattered pattern with respect to IASI in the western and central tropical Pacific at 905 cm^{-1} . In addition to that, the spatial pattern at 905 cm^{-1} shows a less extent region of negative slopes in the west Pacific, constituting another reason for the higher slopes of AIRS.

The response pattern is qualitatively well reproduced at 905 cm^{-1} through the kernel reconstruction, although the magnitude of the negative slopes within the west Pacific is clearly overestimated. Higher discrepancies are obtained for the reconstructed response pattern at 1025 cm^{-1} . Positive slopes characterize the eastern and central Pacific but their magnitude is smaller than observations and the peak is shifted eastward, with a region of negative slopes in the western Pacific, partly resembling the 905 cm^{-1} pattern. The anomalous positive feedback can be attributed to the water vapor ENSO feedback, which shows a positive signal in the western and central parts of the Tropical Pacific Ocean at both 905 cm^{-1} and 1025 cm^{-1} (Figure 4.12). These differences consolidate our hypothesis of an overestimation of the water vapor feedback, that would also overcompensate the Planck contribution below 600 cm^{-1} and above 1300 cm^{-1} in the kernel reconstruction.

4.7 Discussion

The main effect of ENSO on the climate system is the anomalous SST pattern across the tropical Pacific Ocean, accompanied by a shift of the Walker Circulation (WC) Bjerknes

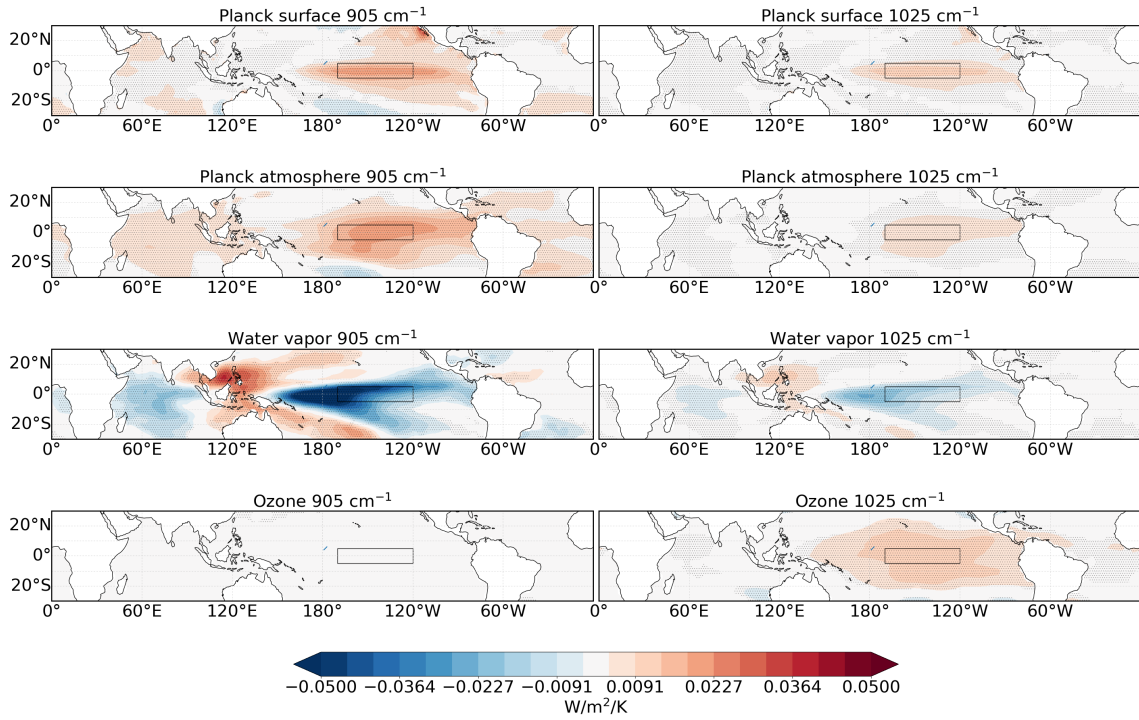


Figure 4.12: Same as Figure 4.11, but for each of the ENSO feedback considered.

1966. During the positive El-Niño phase warmer SST anomalies characterize the eastern and central part of the basin, while cooler SST are found in its western part. The WC is shifted eastward, with an increase in convective activity over the central Pacific and a decrease over the West Pacific warm pool. The negative ENSO phase, La-Niña, brings to the opposite conditions, accompanied by a strengthening of the Walker circulation.

In clear-sky conditions, the climate system responds to ENSO through an increase in OLR emission, that comes primarily from the tropospheric heating caused by the increase in surface temperature and by the increased latent heat release in the upper troposphere. In general agreement with Ceppi and Fueglistaler 2021, this response is observed to reach its peak after and slowly decaying. The observed lag of the radiative response can be explained by the SST pattern effect induced by ENSO, which causes warm SST anomalies to migrate across the tropical Pacific ocean from the east, at the beginning of an El-Niño event, to the west, where positive anomalies persist up to five months after ENSO peak (Ceppi and Fueglistaler 2021).

Broadband lagged regressions show a peak of the OLR response at 2-month lag. The spectral analysis shows that channels associated to this lag are the two atmospheric windows, whose radiance is mainly sensitive to the surface temperature. Radiative kernels analysis further support that the delay of the clear-sky OLR response is likely driven by the Planck surface feedback. Indeed, it is the only one that peaks with a lag of 2 months.

However, a deeper insight is provided by spectrally-resolved OLR measurements. The

strongest positive response is associated to the ozone absorption band and peaks at a 3-month lag. Others interesting features are the positive slopes at the wings of the carbon dioxide absorption band, where channels sensitive to tropospheric temperatures, which also peak at 3-month lag, and the negative slopes at the center of it, where radiation is sensitive to the stratospheric temperature. Their peak is the last at 5-month lag. With the aid of spectral radiative kernels, these features can be associated to the relevant physical processes that shape the OLR response to ENSO and its timing.

An increase in the time-lag of the OLR response is observed moving from the lower atmospheric layers to the higher. Specifically, the surface shows the earliest response at a lag of 2 months, followed by the troposphere, where the response peak lags ENSO of 3 months and the stratosphere, where a lag of 5 months is observed. As for regard the magnitude of the response, it is highest for channels sensitive to the troposphere, followed by channels sensitive to the stratosphere and the surface.

The tropospheric response instead, is shaped by two main feedbacks, the water vapor and the Planck atmosphere. The first informs on the radiative changes driven by humidity changes arising from the anomalous WC during ENSO. An increase in water vapor is related to the ascending branch of the WC. It acts to dampen the emission of OLR (positive feedback), absorbing most of the radiation emitted by the surface resulting from the increased SST. As a consequence, the main cooling mechanisms is the emission related to the warming of the troposphere (H. Huang, Y. Huang, and Hu 2021). The Planck atmosphere feedback is negative enhancing the OLR emission. Therefore, they act to counteract each other and this is true also from a spectral point of view. We see that their lag is the same throughout all the spectrum, except in the FIR between $400 - 600 \text{ cm}^{-1}$, where the temperature peaks one month later than water vapor. This evidences that the tropospheric cooling is maximum in this spectral region and is associated to the temperature feedback coming from the upper troposphere.

Moving to the stratosphere, the strong negative feedback within the ozone absorption band, together with the positive feedback associated to the stratospheric temperature, bear evidence of the ENSO stratospheric signal (Zeng and Pyle 2005; Randel et al. 2009; Calvo, García-Herrera, and Garcia 2008; Manzini 2009; Konopka et al. 2016; Manatsa and Mukwada 2017; Garfinkel et al. 2018). According to Domeisen, Garfinkel, and Butler 2019, a reduction in ozone concentration near and above the tropopause is observed as a result of the anomalous upwelling during El-Niño, which cause an increase of ozone-poor air in the central and eastern tropical Pacific. This agrees with the spatial pattern reported in Figure 4, which show that the ozone feedback is located in regions of increased convective activity. In addition to composition changes, El-Niño also affects the stratospheric temperature. Specifically, an opposite response respect to the troposphere is observed. If the troposphere experiences an increase in temperature during El-Niño, the stratosphere cools. The ENSO impact on stratospheric temperature is the result of

the upward propagation of Rossby waves forced by El-Niño and the strengthening of the Brewer Dobson Circulation (BDC) Domeisen, Garfinkel, and Butler [2019](#). The stratospheric temperature decrease related to ENSO can explain the coherent decrease in TOA OLR emission observed at the center of the carbon dioxide absorption band. Despite also involving a stratospheric signal, the OLR decrease is not observed in the ozone band, since the ozone concentration is also co-varying with ENSO near and above the tropopause, reversing the overall signal there. These findings confirm that the ENSO stratospheric signal plays an important role in shaping the LW radiative response peak.

Chapter 5

Testing ENSO-driven OLR variability of CMIP6 models with spectral satellite observations

This chapter covers the final step of the work: the evaluation of ENSO-driven OLR variability in climate models using spectral measurements. The comparison of OLR climate models outputs with broadband observations performed in Chapter 3 showed that CMIP6 AMIP and historical simulations do not fully capture the timing and magnitude of the TOA LW radiative response to ENSO as obtained from CERES observations. The main climate drivers of the radiative response were thus investigated in Chapter 4, using spectral OLR measurements acquired by AIRS and IASI. The additional information provided by the spectral dimension is now used to gain a deeper insight into the biases of climate models. First, the spectral OLR response to ENSO is reconstructed using CMIP6 AMIP and historical outputs of water vapor, surface and air temperature and spectral radiative kernels. Then, the corresponding ENSO feedback is calculated and compared with AIRS spectral observations to reveal biases in different spectral regions that may cancel each other out when the broadband OLR flux is considered.

5.1 The importance of spectral observations for climate science

Important information on the main factors behind the OLR variability are provided by spectral observations. Comparing observations acquired by IRIS and AIRS relative to two different periods of time, Griggs and JE Harries 2007 observed different spectral signatures associated to long-term changes in GHGs, especially methane and carbon dioxide. A similar work has been carried out by RJ Bantges et al. 2016, but using IASI observations instead of AIRS. Y. Huang and Venkatachalam Ramaswamy 2009 analyses interannual

variability of the OLR from AIRS observations, comparing and extending them with radiances simulated using a radiative transfer model. Changes due to external forcing such as GHGs increase and feedback of water vapor and temperature are evaluated. Spectral OLR observations have been used by Y. Huang and Ramaswamy 2008 to study the role of water vapor and clouds on the relationship between OLR and SST across the Tropical Pacific Ocean. The interannual variability of OLR from the first 5 years of measurements from IASI has been examined for different latitudinal bands Helen Brindley et al. 2015. X. Huang, X. Chen, Fan, et al. 2022, Simon Whitburn, Clarisse, Bouillon, et al. 2021, Della Fera, Fabiano, Raspollini, Ridolfi, Hardenberg, et al. 2025 show that the trends in spectral fluxes derived from AIRS and IASI observations carry the signal of the recent evolution of key climate variables (temperature, surface temperature, water vapor), the ongoing changes in GHGs atmospheric concentration, as well as the signal related to internal climate variability. In this context, the spectral longwave feedback parameter shows variations across the different spectral regions enabling to relate it to the dominant process Roemer et al. 2023.

Goody, Anderson, and North 1998 early proposed to test climate models performance by exploiting spectrally resolved measurements of Earth emission, due to their high radiometric accuracy and spectral resolution, and the fact that they contain the fingerprint of the climate system response along with information on the climate variable responsible for it. With the availability of the first years of AIRS measurements Y. Huang, Ramaswamy, X. Huang, et al. 2007 compared spectral radiances simulated by a GCM against AIRS observations, finding discrepancies in the water vapor and carbon dioxide bands that were consistent with biases in model’s atmospheric temperature and water vapor. Leroy et al. 2008 calculated the spectral longwave feedback associated to water vapor, tropospheric and stratospheric temperature change in a set of CMIP3 climate models and estimated that at least a 20-years observational record is necessary to test climate models longwave radiative feedback. This work also highlights how the largest source of uncertainty is related to internal variability. The spectral longwave feedback has been evaluated by X. Huang, X. Chen, B. J. Soden, et al. 2014 in CMIP3 and CMIP5 models, showing relevant differences across climate models in reproducing the water vapor and lapse rate spectral feedbacks. Spectral OLR have been proven to be a powerful method to assess performances of the EC-Earth3 climate model allowing to reveal biases otherwise hidden by compensation effects when broadband fluxes are considered (Della Fera, Fabiano, Raspollini, Ridolfi, Ugo Cortesi, et al. 2023).

5.2 Data and methods

Similarly to what was done for the ERA5 reanalysis in Chapter 4, spectral radiative kernels are used to calculate the radiative perturbation caused by changes in the sur-

face and atmospheric temperatures and water vapour profiles, as simulated by CMIP6 climate models. The following outputs were selected from CMIP6 AMIP and historical simulations: specific humidity ("*hus*" in CMIP6 variables table), air temperature ("*ta*" in CMIP6 variables table) and surface temperature ("*tos*" in CMIP6 historical and *ts* in AMIP simulations variables table). As with OLR fluxes, monthly-mean outputs were selected. Although they span the years from 1850 to 2014, and from 1979 to 2014 for CMIP6 historical and AMIP, respectively, only the time period from September 2002 to December 2014, during which simulations and observations overlap, was used for the analysis. All the outputs were bilinearly interpolated to a common grid with a resolution of 2.5° latitude by 2.5° longitude. The water vapour and air temperature data are also defined at 19 pressure levels (Pa). Only the data corresponding to the same 17 pressure levels used for the kernels were selected. Where the models vertical grid differed from that of the radiative kernels, the simulated values were linearly interpolated onto the kernel grid.

The radiative perturbation of each variable is given by the product of the anomaly of that variable and its corresponding radiative kernel. The variable anomalies were defined over the years from September 2002 to December 2014 and calculated by removing the seasonality from the time series over that period. Anomalies were multiplied by the corresponding spectral radiative kernel defined in section 4.5.1. The final output is the radiative perturbation ($\text{W/m}^2/\text{cm}^{-1}$) caused by the change in each climate variable, computed at a spectral sampling of 10 cm^{-1} , covering the spectral range from 110 to 2750 cm^{-1} .

Radiative perturbations caused by changes in water vapour, surface temperature and air temperature, as calculated using climate model outputs, were used to assess the temporal relationship between radiative anomalies and ENSO in CMIP6 AMIP and historical simulations. Linear regressions were performed between radiative contributions and the Niño 3.4 index, shifted from -12 to +12 of one month at a time, for a total of 25 regression coefficients. The regression between the radiative perturbation and the SST anomaly, as defined by the Niño 3.4 index, provides information on the ENSO spectral feedback relating to water vapour, the Planck surface and atmospheric effects. Lagged regressions enable us to study their evolution within the ENSO life cycle.

Therefore, the spectral radiative responses obtained from climate models outputs are compared to the observed spectral radiative responses of AIRS. Indeed, given the different time spans covered by models and observations, the comparison with IASI spectral flux would be limited to the period from 2008 to 2014. Instead, AIRS allows comparisons to be made over a longer period of time, from September 2002 to December 2014, which ensures that ENSO variability is properly sampled. As for the rest of the work, the analysis was limited to oceans under clear-sky conditions.

5.3 Spectral ENSO feedbacks in CMIP6 models

ENSO feedbacks obtained using climate model outputs of water vapor, surface and air temperature are showed in Figures 5.1 and 5.2, for AMIP and historical simulations, respectively. The feedbacks are plotted as a function of wavenumber for a time lag of two months, at the point when the peak of the broadband lagged regression is reached, as showed in Chapter 4).

The correct sign of the feedbacks is reproduced by both CMIP6 AMIP and historical simulations. The Planck surface and atmospheric feedbacks are positive meaning that they act to enhance the OLR emission at the TOA (OLR is considered positive upward). In contrast, the negative sign of the water vapor feedback denotes a reduction in OLR emission to space.

The Planck surface feedback simulated by CMIP6 AMIP experiments is characterized by a very small inter-model spread. This is consistent with the fact they are all forced with the same SSTs prescribed to observed values. More spread is observed for the Planck atmospheric feedback, which is highest between 100 and 600 cm^{-1} , across the FIR spectral region, and around 667 cm^{-1} , at the center of the carbon dioxide absorption band. Here there is a model that simulate a positive feedback, while the other all show a negative feedback. This same model also differs from the others around 1043 cm^{-1} , where the ozone absorption band is located. A great inter-model spread within the FIR is also obtained for the water vapor feedback, where few models are biased toward more negative values.

CMIP6 historical simulations also exhibit a low inter-model spread with regard to Planck surface feedback. However, a higher variability is observed across Planck atmospheric feedback than in AMIP. There is the same climate model (Figure 5.2, middle panel, pink thin line) which gives a positive response within the carbon dioxide absorption band. The Planck atmospheric feedback seems to be biased toward higher positive values, as it was for the AMIP case. The same situation is obtained for the water vapor feedback, which shows the highest inter-model spread in the FIR spectral region.

The sum of the feedbacks of AMIP and historical simulations is compared to the radiative response of AIRS in Figure 5.3.

The greatest differences are observed within the FIR and the ozone absorption band, where the radiative feedback reconstructed by the models outputs underestimate the observed one. The observed difference can be partly explained by the fact that the O_3 feedback was not considered. Some CMIP6 AMIP and historical models provide the O_3 profiles among their outputs, and their contribution to the total LW response will be added in a second moment. However, in Chapter 4, when the total LW response was reconstructed summing the different ENSO feedbacks but calculated using ERA5 variables fields as input profiles, these same differences respect to observations were obtained, even if the O_3 feedback was included. This was attributed to an overestimation of the water

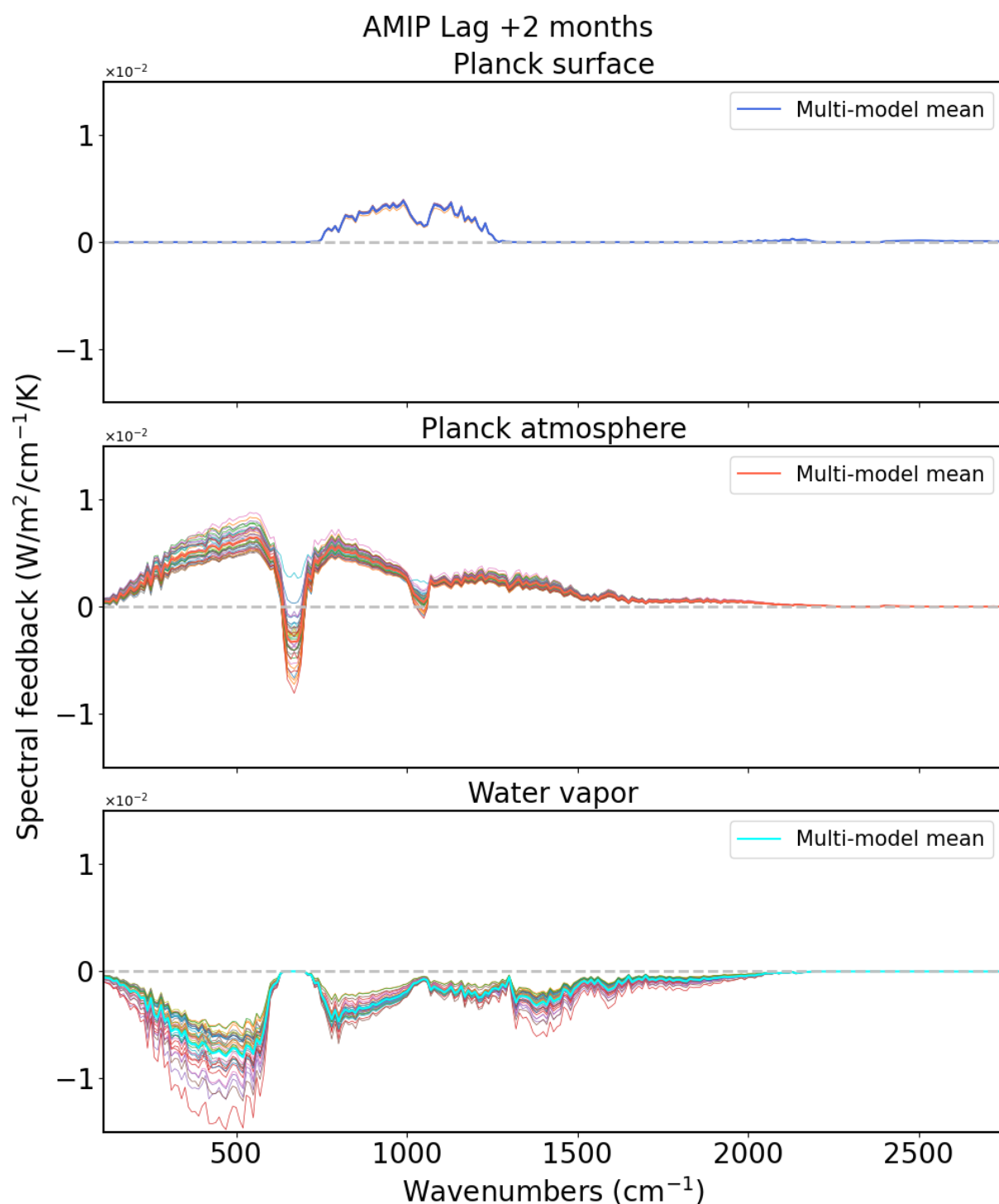


Figure 5.1: Spectral ENSO feedbacks (Planck surface in blu, Planck atmosphere in red and water vapor in cyan) calculated using spectral radiative kernels and variables fields simulated by AMIP (top panel) and CMIP6 historical models (middle panel) as a function of wavenumber for a time-lag of two months.

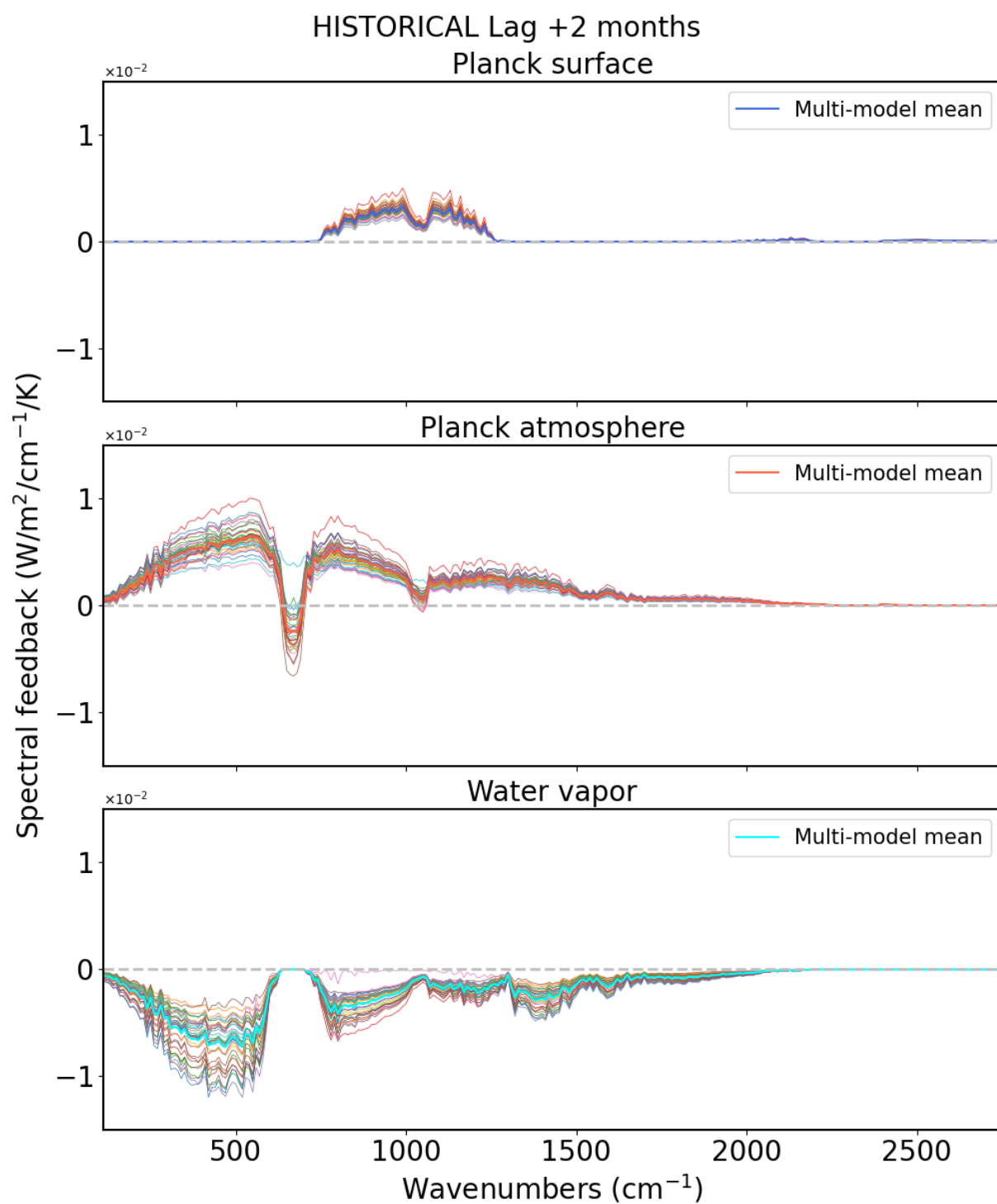


Figure 5.2: Same as Figure 5.1 but for CMIP6 historical simulations.

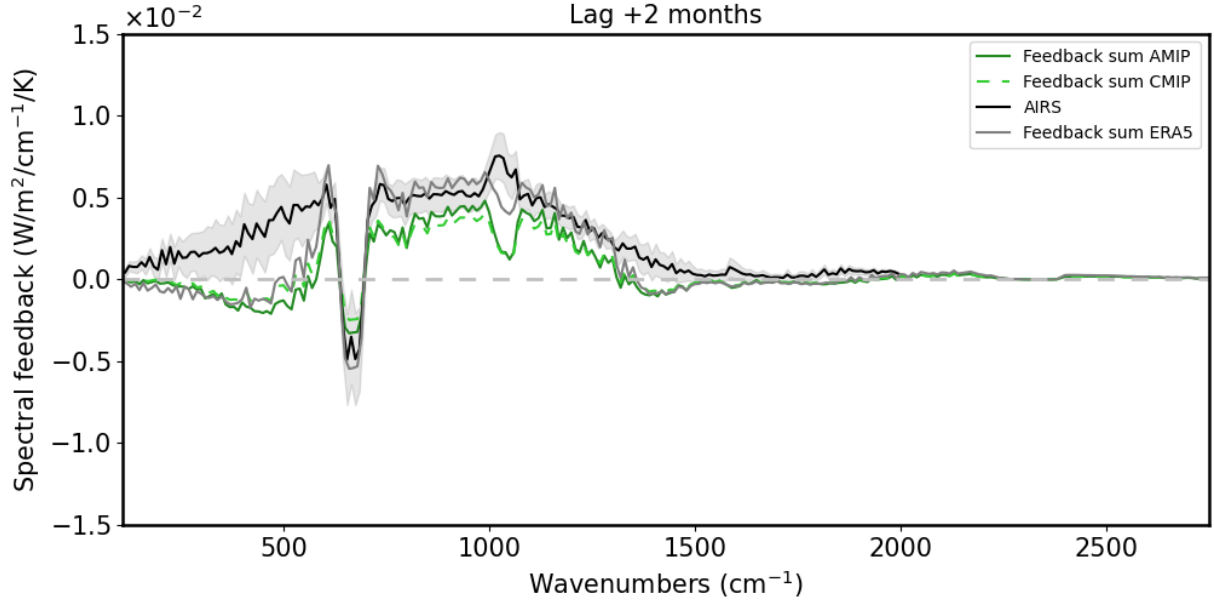


Figure 5.3: The feedback sum of AMIP (solid dark green) and CMIP6 historical (dashed light green) is compared to the total ENSO signal obtained by AIRS spectral flux (black) in the bottom panel. Grey shades envelope the 95% confidence interval of AIRS regression coefficients.

vapor feedback. This was particularly evident in the FIR, where the water vapor feedback is strongest. According to AIRS OLR fluxes the total LW response in this spectral range is positive, while the feedback sum obtained using ERA5 profiles is near to zero (Figure 4.4). Such as for ERA5, water vapor profiles provided by AMIP and historical simulations are referred to all-sky conditions, therefore the overestimations of the humidity air content lead to a stronger water vapor feedback than clear-sky conditions of AIRS OLR fluxes. Other minor differences interest the window regions between 900 and 1000 cm^{-1} , and 1100-1200 cm^{-1} . In general, the radiative response is underestimated by models at all wavenumbers.

The agreement between AMIP and historical simulations is good. Their feedback sum shows almost the same magnitude throughout the spectrum. The only differences are observed across the FIR, in the center of the carbon dioxide absorption band, and in the atmospheric window between 900 and 1000 cm^{-1} . The bias between models and observations is slightly smaller for AMIP models, except in the FIR spectral region, where the opposite situation is observed.

ENSO spectral feedbacks are plotted as a function of both wavenumber and lag in Figure 5.4 and 5.5, for the multi-model mean of CMIP6 AMIP and historical simulations, respectively, and for each single model from Figure 5.7 to Figure 5.11. Both AMIP and historical simulations capture the same 2-month lag of the peak of the Planck surface feedback, in agreement with observational data. Instead, the peak of the water vapor feedback is postponed by coupled models of one month respect to AMIP across the whole

spectrum. More in detail, between 400 and 600 cm^{-1} they both show a change in the timing of water vapor response, which moves to 2-month and 4-month lag, in AMIP and historical, respectively. The Planck atmospheric feedback peaks at 5-month lag in coupled models across the whole spectrum, except between 600 and 700 cm^{-1} , in correspondence of the CO_2 absorption band, where it is located at 4-month lag. AMIP multi-model mean shows a higher variability. In addition to the features described for historical models, a 4-months lag is observed within the window region. For these models the response associated to the CO_2 absorption band is further anticipated at 3-month lag. The individual contribution of Planck surface and atmospheric, and water vapor feedback are summed together to obtain the total LW feedback (Figure 5.4 and Figure 5.5, bottom panels). The positive response associated to the atmospheric window and to the wings of the CO_2 absorption band obtained with AIRS and IASI observations is correctly reproduced in AMIP and historical simulations, as well as the negative response associated to the center of it, although its magnitude is lower than the observed one. Below 600 cm^{-1} , the historical multi-model mean shows a perfect compensation between water vapor and Planck atmospheric feedback, AMIP multi-model mean is slightly positive but towards higher positive lags than observations. When considering the response of each model separately, it can be seen that the response at the centre of the CO_2 band is most often misrepresented in both AMIP and historical simulations. It is generally underestimated, but the difference with observations is most notable in the associated lag. The peak occurs either too early or too late.

5.4 Discussion

In Chapter 3 the broadband OLR response to ENSO in AMIP and historical simulations provided by CMIP6 models was investigated. In the analysis, many climate models exhibited different time lag in their radiative responses respect to ENSO peak.

While in Chapter 4 the main climate drivers of this relationship have been examined using spectral observations and calculating their individual contribution with spectral radiative kernels, in this Chapter the same spectral kernel analysis has been applied to CMIP6 AMIP and historical experiments. The anomalies in water vapor and air temperature profiles and surface temperature simulated by climate models have been multiplied by the corresponding spectral radiative kernel to obtain the radiative perturbation associated to their change. Then, as in Chapter 4, the ENSO spectral feedback has been calculated at different time lags to study the evolution of the water vapor, the Planck surface and atmospheric feedback during ENSO life cycle.

From a first comparison, AMIP and historical models correctly reproduce the main ENSO spectral footprints obtained from the analysis performed on AIRS and IASI observations presented in Chapter 4. Namely, the positive Planck surface feedback within

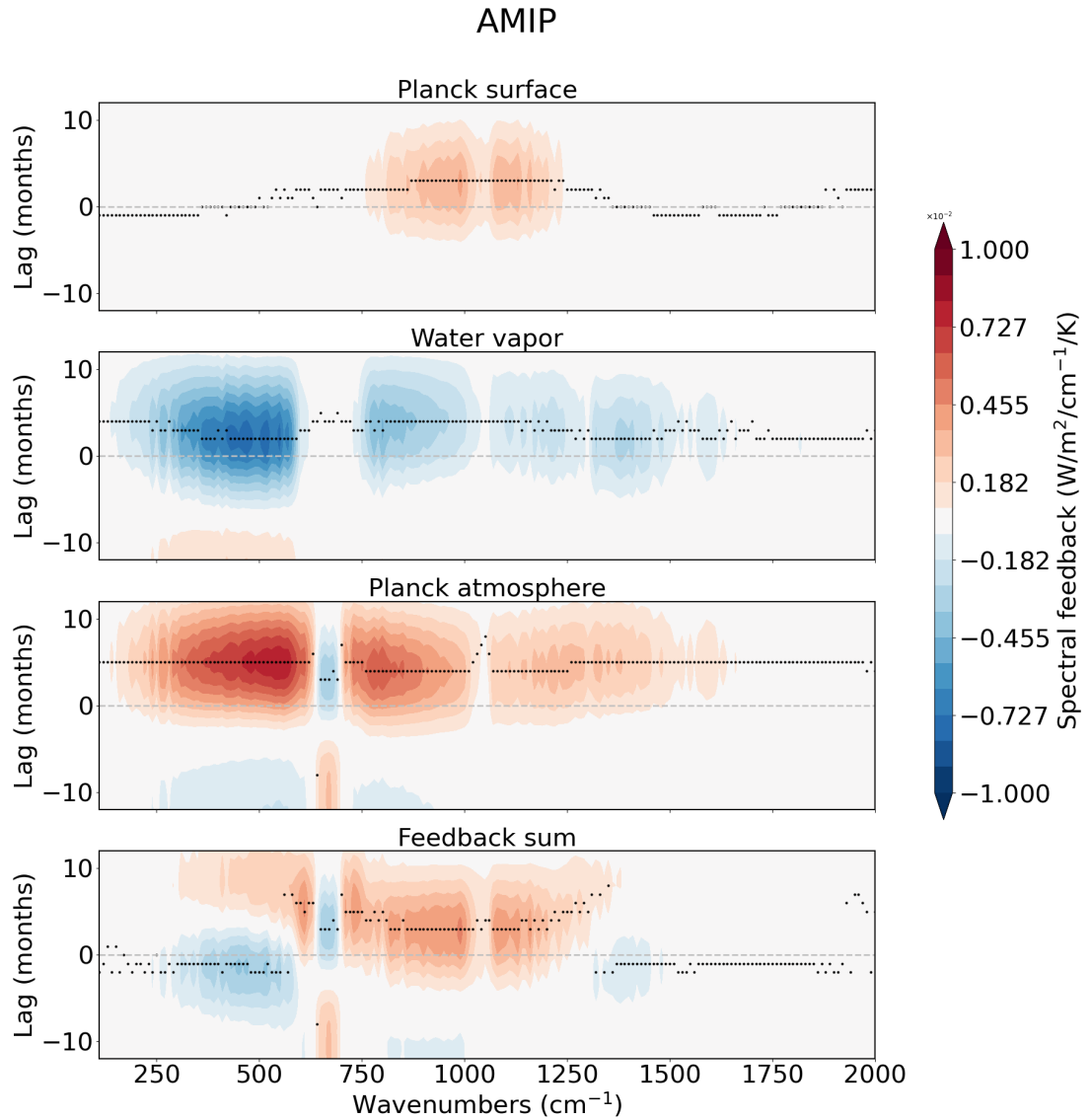


Figure 5.4: Spectral ENSO feedback as a function of wavenumber and lag. From top to bottom panel the multi-model mean of Planck surface, water vapor and Planck atmosphere feedback, calculated using variable field simulated by AMIP experiments. Black dots mark the lag corresponding to the peak of the radiative response at each wavenumber.

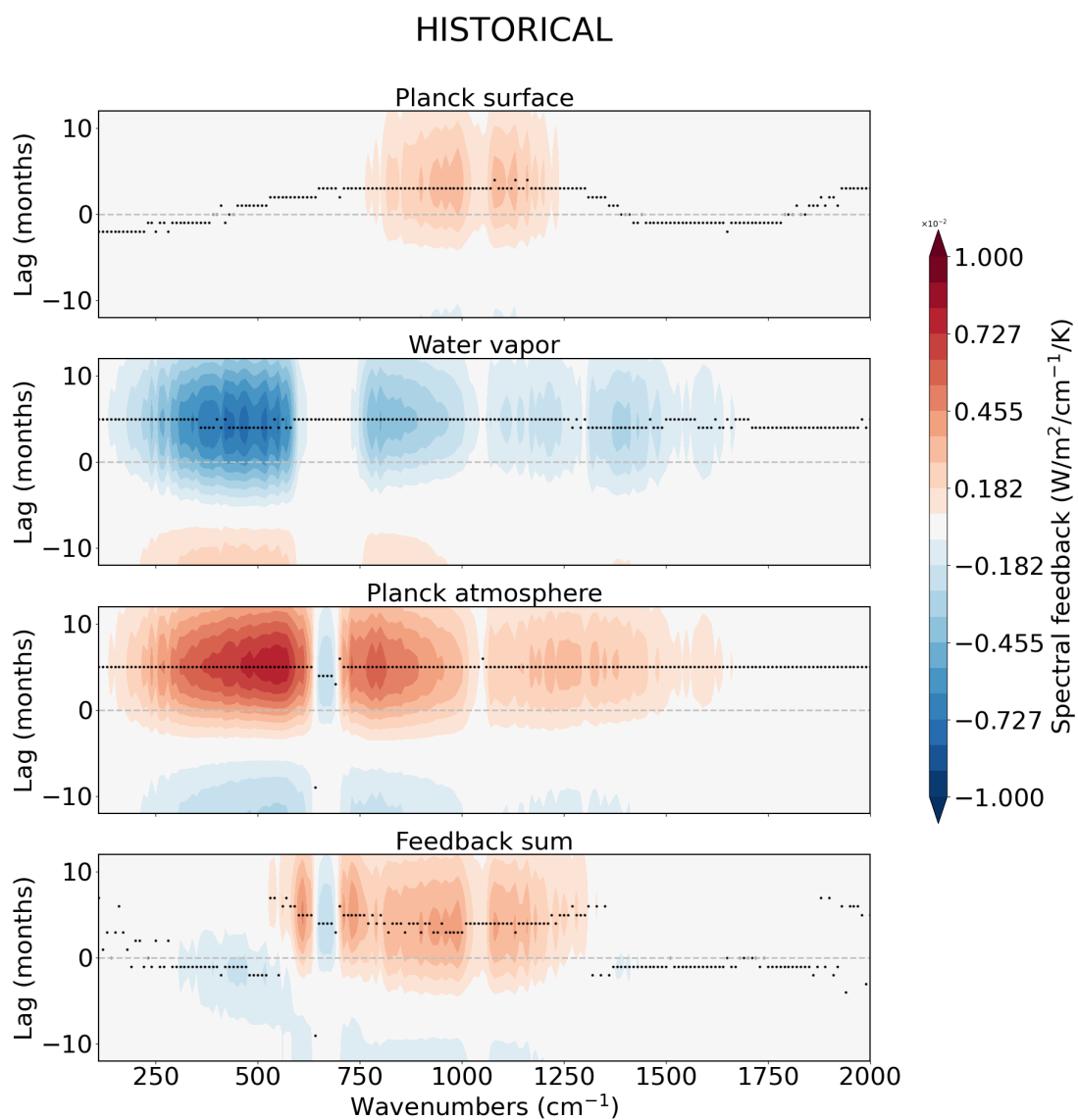


Figure 5.5: Same as Figure 5.4 but for CMIP6 historical simulations.

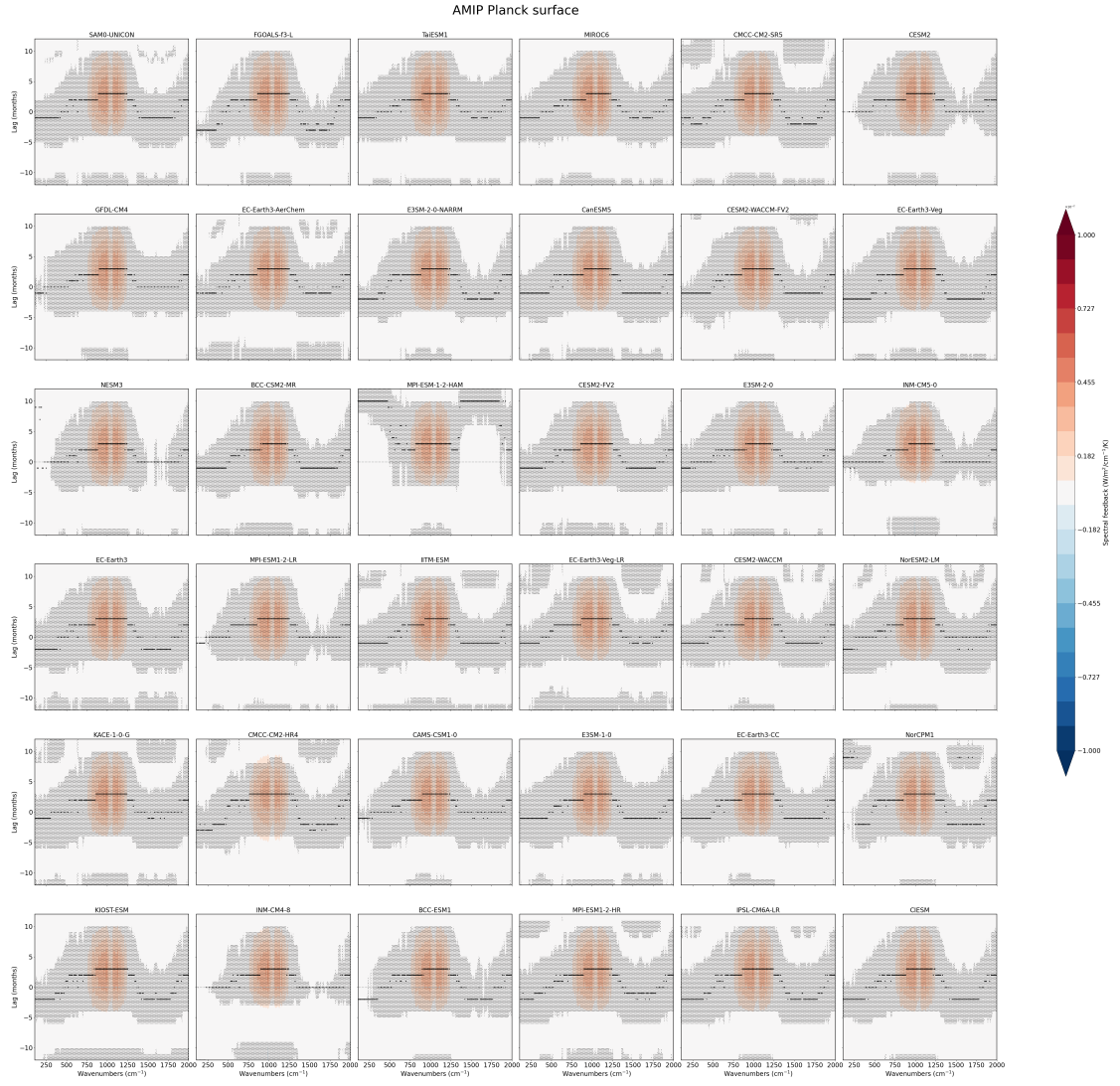


Figure 5.6: Planck surface ENSO feedback as a function of wavenumber and lag for all the CMIP6 AMIP models considered.

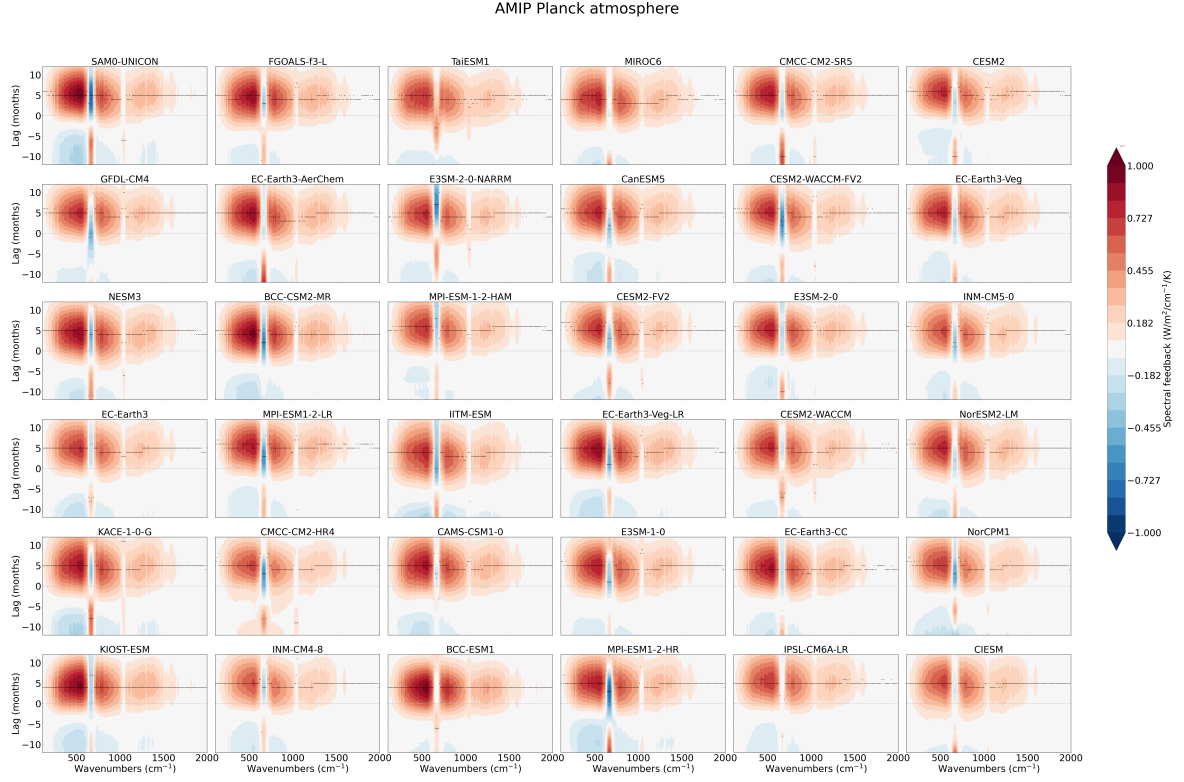


Figure 5.7: Planck atmosphere ENSO feedback as a function of wavenumber and lag for all the CMIP6 AMIP models considered.



Figure 5.8: Water vapor ENSO feedback as a function of wavenumber and lag for all the CMIP6 AMIP models considered.

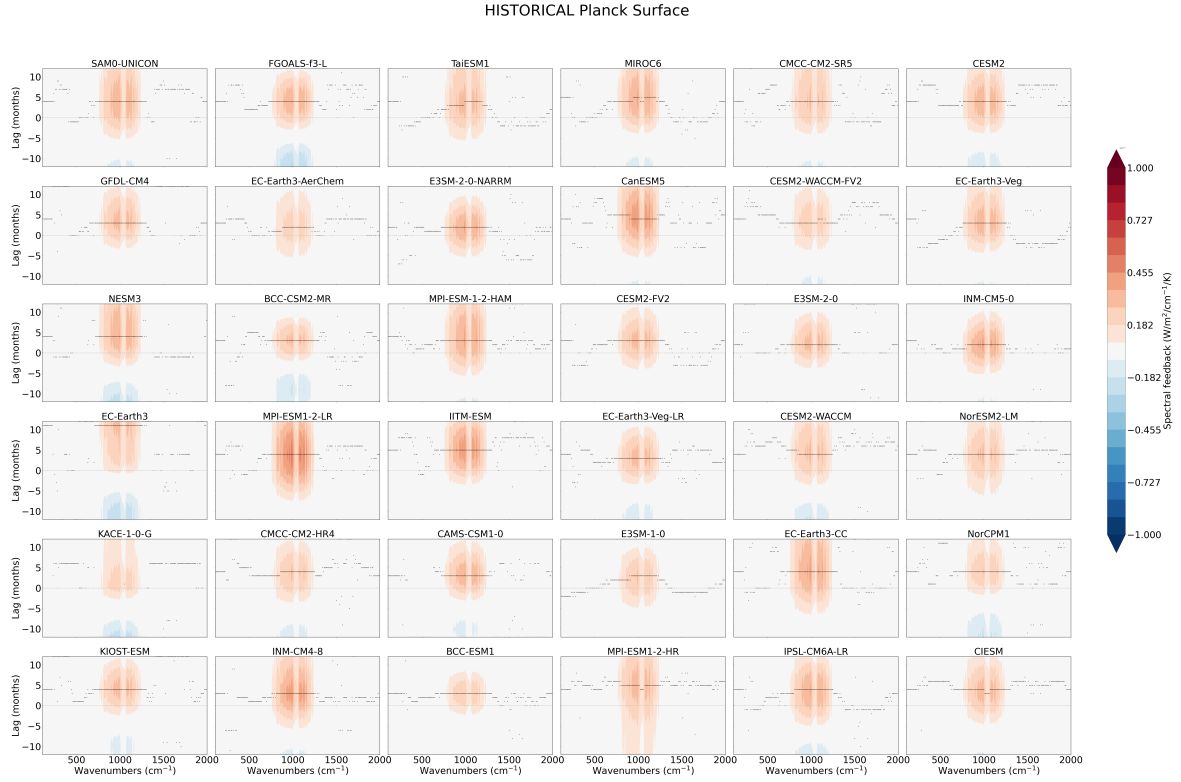


Figure 5.9: Planck surface ENSO feedback as a function of wavenumber and lag for all the CMIP6 historical models considered.

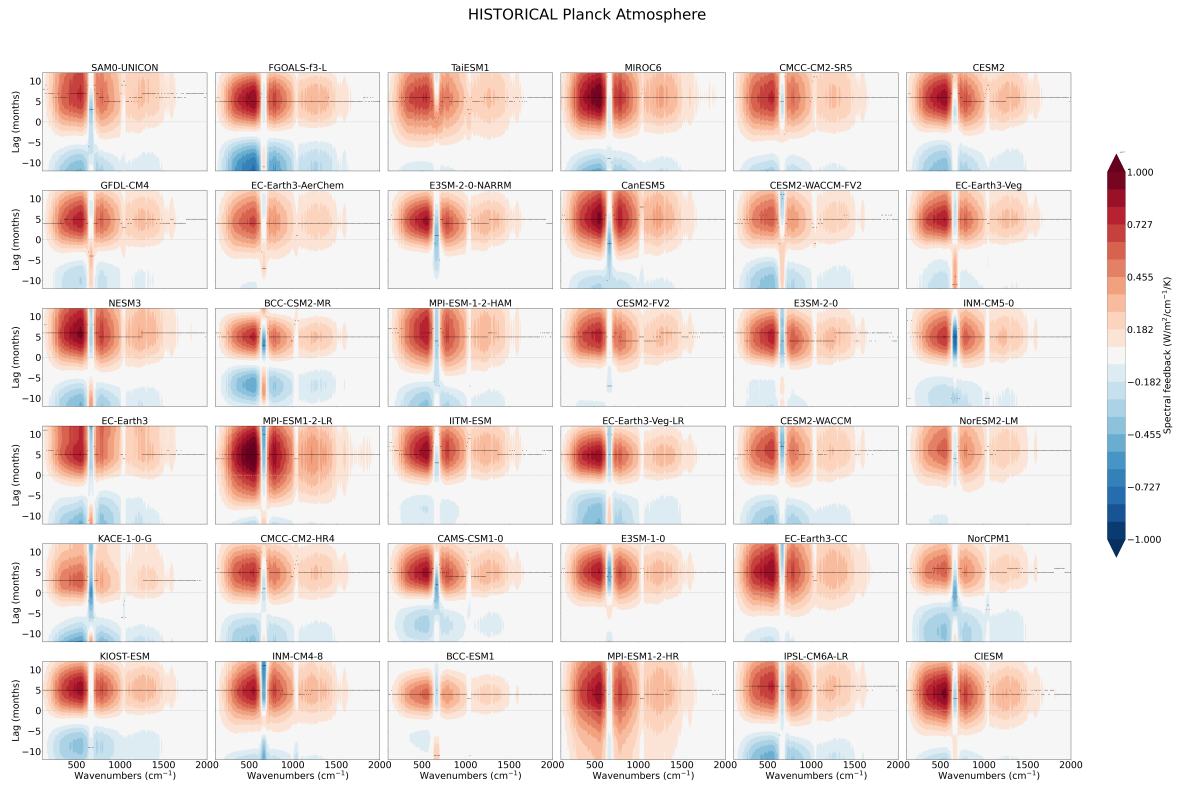


Figure 5.10: Planck atmosphere ENSO feedback as a function of wavenumber and lag for all the CMIP6 historical models considered.



Figure 5.11: Water vapor ENSO feedback as a function of wavenumber and lag for all the CMIP6 historical models considered.

the atmospheric window; the negative water vapor feedback and the Planck atmospheric feedback, which is positive throughout the whole spectrum and negative between 600 and 700 cm^{-1} .

When the time lag of the radiative response is taken into account, it is correctly reproduced, as is the case of the Planck surface feedback. Indeed, the same lag is observed across the atmospheric windows for both AMIP and historical simulations. The other feedbacks show more pronounced differences: in historical simulations, the peak of the water vapor feedback is postponed compared to AMIP ones, while the Planck atmospheric feedback shows a constant time lag of 5-months across the whole spectrum, whereas the observations from IASI and AIRS indicate that the peak should change, occurring earlier within the atmospheric window.

The greatest difference is obtained for the Planck atmospheric feedback between 600 and 700 cm^{-1} . Here, both AMIP and historical simulations fail in reproducing the negative response associated to the stratospheric cooling, in both magnitude and time lag. This suggests that the actual simulations of the Planck atmospheric feedback driven by ENSO may play a role in the differences observed among climate models in Chapter 3 in term of broadband response.

The lagged regression analysis provided an insight into the radiative response to ENSO as simulated by climate models. Particularly, it showed their ability in reproducing the

main radiative feedbacks involved and how these influence the total LW response.

Conclusions and perspectives

Spectral observations of the OLR acquired by satellites have proven to be particularly powerful to study atmospheric and surface processes that drive the evolution of the Earth climate. Their main advantages are the possibility to isolate individual spectral regions and trace them back to the physical processes associated. In this regard, spectral observations are particularly suitable to climate models evaluation. Indeed, they allow to disclose climate models biases that may be hidden due to compensating errors when broadband OLR fluxes are considered. In this work, we used spectral OLR fluxes derived from AIRS and IASI measurements to investigate how climate models reproduce the variability of the OLR driven by ENSO.

We started considering the broadband OLR simulated by CMIP6 AMIP and historical experiments. The comparison between climate models outputs and broadband OLR observations of the CERES instrument showed biases in climate models in reproducing OLR variability driven by ENSO. Specifically, the strength of the relationship is underestimated in both kind of simulations in the eastern Tropical Pacific Ocean.

The second aspect investigated is the time relationship between OLR and ENSO. According to CERES OLR fluxes, the tropical mean radiative response, for the period 2000 - 2014, shows a peak in OLR emission at TOA 3 months after the peak of ENSO activity. There are some models, from both CMIP6 AMIP and historical experiments, that are able to correctly reproduce the timing and magnitude of the observed CERES response. Instead, others show a response that is either anticipated or postponed of one/two months, and the magnitude that is overestimated or underestimated. When the spatial pattern of the OLR response to ENSO is considered, the main bias between models and observations is again within the eastern part of the tropical pacific, for both AMIP and historical simulations. For the coupled models, the largest inter-model spread is observed in the western part of the basin suggesting that their responses are characterized by a greatest variability across this region.

Using AIRS and IASI measurements, we explored the spectral dimension of the ENSO feedback, which showed that the peak and magnitude of the OLR response are spectrally dependent. The response is positive across the entire spectrum, except at the center of the carbon dioxide band, where it is negative, denoting a decrease in OLR emission at the TOA. The strongest response is associated to the ozone absorption band which is sensitive

to surface temperature and ozone concentration. Moreover, regions sensitive to the surface and lower atmospheric layers peak earlier than regions sensitive to the upper ones. The total OLR response can be mainly explained in terms of water vapor, Planck surface and atmospheric feedbacks, as showed by the spectral kernels analysis. The balance between water vapor and Planck atmospheric feedback drives the sign of the OLR response in the FIR spectral region.

These preliminary results set the basis for a diagnostic to assess models performances in reproducing the ENSO dynamics, including atmospheric feedbacks and the stratospheric cooling, and better constrain their projections. The investigation of the spatial pattern of the response for selected spectral channels, as performed in Chapter 4, for example, can shed light on the atmospheric processes driven by ENSO. These aspects will be the object of further studies.

Within the final step of the thesis, the diagnostic developed in Chapter 4 has been applied to the CMIP6 models ensemble. The ENSO spectral feedback has been calculated using water vapor, surface and atmospheric fields simulated by models both in atmosphere-only and in coupled mode. The comparison between the simulated and observed spectral response showed differences in reproducing the LW response peak across the spectrum. Preliminary results suggest a possible bias in climate models in reproducing the stratospheric temperature response to ENSO. Indeed, the higher discrepancy is observed at the center of the carbon dioxide absorption band.

This study has been limited to the clear-sky case due to the unavailability of observed fluxes for the all-sky case. However, clouds plays a fundamental role in shaping OLR variability and the clouds feedback is characterized by the greatest uncertainty among climate models estimates. A future step will therefore involve the inclusion in the analysis of all-sky OLR observations and models simulations. Investigating the clouds feedback related to ENSO could provide an important contribution for the understanding of the mechanisms behind the SST pattern effect, which is suggested to be mediated by clouds changes (Wills, Battisti, et al. 2020).

The spectral dimension of the OLR contains additional information to the main surface and atmospheric processes that shape the radiative response of the climate system. This work further demonstrates the contribution of spectral measurements for climate studies.

Within this thesis we had to rely on simulated OLR fluxes in the FIR spectral region, since this region is not covered by any of the current hyperspectral sounders. Indeed, despite its importance for the EEB, measurements in the FIR suffered for technology limitations. However, this observational gap will be closed in the near future. The Polar Radiant Energy in the Far-InfraRed Experiment (PREFIRE) (Drouin et al. 2025) has been launched in May 2024. PREFIRE is the first to measure the FIR spectral region of the Earth emission spectrum, providing the full spectrum of the Antarctic and Arctic regions, from 3 to 54 μm . Global coverage of the Earth emission spectrum from 100 to 1600

cm^{-1} , will be accomplished by the Far-infrared Outgoing Understanding and Monitoring (FORUM) mission (Palchetti et al. 2020), the 9th Earth Explorer mission of the European Space Agency, whose launch is scheduled for 2027. It will provide highly resolved and stable measurements of the FIR spectral region. FORUM will fly in loose formation with the Infrared Atmospheric Sounding Interferometer - Next Generation (IASI-NG) (Crevoisier et al. 2014). As its precursor IASI, it will measure the Earth emission spectrum between 645-2760 cm^{-1} , but with an improved resolution and radiometric accuracy. The FORUM-IASI synergy will provide important insights into the spectral signature of present-day climate change. Moreover, in 2026 the CMIP project will enter its seventh phase. At these stage the development of a new climate models diagnostic would be even more important to provide feedbacks on the performances of current climate models and guide lines for the next generation.

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Bibliography

- AchutaRao, Krishna and Kenneth R Sperber (2006). “ENSO simulation in coupled ocean-atmosphere models: are the current models better?” In: *Climate Dynamics* 27.1, pp. 1–15.
- Allan, Richard Philip et al. (1999). “The dependence of clear-sky outgoing long-wave radiation on surface temperature and relative humidity”. In: *Quarterly Journal of the Royal Meteorological Society* 125.558, pp. 2103–2126.
- Andrews, Timothy, Alejandro Bodas-Salcedo, et al. (2022). “On the effect of historical SST patterns on radiative feedback”. In: *Journal of Geophysical Research: Atmospheres* 127.18, e2022JD036675.
- Andrews, Timothy, Jonathan M Gregory, and Mark J Webb (2015). “The dependence of radiative forcing and feedback on evolving patterns of surface temperature change in climate models”. In: *Journal of Climate* 28.4, pp. 1630–1648.
- Armour, Kyle et al. (2021). “The Earths energy budget, climate feedbacks, and climate sensitivity”. In: *AGU Fall Meeting Abstracts*. Vol. 2021, U13B–07.
- Armour, Kyle C et al. (2024). “Sea-surface temperature pattern effects have slowed global warming and biased warming-based constraints on climate sensitivity”. In: *Proceedings of the National Academy of Sciences* 121.12, e2312093121.
- Aumann, Hartmut H et al. (2003). “AIRS/AMSU/HSB on the Aqua mission: Design, science objectives, data products, and processing systems”. In: *IEEE Transactions on Geoscience and Remote Sensing* 41.2, pp. 253–264.
- Bantges, RJ et al. (2016). “On the detection of robust multidecadal changes in Earth’s outgoing longwave radiation spectrum”. In: *Journal of Climate* 29.13, pp. 4939–4947.
- Barkstrom, BR and JB Hall Jr (1982). “Earth radiation budget experiment (ERBE): An overview”. In: *Journal of Energy* 6.2, pp. 141–146.
- Barnston, Anthony G, Muthuvel Chelliah, and Stanley B Goldenberg (1997). “Documentation of a highly ENSO-related SST region in the equatorial Pacific.” In: *Atmosphere-Ocean (Canadian Meteorological & Oceanographic Society)* 35.3.
- Bayr, Tobias et al. (2018). “Mean-state dependence of ENSO atmospheric feedbacks in climate models”. In: *Climate Dynamics* 50.9, pp. 3171–3194.
- Beobide-Arsuaga, Goratz et al. (2021). “Uncertainty of ENSO-amplitude projections in CMIP5 and CMIP6 models”. In: *Climate Dynamics* 56.11, pp. 3875–3888.

- Bjerknes, Jacob (1966). “A possible response of the atmospheric Hadley circulation to equatorial anomalies of ocean temperature”. In: *Tellus* 18.4, pp. 820–829.
- Bordoni, S et al. (2025). “The futures of climate modeling”. In: *npj Climate and Atmospheric Science* 8.1, p. 99.
- Brindley, HE and RJ Bantges (2016). “The spectral signature of recent climate change”. In: *Current Climate Change Reports* 2.3, pp. 112–126.
- Brindley, Helen et al. (2015). “Spectral signatures of Earth’s climate variability over 5 years from IASI”. In: *Journal of Climate* 28.4, pp. 1649–1660.
- Brindley, Helen E and Richard P Allan (2003). “Simulations of the effects of interannual and decadal variability on the clear-sky outgoing long-wave radiation spectrum”. In: *Quarterly Journal of the Royal Meteorological Society: A journal of the atmospheric sciences, applied meteorology and physical oceanography* 129.594, pp. 2971–2988.
- Calvo, Natalia, Ricardo García-Herrera, and Rolando R Garcia (2008). “The ENSO signal in the stratosphere”. In: *Annals of the New York Academy of Sciences* 1146.1, pp. 16–31.
- Ceppi, Paulo and Stephan Fueglistaler (2021). “The el niño–southern oscillation pattern effect”. In: *Geophysical Research Letters* 48.21, e2021GL095261.
- Chen, Deliang et al. (2023). “Framing, Context, and Methods (Chapter 1)”. In: *IPCC 2021: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, pp. 147–286.
- Chen, Junye, Barbara E Carlson, and Anthony D Del Genio (2002). “Evidence for strengthening of the tropical general circulation in the 1990s”. In: *Science* 295.5556, pp. 838–841.
- Clough, Shepard A, Michael J Iacono, and Jean-Luc Moncet (1992). “Line-by-line calculations of atmospheric fluxes and cooling rates: Application to water vapor”. In: *Journal of Geophysical Research: Atmospheres* 97.D14, pp. 15761–15785.
- Crevoisier, Cyril et al. (2014). “Towards IASI-New Generation (IASI-NG): Impact of improved spectral resolution and radiometric noise on the retrieval of thermodynamic, chemistry and climate variables”. In: *Atmospheric Measurement Techniques* 7.12, pp. 4367–4385.
- Della Fera, Stefano, Federico Fabiano, Piera Raspollini, Marco Ridolfi, Ugo Cortesi, et al. (2023). “On the use of Infrared Atmospheric Sounding Interferometer (IASI) spectrally resolved radiances to test the EC-Earth climate model (v3. 3.3) in clear-sky conditions”. In: *Geoscientific Model Development* 16.4, pp. 1379–1394.
- Della Fera, Stefano, Federico Fabiano, Piera Raspollini, Marco Ridolfi, Jost von Hardenberg, et al. (2025). “Reproducing and Attributing IASI Radiance Trends with EC-Earth Climate Model Simulations”. In: *Journal of Climate*.

- Dessler, AE, Z Zhang, and P Yang (2008). “Water-vapor climate feedback inferred from climate fluctuations, 2003–2008”. In: *Geophysical Research Letters* 35.20.
- Dessler, Andrew E (2010). “A determination of the cloud feedback from climate variations over the past decade”. In: *Science* 330.6010, pp. 1523–1527.
- (2013). “Observations of climate feedbacks over 2000–10 and comparisons to climate models”. In: *Journal of Climate* 26.1, pp. 333–342.
- Dewitte, Steven and Nicolas Clerbaux (2018). *Decadal changes of earth’s outgoing long-wave radiation*.
- Domeisen, Daniela IV, Chaim I Garfinkel, and Amy H Butler (2019). “The teleconnection of El Niño Southern Oscillation to the stratosphere”. In: *Reviews of Geophysics* 57.1, pp. 5–47.
- Dong, Yue et al. (2021). “Biased estimates of equilibrium climate sensitivity and transient climate response derived from historical CMIP6 simulations”. In: *Geophysical Research Letters* 48.24, e2021GL095778.
- Dozier, Jeff and Alexander FH Goetz (1989). “HIRIS—Eos instrument with high spectral and spatial resolution”. In: *Photogrammetria* 43.3-4, pp. 167–180.
- Drouin, Brian J et al. (2025). “Thermal infrared spectrometers for the polar radiant energy in the far-infrared experiment (PREFIRE)”. In: *Earth and Space Science* 12.10, e2024EA003711.
- Eyring, Veronika et al. (2016). “Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization”. In: *Geoscientific Model Development* 9.5, pp. 1937–1958.
- Fasullo, John T, AS Phillips, and C Deser (2020). “Evaluation of leading modes of climate variability in the CMIP archives”. In: *Journal of Climate* 33.13, pp. 5527–5545.
- Frankcombe, Leela M et al. (2015). “Separating internal variability from the externally forced climate response”. In: *Journal of Climate* 28.20, pp. 8184–8202.
- Garfinkel, Chaim I et al. (2018). “Nonlinear response of tropical lower-stratospheric temperature and water vapor to ENSO”. In: *Atmospheric chemistry and physics* 18.7, pp. 4597–4615.
- Goddard, Lisa and Maxx Dilley (2005). “El Niño: catastrophe or opportunity”. In: *Journal of climate* 18.5, pp. 651–665.
- Goody, Richard, James Anderson, and Gerald North (1998). “Testing climate models: An approach”. In: *Bulletin of the American Meteorological Society* 79.11, pp. 2541–2549.
- Griggs, JA and JE Harries (2007). “Comparison of spectrally resolved outgoing longwave radiation over the tropical Pacific between 1970 and 2003 using IRIS, IMG, and AIRS”. In: *Journal of climate* 20.15, pp. 3982–4001.
- Guilyardi, Eric et al. (2009). “Understanding El Niño in ocean–atmosphere general circulation models: Progress and challenges”. In: *Bulletin of the American Meteorological Society* 90.3, pp. 325–340.

- Guilyardi, Éric et al. (2004). “Representing El Nino in coupled ocean–atmosphere GCMs: the dominant role of the atmospheric component”. In: *Journal of Climate* 17.24, pp. 4623–4629.
- Hanley, Deborah E et al. (2003). “A quantitative evaluation of ENSO indices”. In: *Journal of Climate* 16.8, pp. 1249–1258.
- Harries, John et al. (2008). “The far-infrared Earth”. In: *Reviews of Geophysics* 46.4.
- Hersbach, H et al. (2023). “ERA5 monthly averaged data on pressure levels from 1940 to present”. In: *Copernicus Climate Change Service (C3S) Climate Data Store (CDS)* 10.
- Huang, Han, Yi Huang, and Yongyun Hu (2021). “Quantifying the energetic feedbacks in ENSO”. In: *Climate Dynamics* 56, pp. 139–153.
- Huang, Xianglei, Xiuhong Chen, Chongxing Fan, et al. (2022). “A synopsis of AIRS global-mean clear-sky radiance trends from 2003 to 2020”. In: *Journal of Geophysical Research: Atmospheres* 127.24, e2022JD037598.
- Huang, Xianglei, Xiuhong Chen, Brian J Soden, et al. (2014). “The spectral dimension of longwave feedback in the CMIP3 and CMIP5 experiments”. In: *Geophysical Research Letters* 41.22, pp. 7830–7837.
- Huang, Xianglei, AIRS JPL, et al. (2019). “Aqua AIRS level 3 spectral outgoing longwave radiation (OLR) monthly”. In: *NASA Goddard Earth Sciences Data and Information Services Center (DAAC) data set*, 5P7KQ31XI7XJ.
- Huang, Xianglei, Wenze Yang, et al. (2008). “Spectrally resolved fluxes derived from collocated AIRS and CERES measurements and their application in model evaluation: Clear sky over the tropical oceans”. In: *Journal of Geophysical Research: Atmospheres* 113.D9.
- Huang, Xianglei and Yuk Ling Yung (2005). “Spatial and spectral variability of the outgoing thermal IR spectra from AIRS: A case study of July 2003”. In: *Journal of Geophysical Research: Atmospheres* 110.D12.
- Huang, Yi (2013). “A simulated climatology of spectrally decomposed atmospheric infrared radiation”. In: *Journal of climate* 26.5, pp. 1702–1715.
- Huang, Yi and V Ramaswamy (2008). “Observed and simulated seasonal co-variations of outgoing longwave radiation spectrum and surface temperature”. In: *Geophysical Research Letters* 35.17.
- Huang, Yi, V Ramaswamy, Xianglei Huang, et al. (2007). “A strict test in climate modeling with spectrally resolved radiances: GCM simulation versus AIRS observations”. In: *Geophysical Research Letters* 34.24.
- Huang, Yi, V Ramaswamy, and Brian Soden (2007). “An investigation of the sensitivity of the clear-sky outgoing longwave radiation to atmospheric temperature and water vapor”. In: *Journal of Geophysical Research: Atmospheres* 112.D5.

- Huang, Yi and Venkatachalam Ramaswamy (2009). “Evolution and trend of the outgoing longwave radiation spectrum”. In: *Journal of climate* 22.17, pp. 4637–4651.
- Jacobowitz, H et al. (1979). “The first 18 months of planetary radiation budget measurements from the Nimbus 6 ERB experiment”. In: *Journal of Atmospheric Sciences* 36.3, pp. 501–507.
- Jacobowitz, Herbert et al. (1984). “The earth radiation budget (ERB) experiment: An overview”. In: *Journal of Geophysical Research: Atmospheres* 89.D4, pp. 5021–5038.
- Jain, Shipra et al. (2023). “Importance of internal variability for climate model assessment”. In: *npj Climate and Atmospheric Science* 6.1, p. 68.
- Kandel, R et al. (1998). “The ScaRaB earth radiation budget dataset”. In: *Bulletin of the American Meteorological Society* 79.5, pp. 765–784.
- Kato, Seiji (2009). “Interannual variability of the global radiation budget”. In: *Journal of climate* 22.18, pp. 4893–4907.
- Kayano, Mary T, V Brahmananda Rao, and Rita V Andreoli (2005). “A review of short-term climate variability mechanisms”. In: *Advances in Space Research* 35.5, pp. 843–851.
- Klein, Stephen A, Brian J Soden, and Ngar-Cheung Lau (1999). “Remote sea surface temperature variations during ENSO: Evidence for a tropical atmospheric bridge”. In: *Journal of climate* 12.4, pp. 917–932.
- Kolly, A and Yi Huang (2018). “The radiative feedback during the ENSO cycle: Observations versus models”. In: *Journal of Geophysical Research: Atmospheres* 123.17, pp. 9097–9108.
- Konopka, Paul et al. (2016). “Zonally resolved impact of ENSO on the stratospheric circulation and water vapor entry values”. In: *Journal of Geophysical Research: Atmospheres* 121.19, pp. 11–486.
- Lehner, Flavio and Clara Deser (2023). “Origin, importance, and predictive limits of internal climate variability”. In: *Environmental Research: Climate* 2.2, p. 023001.
- Leroy, Stephen et al. (2008). “Testing climate models using thermal infrared spectra”. In: *Journal of Climate* 21.9, pp. 1863–1875.
- Loeb, Norman G, Seung-Hee Ham, et al. (2024). “Observational assessment of changes in Earth’s energy imbalance since 2000”. In: *Surveys in Geophysics* 45.6, pp. 1757–1783.
- Loeb, Norman G, Seiji Kato, et al. (2012). “Advances in understanding top-of-atmosphere radiation variability from satellite observations”. In: *Surveys in geophysics* 33.3, pp. 359–385.
- Loeb, Norman G, Fred G Rose, et al. (2020). “Toward a consistent definition between satellite and model clear-sky radiative fluxes”. In: *Journal of Climate* 33.1, pp. 61–75.
- Loeb, Norman G, Hailan Wang, et al. (2020). “New generation of climate models track recent unprecedented changes in Earth’s radiation budget observed by CERES”. In: *Geophysical Research Letters* 47.5, e2019GL086705.

- Manatsa, Desmond and Geoffrey Mukwada (2017). “A connection from stratospheric ozone to El Niño-Southern Oscillation”. In: *Scientific Reports* 7.1, p. 5558.
- Manzini, Elisa (2009). “ENSO and the stratosphere”. In: *Nature Geoscience* 2.11, pp. 749–750.
- Matricardi, Marco (2009). “An assessment of the accuracy of the RTTOV fast radiative transfer model using IASI data”. In: *Atmospheric Chemistry and Physics* 9.18, pp. 6899–6913.
- McPhaden, Michael J, Agus Santoso, and Wenju Cai (2020). “Introduction to El Niño Southern Oscillation in a changing climate”. In: *El Niño Southern Oscillation in a changing climate*, pp. 1–19.
- Palchetti, L et al. (2020). “unique far-infrared satellite observations to better understand how Earth radiates energy to space”. In: *Bulletin of the American meteorological society* 101.12, E2030–E2046.
- Palmer, MD and DJ McNeall (2014). “Internal variability of Earth’s energy budget simulated by CMIP5 climate models”. In: *Environmental Research Letters* 9.3, p. 034016.
- Pan, Fang et al. (2017). “The stratospheric changes inferred from 10 years of AIRS and AMSU-A radiances”. In: *Journal of Climate* 30.15, pp. 6005–6016.
- Planton, Yann Y et al. (2021). “Evaluating climate models with the CLIVAR 2020 ENSO metrics package”. In: *Bulletin of the American Meteorological Society* 102.2, E193–E217.
- Proistosescu, Cristian et al. (2018). “Radiative feedbacks from stochastic variability in surface temperature and radiative imbalance”. In: *Geophysical Research Letters* 45.10, pp. 5082–5094.
- Quispe, Janeet Margarita Sanabria (2018). “Interannual variability of the rainfall regime and strong ENSO events along the Peruvian Pacific Basin: large-scale control mechanisms”. PhD thesis. Université Toulouse 3 Paul Sabatier (UT3 Paul Sabatier).
- Randel, William J et al. (2009). “ENSO influence on zonal mean temperature and ozone in the tropical lower stratosphere”. In: *Geophysical Research Letters* 36.15.
- Rasmusson, Eugene M and Thomas H Carpenter (1982). “Variations in tropical sea surface temperature and surface wind fields associated with the Southern Oscillation/El Niño”. In: *Monthly Weather Review* 110.5, pp. 354–384.
- Roemer, Florian E et al. (2023). “Direct observation of Earth’s spectral long-wave feedback parameter”. In: *Nature Geoscience* 16.5, pp. 416–421.
- Rugenstein, Maria, Shreya Dhame, et al. (2023). “Connecting the SST pattern problem and the hot model problem”. In: *Geophysical Research Letters* 50.22, e2023GL105488.
- Rugenstein, Maria, Senne Van Loon, and Elizabeth A Barnes (2025). “Convolutional neural networks trained on internal variability predict forced response of TOA radiation by learning the pattern effect”. In: *Geophysical Research Letters* 52.4, e2024GL109581.

- Salby, Murry L (2012). *Physics of the Atmosphere and Climate*. Cambridge University Press.
- Seager, Richard, Naomi Henderson, and Mark Cane (2022). “Persistent discrepancies between observed and modeled trends in the tropical Pacific Ocean”. In: *Journal of Climate* 35.14, pp. 4571–4584.
- Simeoni, Denis et al. (2004). “Design and development of IASI instrument”. In: *Infrared Spaceborne Remote Sensing XII*. Vol. 5543. Spie, pp. 208–219.
- Smith, G Louis et al. (2006). “Comparison of measurements from satellite radiation budget instruments”. In: *Journal of Geophysical Research: Atmospheres* 111.D4.
- Soden, Brian J et al. (2008). “Quantifying climate feedbacks using radiative kernels”. In: *Journal of Climate* 21.14, pp. 3504–3520.
- Stevens, Bjorn et al. (2016). “Prospects for narrowing bounds on Earth’s equilibrium climate sensitivity”. In: *Earth’s Future* 4.11, pp. 512–522.
- Stumpf, Kenneth D and Jay Alan Overbeck (2002). “CrIS optical system design”. In: *Infrared Spaceborne Remote Sensing IX*. Vol. 4486. SPIE, pp. 437–444.
- Su, W et al. (2015). “Next-generation angular distribution models for top-of-atmosphere radiative flux calculation from CERES instruments: Methodology”. In: *Atmospheric Measurement Techniques* 8.2, pp. 611–632.
- Suomi, VE (1960). “The thermal radiation balance experiment on board explorer VII”. In: *JUNO ZZ Summary Project Rep*, pp. 247–278.
- Susskind, Joel et al. (2012). “Interannual variability of outgoing longwave radiation as observed by AIRS and CERES”. In: *Journal of Geophysical Research: Atmospheres* 117.D23.
- Taddia, Martina et al. (2025). “A Spectral Perspective of ENSO Driven OLR Variability”. In: *EGUsphere* 2025, pp. 1–21.
- Trenberth, Kevin E (1997). “The definition of el nino”. In: *Bulletin of the American Meteorological Society* 78.12, pp. 2771–2778.
- Uribe, Alejandro, Frida A-M Bender, and Thorsten Mauritsen (2022). “Observed and CMIP6 modeled internal variability feedbacks and their relation to forced climate feedbacks”. In: *Geophysical Research Letters* 49.24, e2022GL100075.
- (2024). “Constraining net long-term climate feedback from satellite-observed internal variability possible by the mid-2030s”. In: *Atmospheric Chemistry and Physics* 24.23, pp. 13371–13384.
- Vijayeta, Asha and Dietmar Dommenges (2018). “An evaluation of ENSO dynamics in CMIP simulations in the framework of the recharge oscillator model”. In: *Climate Dynamics* 51.5, pp. 1753–1771.
- Wang, Chunzai and Joël Picaut (2004). “Understanding ENSO physics—A review”. In: *Earth’s Climate: The Ocean–Atmosphere Interaction, Geophys. Monogr* 147, pp. 21–48.

- Whitburn, S. (2021). “IASI-FT spectrally resolved Outgoing Longwave Radiation (from IASI/Metop-A, B and C)”. In: *ULB/LATMOS data set*.
- Whitburn, Simon, Lieven Clarisse, Sophie Bauduin, et al. (2020). “Spectrally resolved fluxes from IASI data: Retrieval algorithm for clear-sky measurements”. In: *Journal of Climate* 33.16, pp. 6971–6988.
- Whitburn, Simon, Lieven Clarisse, Marie Bouillon, et al. (2021). “Trends in spectrally resolved outgoing longwave radiation from 10 years of satellite measurements”. In: *npj climate and atmospheric science* 4.1, p. 48.
- Wielicki, Bruce A, Bruce R Barkstrom, et al. (1996). “Clouds and the Earth’s Radiant Energy System (CERES): An earth observing system experiment”. In: *Bulletin of the American Meteorological Society* 77.5, pp. 853–868.
- Wielicki, Bruce A, Takmeng Wong, et al. (2002). “Evidence for large decadal variability in the tropical mean radiative energy budget”. In: *Science* 295.5556, pp. 841–844.
- Wild, Martin (2020). “The global energy balance as represented in CMIP6 climate models”. In: *Climate Dynamics* 55.3, pp. 553–577.
- Wills, Robert CJ, David S Battisti, et al. (2020). “Pattern recognition methods to separate forced responses from internal variability in climate model ensembles and observations”. In: *Journal of Climate* 33.20, pp. 8693–8719.
- Wills, Robert CJ, Yue Dong, et al. (2022). “Systematic climate model biases in the large-scale patterns of recent sea-surface temperature and sea-level pressure change”. In: *Geophysical Research Letters* 49.17, e2022GL100011.
- Zelinka, Mark D et al. (2020). “Causes of higher climate sensitivity in CMIP6 models”. In: *Geophysical Research Letters* 47.1, e2019GL085782.
- Zeng, Guang and John A Pyle (2005). “Influence of El Nino Southern Oscillation on stratosphere/troposphere exchange and the global tropospheric ozone budget”. In: *Geophysical research letters* 32.1.

Appendix A

Radiative transfer in the atmosphere

The OLR that is ultimately emitted to space depends on the atmospheric transmission properties, which in turn are related to the atmospheric composition and the interaction between the electromagnetic radiation and the matter. The link between surface and atmospheric features that shape the OLR and its value at the TOA is provided by the radiative transfer equation, which takes into account all the surface and atmospheric features as a whole and provides a theoretical calculation for the radiance at TOA. Within the approximation of a plane parallel atmosphere, and considering only atmospheric gases absorption and emission, the Swartzchild's equation provides the intensity of a beam of radiance after passing upward through an atmospheric layer of a certain depth.

Radiant energy is measured by its intensity or radiance, which is the energy per unit time, per unit area, per unit of frequency interval, per unit of solid angle (e.g. $\text{W}/\text{m}^2 \text{ Hz sr}$). The change in intensity of a radiation beam crossing a layer of depth dz , with an angle θ , is equal to the emission minus the absorption processes experienced along the path ds :

$$dI_\nu = E_\nu - A_\nu \quad (\text{A.1})$$

The absorption term A_ν can be expressed following the Lambert-Bouguet-Beer-Law, which states that absorption is proportional to the intensity of radiation and the absorber amount. Following the Lambert-Bouguet-Beer-Law the absorption term can be written as:

$$A_\nu = \rho_a ds k_\nu I_\nu \quad (\text{A.2})$$

where, ρ_a is the density of the absorbers, ds is the path and k_ν is the absorption coefficient, related to the absorption properties of the absorber. The atmospheric emission E_ν can be expressed as:

$$E_\nu = \epsilon_\nu B_\nu(T) \quad (\text{A.3})$$

where $B_\nu(T)$ is given by the Planck's law, which express the radiant intensity emitted by a blackbody with a temperature T , at a frequency ν , and ϵ_ν is the emissivity. Within

the troposphere and the lower stratosphere, where the atmospheric pressure is relatively high, the condition of local thermodynamic equilibrium can be considered satisfied, since collisions between molecules are much frequent than radiative transitions. Under this condition the Kirchoff's law states that the emissivity of a substance must be equal to its absorptivity, as such $\epsilon_\nu = \rho_a dsk_\nu$. Substituting all the terms the equation A.1 becomes:

$$dI_\nu = \rho_a dsk_\nu (B_\nu(T) - I_\nu) \quad (\text{A.4})$$

Exploiting the relationship $dz = -\cos\theta ds$, between the pathlength and the altitude, the radiative transfer equation is then obtained differentiating along the path ds :

$$\cos\theta \frac{dI_\nu}{dz} = \rho_a k_\nu (B_\nu(T) - I_\nu) \quad (\text{A.5})$$

Equation A.5 can be rewritten as a function of the vertical optical depth τ_ν :

$$\tau_\nu = \int_0^z \rho_a k_\nu dz \quad (\text{A.6})$$

$$\cos\theta \frac{dI_\nu(\tau_\nu(z), \theta)}{d\tau_\nu(z)} = B_\nu(T(\tau_\nu(z))) - I_\nu(\tau_\nu(z), \theta) \quad (\text{A.7})$$

All variables depend on altitude. Only the radiance intensity is a function of the zenith angle θ (infrared radiation can be considered independent from the azimuth φ). Black-body emission is isotropic therefore independent from both θ and φ . The solution of the Swarzchild's equation is the following:

$$I_\nu(\tau_\nu(z), \mu) = I_\nu(0, \mu) e^{-\tau_\nu(z)/\mu} + \int_0^{\tau_\nu(z)} \mu^{-1} B_\nu(T(\tau'_\nu)) e^{(\tau'_\nu - \tau_\nu(z))/\mu} d\tau'_\nu \quad (\text{A.8})$$

The first term on the right is the emission of radiation from the surface which is attenuated by the extinction along the path from the surface to an altitude z ; the second term is the sum of the emission from all the layers up to the altitude z , it thus represent the radiation that reaches the level z without being absorbed by the underling layers. This equation only considers absorption and emission processes, however, a comprehensive description of the radiative transfer in the atmosphere considers also the scattering processes.

Appendix B

CMIP6 models

Table B.1: Institutions and corresponding climate models used for this study.

Institution	Model
NUIST	NESM3
EC-Earth Consortium	EC-Earth3-CC
NCAR	CESM2
MPI	MPI-ESM1-2-HR
THU Department of Earth System Science	CIESM
EC-Earth Consortium	EC-Earth3-Veg
CCCMa	CanESM5
HAMMOZ	MPI-ESM1-2-HAM
CMCC	CMCC-CM2-HR4
AS-RCEC	TaiESM1
NIMS-KMA	KACE-1-0-G
MRI	MRI-ESM2-0
CCCR-IITM	IITM-ESM
EC-Earth Consortium	EC-Earth3
NCAR	CESM2-WACCM-FV2
BCC	BCC-CSM2-MR
SNU	SAM0-UNICON
MPI-M	MPI-ESM1-2-LR
CSIRO	ACCESS-ESM1-5
NOAA-GFDL	GFDL-CM4
INM	INM-CM4-8
NCC	NorESM2-LM
NCAR	CESM2-WACCM
	CAS-ESM2-0
INM	INM-CM5-0
IPSL	IPSL-CM6A-LR
CSIRO-ARCCSS	ACCESS-CM2
EC-Earth Consortium	EC-Earth3-AerChem
E3SM	E3SM-1-0
EC-Earth Consortium	EC-Earth3-Veg-LR
CAS	FGOALS-f3-L
CMCC	CMCC-CM2-SR5
BCC	BCC-ESM1
E3SM	E3SM-2-0
MIROC Consortium, JAMSTEC, AORI, NIES, R-CCS	MIROC6
NCAR	CESM2-FV2