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Abstract To test the impact of modeling uncertainties and biases on the simulation of cloud feedbacks, several configurations of the EC-Earth climate model are built altering physical parameterizations. An overview of the various radiative feedbacks diagnosed from the reference EC-Earth configuration is documented for the first time. The cloud feedback is positive and small. While the total feedback parameter is almost insensitive to model configuration, the cloud feedback, in particular its shortwave (SW) component, can vary considerably depending on the model settings. The lateral mass exchange rate of penetrative convection and the conversion rate from condensed water to precipitation are leading uncertain parameters affecting the radiative feedbacks diagnosed. Consistent with other studies, we find a strong correlation between low-cloud model fidelity and low-cloud response under global warming. It is shown that this relationship holds only for stratocumulus regimes and is contributed by low-cloud cover, rather than low-cloud optical thickness. Model configurations simulating higher stratocumulus cover, which is closer to the observations, exhibit a stronger positive SW cloud feedback. This feedback is likely underestimated in the reference EC-Earth configuration, over the eastern basins of the tropical oceans. In addition, connections between simulated high-cloud top altitude in present-day climate and longwave cloud feedback are discussed.

1. Introduction

Clouds represent a key challenge for climate modeling and substantial disagreement between general circulation models (GCMs) and observations still exists [Bodas-Salcedo et al., 2011; Lauer and Hamilton, 2013]. Clouds are particularly difficult to simulate in GCMs, because they result from an intricate balance between dynamical, thermodynamical, and microphysical processes, which are often treated by means of parameterizations.

Due to the broad impact of clouds on the way energy and water are cycled through the atmosphere, even small changes in cloud properties can have a dramatic impact on climate [e.g., Hartmann and Doelling, 1991]. Therefore, poor simulation of present-day clouds casts doubts on the reliability of GCMs in representing cloud feedback processes in climate change projections. It is a matter of fact that cloud feedbacks constitute the primary source of uncertainty in GCMs estimates of climate sensitivity [Bony et al., 2006; Andrews et al., 2012]. The implicit assumption is that our confidence in model simulation of cloud feedbacks under climate change is proportional to how well a GCM represents the current climate [Webb et al., 2001; Lacagnina and Selten, 2013b].

The effect of clouds on the sensitivity of GCMs to external perturbations is a long-standing issue in climate research and received a major boost with the study by Cess et al. [1990]. Their analyses were centered around idealized experiments, where the sea surface temperature (SST) was uniformly perturbed by ±2 K. The resulting imbalance in the radiation budget at the top-of-atmosphere (TOA) was used to evaluate the climate sensitivity of each model.

These types of intercomparisons are useful to identify the general problem areas responsible for the model disagreement, but do not give more in-depth insights into the causes for such a disagreement. Indeed, differences in cloud feedbacks among the models can be due to differences in the cloud parameterizations or due to substantial differences in model structure formulation [Colman and McAvaney, 1997]. Using the same model with different parameterizations might help to unravel this issue.
Typical parameterizations include determining the fraction of the grid box that a cloud occupies, representing convective processes and estimating the size and number of the cloud droplets. Each of those represents a crucial challenge for climate modeling and can be identified as primary source of model biases [e.g., Lacagnina and Selten, 2014]. It has been argued that the value of the cloud feedbacks, and thus of the climate sensitivity, in the model is influenced by the details of the physical parameterizations chosen [Yokohata et al., 2005; Naud et al., 2006; Qu et al., 2014]. Therefore, parameterizations impact both climate sensitivity estimates of future climate and systematic errors of current climate simulations. Every parameterization contains one or more adjustable parameters to relate subgrid processes to large-scale variables explicitly calculated at the grid-box scale. These parameters cannot often be determined on the basis of fundamental principles, but rather are carefully calibrated (tuned) to optimize the agreement between observations and simulations (e.g., ensuring the global earth radiation balance at TOA). Tuning is part of the model developing process and arises by an inadequate representation of some climate features, in particular of clouds [Mauritsen et al., 2012]. During the model developing process, the impact of the choice of tunable parameters on the model climate sensitivity is often not explored [e.g., Hourdin et al., 2013]. However, intriguing questions arise from understanding how model shortcomings impact climate projections and to what extent radiative feedbacks are sensitive to fairly small changes in model formulation.

We aim to investigate the consequences of the cloud-related uncertainties on model biases and climate feedbacks in the EC-Earth GCM [Hazeleger et al., 2012]. These analyses intend to make a hierarchy among the different processes contributing to the uncertainty of future climate projections, thereby providing guidance regarding necessary model developments. The dependence of various physical processes on the model formulation is assessed by analysing the response of the cloud field to an idealized climate change, simulated by different configurations of EC-Earth. Each configuration is built by varying one uncertain parameter or parameterization. The new model configurations do not ensure the TOA radiative balance, as in the default configuration and thus should not be considered plausible new versions of EC-Earth. However, more tunable variables would need to be changed simultaneously to restore TOA energy balance, making it more difficult to understand which parameter variation is responsible for the feedback changes. The approach we follow is sometimes referred to as “perturbed physics ensembles” [Webb et al., 2006; Sanderson et al., 2010]. Such a framework allows the physical feedback processes to be related with the parameter perturbations made within the ensemble [Sanderson et al., 2010]. It is the first time that analyses focus on the sensitivity of the EC-Earth model to the structure and parameter settings.

Using feedbacks as a diagnostic tool has been recognized as an essential step in understanding and constraining the future climate system response [Bony et al., 2006]. The methodology employed to estimate those is presented in section 2. In section 3, the model and the sensitivity experiments carried out are explained, along with the impact of the tunable parameters on the present-day climate simulation. Two additional sensitivity experiments, where the parameterization structure of the model is partly revised, are performed. These aim to reduce some EC-Earth biases found in Lacagnina and Selten [2014], such as too few stratocumulus and too small cloud liquid droplets. Their effects are compared with observations in subsection 3.1. Moreover, for the first time, the various radiative feedback factors in the EC-Earth model are documented (section 4). The physical parameterizations and regions that determine shifts in these feedbacks are identified in section 5. The relationship between the cloud feedback processes and the current climate states is investigated as well (subsection 5.1). Finally, we present our concluding remarks in section 6.

### 2. Methodology for the Feedback Analysis

Let $Q$ and $F$ be the TOA absorbed shortwave (SW) and outgoing longwave (LW) radiative fluxes, respectively, depending on a certain number of climate variables, so that $Q = Q(X)$ and $F = F(X)$. Where $X$ represents a set of $n$ climate variables, which may affect the radiative fluxes, such as temperature, water vapor, cloud properties, and surface albedo. Suppose there are two climate states: $A$ and $B$, where $B$ is a perturbation from $A$ obtained by changing SST. Typically, changes in SST induce changes in the other climate variables. The difference in the radiative fluxes between the two climate states may be written as:

$$
\Delta Q = Q(X^B) - Q(X^A)
$$

(1a)
The radiative imbalance at TOA can be related to the change in global mean surface-air temperature ($\Delta T_s$) through a total feedback parameter ($\lambda$):

$$\Delta F = F(X^0) - F(X^a)$$  \hspace{1cm} (1b)

At first order, by neglecting interactions among variables, $\lambda$ is commonly split as the sum of the Planck ($\lambda_P$), lapse rate ($\lambda_l$), water vapor ($\lambda_w$), surface albedo ($\lambda_a$), and cloud ($\lambda_c$) feedback parameters, plus a residual term ($Re$) [Zhang et al., 1994]. The latter accounts for nonlinearities in the relationship between TOA radiation imbalance and $\Delta T_s$.

Various methodologies have been proposed to separate feedbacks in climate models. Here we follow the computationally efficient radiative kernel technique [Soden and Held, 2006]. In such a framework, climate feedbacks are computed as products of two terms: one dependent on the climate response of a specific climate variable and the other one on the radiative transfer algorithm (kernel), which acts as a weighting function. In this framework of analysis, all clear-sky and all-sky feedbacks (except clouds) are derived as follows:

$$\lambda_X = \frac{\partial(Q-F)}{\partial X} \frac{dX}{dT_s} \approx K_X \frac{\Delta X}{\Delta T_s}$$  \hspace{1cm} (3)

Each kernel ($K_X$) is obtained by perturbing the variable $X_i$ by a small amount $\delta X_i$, and by measuring the TOA flux response ($\delta Q$, $\delta F$). $\Delta X_i$ represents the difference in the variable $X_i$ between two climate states, similar to equation (1). Here the two climate states are referred to as the 10 year model predicted climate for present-day SST (A) and the 10 year climate for SST uniformly warmer by 4 K (B). Monthly means of 3 h data are used. As in Soden et al. [2008], tropospheric averages of the water vapor and temperature feedbacks are obtained by integrating vertically from the surface up to the tropopause, defined at 100 hPa at the equator and decreasing linearly with latitude to 300 hPa at the poles. Moreover, the employed kernels in this study are the same as in Block and Mauritsen [2013]. The question, whether using radiative kernels from other models is appropriate, has been addressed by Soden et al. [2008]. They have shown globally that the radiative kernels calculated with different models produce similar results.

Cloud feedbacks cannot be evaluated directly using the kernels approach, because of strong nonlinearities arising from the vertical overlap of clouds. A possible solution is estimating the changes in the cloud radiative effect (CRE), calculated as the difference between the clear-sky and all-sky fluxes at TOA, normalized by $\Delta T_s$. However, CRE itself should not be interpreted as being due to changes in cloud properties alone, since it depends also on changes in the environment (water vapor, surface albedo, temperature), as discussed in Zhang et al. [1994] and Soden et al. [2004]. Following Soden et al. [2008], we adjust CRE by correcting for noncloud feedbacks:

$$\lambda_c = \frac{\Delta CRE}{\Delta T_s} - (\lambda_P - \lambda_P^0) - (\lambda_l - \lambda_l^0) - (\lambda_w - \lambda_w^0) - (\lambda_a - \lambda_a^0) - (\lambda_c - \lambda_c^0)$$  \hspace{1cm} (4)

where the exponent 0 denotes feedbacks calculated using the clear-sky kernels.

### 3. Model and Simulations

The atmospheric component of the coupled ocean-atmosphere EC-Earth model version 2.3 [Hazeleger et al., 2012] is used in isolation, such that the simulations can be considered atmosphere only experiments. The atmosphere GCM is based on cycle 31r1 of the European Centre for Medium-Range Weather Forecasts (ECMWF) integrated forecast system (IFS) and is run at a horizontal spectral resolution of T159, with 62 levels in the vertical. EC-Earth adopts the same tunable parameter values used in IFS. These were adjusted at ECMWF with IFS run for 15 days with prescribed observed SST and sea ice, to achieve best forecast scores. The value of the inhomogeneity scaling factor for shortwave cloud optical depth is different in EC-Earth compared to IFS and has been reduced to achieve radiative balance at TOA. The next versions of EC-Earth are not expected to use the inhomogeneity factor and thus it is not considered in the present study. More information on the EC-Earth model can be found at the website: http://ecearth.knmi.nl.
In the EC-Earth model, clouds are described by prognostic equations for cloud water content and cloud potential to control important aspects of the cloud simulation. The experiments analyzed in this study are representative of realistic climate change scenarios, but yet retain salient characteristics of more complex climate perturbations. Such experiments are not intended to be representative of realistic climate change scenarios, but yet retain salient characteristics of more complex climate perturbations. They have the advantage of providing a simple and computationally inexpensive framework to assess the impact of developments on the main cloud processes under climate change. In addition, a uniform SST increase ensures a large-scale forcing virtually identical for every simulation. (For technical reasons, land surface temperatures are not held constant, but are allowed to change, leading to a slightly different forcing for each simulation).

Furthermore, sensitivity experiments are carried out by conducting simulations where the value of one single tunable parameter in the EC-Earth reference configuration (named "REF") has been perturbed. This yields new EC-Earth configurations, two for each tunable parameter in Table 1 (one for increased and one for decreased value of the tunable parameter), that are integrated for the "AMIPCTL" and "AMIP4K" simulations. In the rest of the paper, a plus (minus) next to the name of the sensitivity experiment indicates increased (decreased) absolute value of the related tunable parameter. All parameters are varied within reasonable limits of physical uncertainty (e.g., Klocke et al., 2011). These parameters are particularly interesting, because they have been used to tune this and many other GCMs (Mauritsen et al., 2012) and have the potential to control important aspects of the cloud simulation. The experiments analyzed in this study are not from development versions of EC-Earth.

In the EC-Earth model, clouds are described by prognostic equations for cloud water content and cloud fraction and are distinguished as convective or stratiform clouds (Tiedtke, 1993). The parameterization of the former is tied to the mass flux (Tiedtke, 1989). In essence, a cloud ensemble within a grid box is approximated by one effective cloud (bulk approach), where upward-moving air is compensated by subsiding air in the cloud-free portion of the grid box. Upward air is controlled by the mass flux, whose vertical profile depends on tunable values of the lateral mass exchange between the cloud and the environment, known as...

### Table 1. List of the Tunable Parameters Perturbed in This Study, Where Label Represents the Name Given in the Model’s Code

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENTRPEN</td>
<td>Entrainment rate for deep and midlevel convection</td>
<td>[0.2, 0.8, 4.0] × 10⁻⁴ m⁻¹</td>
</tr>
<tr>
<td>ENTRSCV</td>
<td>Entrainment rate for shallow convection</td>
<td>[2, 3.9] × 10⁻⁴ m⁻¹</td>
</tr>
<tr>
<td>RTICE</td>
<td>Temperature range where mixed phase is allowed to exist</td>
<td>[15, 23, 34.5] K</td>
</tr>
<tr>
<td>RVICE</td>
<td>Ice sedimentation fall speed</td>
<td>[0.05, 0.15, 0.45] m s⁻¹</td>
</tr>
<tr>
<td>CLCRITb</td>
<td>Condensed water content threshold above which precipitation starts</td>
<td>[1.5, 3.6] × 10⁻⁶ kg kg⁻¹ [2.5, 5, 10] × 10⁻⁶ kg kg⁻¹</td>
</tr>
<tr>
<td>CONa</td>
<td>Conversion rate from condensed water to precipitation (for stratiform and</td>
<td>[0.7, 1.4, 2.8] × 10⁻⁴ s⁻¹ [0.7, 1.4, 2.8] × 10⁻³ s⁻¹</td>
</tr>
</tbody>
</table>

**Note:**
- aDefault values for EC-Earth version 2.3 are in bold.
- bIn the model’s code labeled as: RCLCRIT for stratiform clouds and Z_CLCRIT for convective clouds. These parameters are perturbed together.
- cIn the model’s code labeled as: RKCONV for stratiform clouds and RPRCON for convective clouds. These parameters are perturbed together.
as entrainment and detrainment. Indeed, the free tropospheric moisture affects the rate at which clouds lose buoyancy through entrainment of unsaturated air into the convective column \cite{Bony2005}. Increased lateral mass exchange reduces the buoyancy of the updraft, leading to weaker convection (Figure 1a). The Tiedtke's scheme distinguishes between deep and mid (hereafter considered together as penetrative) and shallow convection. Weaker shallow convection leads to increased amount of moisture retained in the boundary layer and so more low clouds (Figure 1b) and, by implication, stronger SWCRE.

Figure 1. AMIPCTL experiments, period 1999–2008: absolute difference in various climate variables between sensitivity experiment outputs and reference configuration (REF) results. A plus (minus) next to the name of the sensitivity experiment indicates increased (decreased) absolute value of the related tunable parameter. (a) updraft convective mass flux at 500 hPa from ENTREPEN+, (b) low-level cloud cover ($P > 680$ hPa) from ENTRSCV+, (c) vertical profiles of temperature (dashed) and specific humidity (solid) over the tropics ($35^\circ$ N–$35^\circ$ S) from ENTREPEN+, RTICE+, and CON+, note that the specific humidity is plotted as fractional change expressed in percentage, (d) cloud albedo from RTICE+, (e) NetCRE from RVICE+, (f) condensed (liquid + ice) water path from CON+. The dashed lines are $\pm 35^\circ$ latitude lines marking the tropical belt.
Weaker penetrative convection implies a less efficient vertical transport of heat and moisture throughout the tropical atmosphere, that manifests in a cooler and drier troposphere (Figure 1c), with less high clouds.

An additional tunable parameter involves the mixed-phase clouds. The distinction between ice and liquid water phases in EC-Earth is a function of temperature: all the liquid water present below a certain negative temperature threshold is converted into ice. Lowering the negative temperature threshold, closer to observations, leads to a drier and cooler troposphere (Figure 1c), partly because of the reduced release of latent heat, and can impact the precipitation efficiency through the Bergeron-Findeisen effect. Furthermore, more supercooled water implies higher concentrations of liquid droplets, all things being equal; given the smaller size of liquid droplets relative to ice crystals, this tends to enhance cloud reflectivity, particularly at the high latitudes (Figure 1d).

Two other model configurations are built varying the fall speed of the ice crystals. The rate at which ice crystals fall depends on their mass, size, and shape; in EC-Earth their velocity is simply set to a constant value. Previous studies [Grabowski, 2000; Mitchell et al., 2008] have shown that this parameter affects significantly the radiation budget of the planet. Reduced ice fall speed in our model promotes more cirrus, resulting in a less negative NetCRE, especially in the tropics (Figure 1e).

Finally, the generation of precipitation \( G \) in EC-Earth follows the Sundqvist [1978] parameterization:

\[
G \propto c_0 \left(1 - e^{-q_{\text{crit}}/q_{\text{col}}}\right) \tag{5}
\]

where \( c_0 \) represents the conversion rate of condensed water \( q_{\text{col}} \) to precipitation and \( q_{\text{crit}} \) is the threshold value of \( q_{\text{col}} \) above which precipitation starts to occur. Increasing the former leads to lower cloud water content (Figure 1f), less high clouds, and weaker SWCRE. Increasing the latter leads to opposite changes (not shown), but we noticed that changes in \( c_0 \) have a much broader impact on the climatology than \( q_{\text{crit}} \) experiments.

### 3.1. Revised Physics Experiments

Two additional EC-Earth configurations (Table 2) are obtained by revising the parameterization structure of the turbulent mixing and of the liquid droplet effective radius \( r_{\text{eff}} \). These two configurations are integrated for the “AMIPCTL” and “AMIP4K” experiments and aim to reduce biases typical of EC-Earth: too few stratocumulus and too small liquid droplets [Lacagnina and Selten, 2014].

The diffusive turbulent flux of a quantity \( \phi \) at a given model level \( z \) may be written as:

\[
\mathbf{w} \cdot \nabla \phi = -K_0 \frac{\partial \phi}{\partial z} \tag{6}
\]

where \( w \) is the vertical velocity. For statically stable regimes, the exchange coefficients \( K_0 \) in EC-Earth are computed using a revised Louis et al. [1982] K-diffusion scheme. As a consequence, \( K_0 \) are unrealistic above the boundary layer and the turbulent mixing is too strong, promoting the erosion of stratuscumulus layers from the top [Bechtold et al., 2008]. Recent versions of the ECMWF IFS model (Cy32r3) have reduced this bias by using Monin-Obukhov functional dependencies for \( K_0 \) in the free-troposphere [Bechtold et al., 2008]. We follow the same approach by performing a sensitivity experiment (named “TURB”) with EC-Earth.

For present-day conditions (AMIPCTL), low-cloud amount from the TURB experiment agrees better with the observations, especially over the eastern basins of the tropical oceans (Figures 2a–2c). On the other hand, the positive biases get slightly larger over landmasses and Southern Hemisphere (SH) oceans with respect to the REF simulation. Increased low-cloud amount and liquid water path (not shown) reduce the model bias in SWCRE (Figures 2d–2f).

As far as the droplet size is concerned, it is computed based on Martin et al.’s [1994] parameterization. Given a constant aerosol concentration (50 cm\(^{-3}\) over ocean; 900 cm\(^{-3}\) over land), the droplet number...

### Table 2. List of the Revised Physics Experiments Conducted in This Study

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TURB</td>
<td>Turbulent mixing above the boundary layer reduced by revising calculation of vertical diffusion coefficients</td>
</tr>
<tr>
<td>INDIRECT</td>
<td>Liquid droplet number concentration related to the observed aerosol mass distributions to account for the first aerosol indirect effect</td>
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</tbody>
</table>

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concentration \( (N) \) is computed and then used together with the liquid water content to calculate \( r_{\text{eff}} \). Employing constant aerosol concentration values is an oversimplification and does not account for the first aerosol indirect effect \( [\text{Twomey}, 1974] \). We carry out a sensitivity experiment (named “INDIRECT”), where \( N \) is related to the observed aerosol mass distributions, provided by CMIP5, through the \( \text{Menon et al.} \)’s \( [2002] \) parameterization and then passed to the \( \text{Martin et al.} \)’s \( [1994] \) parameterization to compute \( r_{\text{eff}} \).

The impact of a more realistic \( N \) distribution is manifest as richer spatial structure of \( r_{\text{eff}} \) over land and as smaller \( r_{\text{eff}} \), i.e., larger negative bias (Figures 3a and 3b), except over the landmasses of SH (Figure 3c). This implies that the aerosol concentration is tuned too high for these areas in the REF configuration. It is well known that aerosol concentrations are much lower in the SH than in the Northern Hemisphere [e.g., \( \text{Menon et al.}, 2002 \)]. Thus, assuming a constant aerosol concentration for every land areas is far from being realistic. Smaller \( r_{\text{eff}} \) translates into brighter clouds and hence stronger SWCRE (Figure 3d). \( \text{Lacagnina and Selten} \) [2014] have shown that clouds exert an overly strong cooling effect in the REF configuration. Therefore, including only these changes to account for the aerosol indirect effect degrades the radiative balance in the model. However, it is still interesting exploring the impact of this and of the other changes on the EC-Earth climate feedbacks. This is the subject of the next sections.

4. Radiative Feedbacks in EC-Earth

Figure 4 shows radiative feedbacks derived from the EC-Earth REF configuration. The effective feedback factor \( (\lambda_{\text{eff}}) \) is calculated using the TOA fluxes imbalance:

\[
\lambda_{\text{eff}} = \frac{\Delta Q - F}{\Delta T_s}
\]

The difference between \( \lambda_{\text{eff}}^0 \) (as in equation (7) but for clear-sky conditions) and the total feedback factor, calculated based on clear-sky kernels, can be used to measure the accuracy of the kernel approach [\( \text{Jonko et al.}, 2012 \)].
Figure 3. AMIPCTL experiments, period 2003–2007: model outputs are from the EC-Earth configuration with revised physics for aerosol indirect effect (INDIRECT) and from the reference EC-Earth configuration (REF). (top) Difference between model and observations, (bottom) difference between INDIRECT and REF model configurations. (a–c) Effective radius of liquid droplets ($r_{eff}$), (d) SWCRE. MODIS and CERES observations are used.

Figure 4. AMIP4K-AMIPCTL experiments, REF configuration: mean zonally averaged feedbacks. Global mean values are reported next to the legend, along with $\text{Re}_\text{eff}$, $\lambda_{\text{sw}}$, and $\Delta T_s$. 
High latitudes poleward of $65^\circ$ are not shown in Figure 4, since these regions depend strongly on surface properties and the AMIP4K runs have prescribed sea ice, which cannot respond to the warming. Because of the design of this idealized experiment, the globally averaged surface albedo feedback is quite small ($\lambda_c = 0.08 \text{Wm}^{-2}/\text{K}$). The only regions contributing significantly to this feedback are in the Northern Hemisphere, due to the snow melt on land.

The strongest radiative feedback is associated with the Planck response ($\lambda_P$) to the warming. This is a negative feedback, since the increase in $T_s$ implies larger amounts of outgoing longwave radiation (OLR). $\lambda_P$ is the largest in the tropics owing to the great sensitivity of the Stefan-Boltzmann law to temperature.

The positive LW feedback is mainly positive, peaking in the west tropical Pacific. This feature is consistent with the fixed anvil temperature hypothesis (FAT) of Hartmann and Larson [2002]. The present-day climate, high clouds enhance the natural greenhouse effect of the planet emitting less thermal radiation to space than the surface-atmosphere column would under clear-sky conditions. The reason is that these clouds radiate at a much lower temperature than the surface. The larger the temperature difference, the stronger the warming effect. According to the FAT hypothesis, deep convective clouds rise to a higher altitude in a warmer climate in such a way that the emission temperature remains nearly constant. This implies that the difference between surface temperature and cloud-top temperature increases, leading to stronger LWC, thus positive LW feedback, since the increase in $\lambda_P$ dominates the cloud feedback signal, in particular its LW component. Despite $\lambda_c$ and $\Delta\text{CRE}/\Delta T_s$ exhibiting similar latitudinal dependence, the global averages change sign and magnitude ($\Delta\text{CRE}/\Delta T_s = -0.05 \text{Wm}^{-2}/\text{K}$). This emphasizes that a correction for noncloud feedbacks is crucial when studying the global cloud feedback, hence this approach is adopted in the rest of our analyses.

Spatial structure of the $\lambda_c$ components is displayed in Figures 5a–5c. The LW $\lambda_c$ is mainly positive, peaking in the west tropical Pacific. This feature is consistent with the fixed anvil temperature hypothesis of Hartmann and Larson [2002]. In the present-day climate, high clouds enhance the natural greenhouse effect of the planet emitting less thermal radiation to space than the surface-atmosphere column would under clear-sky conditions. The reason is that these clouds radiate at a much lower temperature than the surface.

The larger the temperature difference, the stronger the warming effect. According to the FAT hypothesis, deep convective clouds rise to a higher altitude in a warmer climate in such a way that the emission temperature remains nearly constant. This implies that the difference between surface temperature and cloud-top temperature increases, leading to stronger LWC, thus positive LW $\lambda_c$. The FAT hypothesis is confirmed in Figure 6 for tropical regions (35 N–35 S) characterized by strong convection (vertical pressure velocity at 500 hPa ($\omega_{500}$) $< -30 \text{hPa/d}$, contour lines in Figure 5a).

The positive LW $\lambda_c$ is almost offset by the negative SW $\lambda_c$ in deep convective areas (Figure 5b). This is due to a slight increase in cloud amount (Figures 5d and 5e) and in the natural logarithm of optical depth (Figure 5i). It should be noted that $\ln(c)$ is linearly proportional to the cloud albedo [Twomey, 1977]. The SW $\lambda_c$ is positive over land, in particular over Africa, because of the strong decrease of the cloud amount (Figures 5d and 5e). In contrast, the LW $\lambda_c$ is negative for the same areas, but the magnitude is less than its SW counterpart. This is in agreement with the findings of Zelinka et al. [2012b]: changes in cloud amount have a larger impact on SW $\lambda_c$ than on LW $\lambda_c$. The latter is dominated by changes in $P_c$ (particularly for high clouds), that are negative almost everywhere (Figure 5f). Over the tropical western side of the continents, a decrease in $P_c$ reflects cloud regime changes from low cloud to more midlevel clouds. In these regions, the total cloudiness decreases slightly leading to a weak positive SW $\lambda_c$ (Figure 5b), with similar or weaker $\ln(c)$ (Figure 5i).

\[
\text{Re}_{06} = \frac{\lambda_{06} - \sum_{k=1}^{n} \frac{\partial (Q - F)}{\partial X_k} \frac{\partial X_k}{\partial T_s} }{\lambda_{06}} 
\]

\[
\lambda_{05} = \frac{100}{\lambda_{05}} 
\]

where $n$ is the total number of kernels. The small value $\text{Re}_{06} = 5\%$ indicates that the kernel linear approximation is reasonable for AMIP4K experiments.
The ln(\(s\)) exhibits the largest increase in the extratropics (poleward of 35°). This feature is robust among GCMs [Tsushima et al., 2006] and is due to the increase in high-latitude cloud water content, dominated by the liquid phase (Figures 5g and 5h). This model result is supported by observational [Feigelson, 1978] and analytical evidence [Betts and Harshvardan, 1987; Gordon and Klein, 2014]. Figures 5g and 5h also show that the largest changes arise from mixed-phase clouds, in regions where the temperature ranges from 0°C to -23°C and supercooled water is allowed to exist in the EC-Earth parameterization.

These results show that the feedback values (Figure 4) derived from EC-Earth fall within the range of the feedback strengths diagnosed in the other CMIP5 models [Tomassini et al., 2013]. Moreover, the spatial structure of the changes in the AMIP4K experiment (Figure 5) is comparable to the analyzed changes in the other CMIP5 scenario simulations of Tomassini et al. [2013], which supplies the argument that AMIP4K simulations are in general suitable for investigating radiative feedbacks. In order to ensure the robustness of these calculations, we have repeated them using the whole AMIP run (30 year), instead of just the last 10 years and obtained consistent results. For instance, globally averaged for 30 years, \(\lambda_{\text{eff}}\) equals \(-1.75 \text{ Wm}^{-2}/\text{K}\), while \(\lambda_{\text{eff}}\) is \(-1.72 \text{ Wm}^{-2}/\text{K}\), when only the last 10 years of run are retained. This indicates that the number of years used does not materially affect our evaluation. For practical reasons, all the sensitivity experiments are run for 10 years in this study and thus the results are compared with the last 10 years of the REF simulations.
5. Dependence of Feedbacks Upon Model Formulation

Figure 7 shows the fractional change between feedback parameters derived from the different EC-Earth configurations and the REF configuration (see section 3 for a detailed description of the experiments). First, note that the change in the radiative feedbacks in response to the parameter perturbations does not scale linearly with the perturbation. An extreme case regards the LW and SW \( \kappa_c \) in the CON experiment (Figures 7d and 7e). An increase or decrease of the...
conversion rate both lead to a weakening of both the cloud feedbacks. The total feedback parameter (Figure 7a) exhibits small variations within 10%, apparently $\gamma$ is fairly robust in EC-Earth. This implies that the feedbacks variations compensate each other in order to leave $\gamma$ relatively unchanged, as clearly shown in Figure 8. However, it is immediately clear that some tunable parameters change significantly the partitioning between individual feedbacks in the model. The impact of a decreased entrainment rate for penetrative convection (ENTREPEN) and an increased conversion rate from condensed water to precipitation (CON) are the most striking. Their effects on the climate feedbacks are opposite. The impact of ENTREPEN and CON is relevant in every component of the total feedback, but it is relatively the largest for SW $\gamma_c$ (Figure 7e, note the different scales).

To understand where these large feedback differences originate, we inspect the spatial structure of the changes. As expected, ENTREPEN has the largest impact in the deep tropics (Figures 9a and 9b), mainly due to the stronger increase of upper clouds and cloud-top altitude compared to the REF configuration (Figures 9d and 9e). On the other hand, ln$(\gamma_c)$ does not change significantly (Figure 9f). The LW and the SW components of the cloud feedback tend to be anticorrelated, leading to a modest increase of $\gamma_c$ (Figures 9c and 7f). Similarly to ENTREPEN, the CON experiment most affects the convective regions, with more emphasis on the South Pacific convergence zone (Figures 10a–10c). Variations in the cloud feedbacks are mostly due to the decrease of the upper level cloud amount and cloud-top altitude in this area (Figures 10d and 10e), along with the slight decrease of ln$(\gamma_c)$ (Figure 10f).

The tropics contribute most to the interconfiguration standard deviation in the feedback changes, with the LW and SW $\gamma_c$ exhibiting the largest spread (gray bars in Figure 7). However, their combined effect, i.e., $\gamma_c$, only varies within 20% and the interconfiguration standard deviation reduces, which is an indication of sizable compensating effects. An exception is the INDIRECT experiment, where $\gamma_c$ increases by roughly 40%, owing to the weakening of the SW component not offset by the LW counterpart (squares in Figures 7d–7f). When AMIPCTL simulations are considered, SWCRE is more negative over the tropics and midlatitudes in the INDIRECT configuration than in the REF configuration (Figure 3d). In the AMIP4K simulations, SWCRE is less negative, as manifested in the weakening of the SW $\gamma_c$ (Figure 7e). The other EC-Earth configuration where the parameterization structure has been revised, namely the TURB experiment, exhibits the same shifts on the global climate feedbacks, but less pronounced. Unlike the INDIRECT configuration, SWCRE strengthens almost exclusively in the subtropical stratocumulus regions in TURB compared to REF (Figure 2f), in the AMIPCTL simulations. A possible explanation is that starting with more SWCRE in present-day conditions, a reduction of cloudiness due to external forcings has a stronger impact on the SWCRE response than in a model simulating weaker SWCRE in the current climate. Therefore, regions experiencing positive SW $\gamma_c$ (e.g., stratocumulus regimes in Figure 5b) give rise to a stronger local SW $\gamma_c$, leading to a less negative (weaker) global SW $\gamma_c$ compared to configurations with less SWCRE in present-day conditions. This hypothesis is investigated in the next subsection.

**5.1. Any Link Between Model Bias and Cloud Feedbacks?**

Here we analyze the response of the sensitivity experiments carried out for this study over the tropical belt (35°N–35°S). This is the largest climate region of the world, roughly 50% of the earth surface, and is the region where most of the variability in radiative feedbacks arises among the different EC-Earth configurations (gray bars in Figure 7). A compositing technique centered around the $\omega_{500}$-SST phase-space is used, following Lacagnina and Selten (2013a). Monthly means of cloud-related variables are composited into...
different dynamical and thermodynamical regimes, defined by $\omega_{500}$ and SST. Within this framework, thick low clouds are mostly found over relatively cold pools with large-scale sinking ($\omega_{500} > 0$) motion, while upper level clouds are mainly expected over warmer SSTs with large-scale rising ($\omega_{500} < 0$) motion. Finally, areas of subsidence and warm SSTs are associated with trade cumulus or mostly clear sky regimes [Lacagnina and Selten, 2013a]. Monthly mean values of SWCRE, from the various model configurations for the AMIPCTL and AMIP4K simulations, have been composited using monthly mean values of $\omega_{500}$ and SST from the related configuration. We stress that SST is the same in every experiment, shifted back by 4 K for the

Figure 9. Difference between changes in AMIP4K-AMIPCTL experiments for ENTREPEN- and REF in various cloud-related variables: LW cloud feedback (a), SW cloud feedback (b), NET cloud feedback (c), upper level cloud cover (d), cloud-top pressure (e), and natural logarithm of optical depth (f).
AMIP4K simulations. Such a diagnostic technique is particularly convenient for AMIP experiments, since SSTs remain geographically the same and the large-scale circulation is not dramatically altered, because closely related to the spatial distribution of SST [Lindzen and Nigam, 1987]. Furthermore, the information from the different cloud regimes is aggregated and the relative contribution of these regimes to the tropics-wide climate is easy to quantify.

Figure 11 shows the correlation coefficient between SWCRE in the AMIPCTL climate and its response in the AMIP4K simulations, derived from the ensemble of sensitivity experiments described in section 3. The subsidence cold pool is the only region with strong correlation and high statistical frequency of occurrence. The
strength of the SWCRE response to climate change is strongly correlated with the strength of the SWCRE simulated in the current climate. A possible explanation of the processes leading to such a relationship is given in Brient and Bony [2012]. Cloud radiative cooling in the marine boundary layer (MBL) contributes to maintain MBL cloudiness by increasing the relative humidity. As a consequence, in a warmer climate a reduction of low clouds weakens the cloud radiative cooling, promoting lower relative humidity, that in turn amplifies the initial low-cloud reduction. If this feedback loop is weak in some models, because the cloud-radiation interaction is weak in current climate, then an initial decrease of MBL clouds in a warmer climate feeds back a less pronounced decrease of low clouds and thus a less pronounced weakening of CRE. Brient and Bony [2012] apply this argument to low clouds in general. Here we show that the strong correlation between the simulation of SWCRE in the current climate and its response to climate warming arises only from stratocumulus (and stratus) or stratocumulus to cumulus transition regimes. Other cloud regimes do not exhibit an obvious link between model simulation of present climate and future climate change. It is important to note that $\Delta$SWCRE is fairly similar to $SW_{k_c}$ in the tropics (Figure 4). The former can thus be used as a surrogate of the latter for this type of analysis.

We take a step further by investigating which component of the SW cloud feedback contributes to the aforementioned relationship. We focus on the areas with the highest correlation in Figure 11, namely regimes of subsidence and colder SSTs. Figure 12a shows SWCRE derived from AMIPCTL simulations versus the related change in AMIP4K. Shadings represent the observations and show that the REF configuration underestimates the strength of SWCRE, consistent with Lacagnina and Selten [2014]. Moreover, the relationship between SWCRE and $\Delta$SWCRE is particularly strong with $\rho = -0.84$, statistically significant at the 95% confidence level. Let us consider the green triangle pointing up, corresponding to the ENTRSCV configuration. This corresponds to a much stronger reduction in SWCRE for AMIP4K experiments (Figure 12a). Moreover, the closer to the observations, the stronger the model sensitivity in this region. On the other hand, $\ln(\tau)$ does not show any relationship between AMIPCTL and AMIP4K simulations (Figure 12c). Considering the green triangle pointing up, it is close to the average of the AMIPCTL simulations, whereas it exhibits the largest decrease in $\ln(\tau)$ for AMIP4K. When a relationship between how model simulates current climate and how it simulates future cloud feedbacks is sought, the cloud amount and $\tau$ changes components of the SW $\lambda_c$ behave in different ways, with the former contributing the most to this relationship.

These results suggest that processes underlying the SW stratocumulus feedback are affected by the state of the model present-day climate. This implies that any model development, aiming to improve the representation of stratocumulus, likely affects the SW low-cloud feedback by a factor that is proportional to the
change in the stratocumulus biases. Let us consider once again the ENTRSCV experiment (green triangle pointing up in Figure 12), since it exhibits the closest agreement with observations in terms of cloud cover and SWCRE. It predicts $\frac{\Delta \text{SWCRE}}{\Delta T} \approx 1 \text{Wm}^{-2} / \text{K}$, implying that the reference configuration (black diamond) underestimates $\frac{\Delta \text{SWCRE}}{\Delta T}$ by about 35%, over the eastern basins of the tropical oceans.

As far as the LW $\kappa_c$ is concerned, we find a relationship between high-cloud top altitude simulated in AMIPCTL and high-cloud top altitude change in AMIP4K, in deep convective regions (Figure 13a). We analyze this by calculating the high-cloud top pressure as the average of the pressure values at each level weighted by the cloud amount at that level, following Zelinka and Hartmann [2010]. They assumed that this high-cloud-weighted pressure is a reasonable estimate of the level of the high-cloud emission temperature. Figure 13a shows that the higher the clouds in the AMIPCTL experiment, the larger the rise in AMIP4K. This could impact the LW $\kappa_c$, because the sensitivity of OLR to a given cloud fraction increases with increasing cloud altitude [Zelinka et al., 2012a]. If high-cloud tops were to shift toward lower pressures by the same amount for every model configuration, one would naively expect LW $\kappa_c$ to be smaller for model configurations with high-cloud tops lower in altitude in current climate. This interpretation is misleading. Indeed,
summing all the $\tau$ columns along each cloud-top-pressure row of the joint histogram in Figure 1a of Zelinka et al. [2012a], it can be shown that the LW cloud radiative kernel scales linearly with the pressure, notably below 440 hPa (Figure 13b). However, the LW $\lambda_c$ is equal to the kernel multiplied by the cloud change (normalized by the global temperature change). Because of the linear dependence of the kernel with height, the LW $\lambda_c$ becomes independent of the cloud-top height in AMIPCTL, for the same shift in cloud top height and the same cloud amount change.

Figure 13a does not only show that different model configurations simulate high-cloud tops at different pressures in AMIPCTL, but it also shows that model configurations with high-cloud tops lower in altitude in AMIPCTL, project high-cloud top pressure changes that are systematically smaller than the other configurations. This can have an effect on LW $\lambda_c$ and indeed Figure 13c shows a correlation between cloud-weighted pressure in AMIPCTL and LW $\lambda_c$. However, this relationship is not as systematic as in Figure 13a. For instance, LW $\lambda_c$ in the CON+ experiment (orange triangle pointing up in Figure 13c) is smaller than in REF (black diamond), despite simulating high-cloud top higher in altitude in AMIPCTL and an upward shift higher in AMIP4K with respect to REF. This implies that the different shifts in altitude among the experiments might be too small to impact LW $\lambda_c$, and cloud amount and $\tau$ changes are not negligible in determining this feedback. These results suggest that a correlation exists between high-cloud top pressure in present-day climate and LW $\lambda_c$ and more in depth investigation is needed in future studies. A compelling framework of analysis to disentangle these different influences is the compositing technique proposed in Zelinka et al. [2012b], where the altitude component of the LW $\lambda_c$ can be investigated in isolation with respect to the cloud cover and $\tau$ changes.

6. Summary and Discussion

Radiative feedbacks were analyzed for the EC-Earth atmospheric GCM, applying the kernel approach for a 4 K uniform SST perturbation experiment (AMIP4K). We find that the kernel linear approximation can be used for such AMIP simulations, because the errors are small (roughly 5%). For the first time, the various radiative feedbacks are estimated for EC-Earth. It is shown that this model predicts feedbacks in quantitative agreement with those diagnosed in the other CMIP5 models. The cloud feedback ($\lambda_c$) is calculated correcting $\Delta$CRE for noncloud atmospheric changes using the radiative kernels. With this method, $\lambda_c$ is positive and small in EC-Earth ($\lambda_c=0.24$Wm$^{-2}$/K), with positive LW and negative SW components. When $\Delta$CRE/$\Delta T$, is used as a surrogate of the cloud feedback itself, it reverses the sign. The $\Delta$LWCRE/$\Delta T$, weakens, particularly in the tropics, whereas the SW component is nearly unchanged. This emphasizes that a correction for environmental masking effects is relevant, determining sign and magnitude of the cloud feedback.

We identify the nature of the cloud changes giving rise to $\lambda_c$ in our model. The spatial pattern of the LW $\lambda_c$ is generally positive, peaking in the west tropical Pacific. It is dominated by the general increase of the cloud-top height. The SW $\lambda_c$ is generally negative and tends to offset its LW counterpart, except for the subtropical oceans, where it is positive. These regions experience moderate decrease in low-cloud amount (5% to 10%), whereas the in-cloud albedo tends to remain constant. On the other hand, the largest increase in cloud albedo stems from the extratropics, mainly due to increased cloud liquid water content.

These results are then compared to various EC-Earth configurations, built revising various parameterizations that impact the cloud field. These represent sensitivity experiments whose effects on the present-day and warmer climate conditions are assessed. Two sensitivity experiments concern structural changes: the reduction of the vertical diffusion in free troposphere and the introduction of the first aerosol indirect effect in the model. Only the former leads EC-Earth to perform better compared to the observations. Stratocumulus cover increases and the SWCRE bias reduces, notably over the eastern basins of the tropical oceans. The rest of the sensitivity experiments concerns tunable parameter perturbations.

Regarding the sensitivity of the climate feedbacks in EC-Earth to the model parameter settings, we identify a number of physical processes that play a dominant role in the way clouds are simulated. Specifically, the lateral mass exchange rate of penetrative convection and the conversion rate from condensed water to precipitation are leading parameters affecting the radiative feedbacks in EC-Earth. This supports the findings of Sanderson et al. [2010], who showed a strong impact of the entrainment rate in deep convection on the climate sensitivity. Here we show that decreasing the convective entrainment and increasing the conversion rate have opposite effects on the feedback strengths. Cloud feedbacks can clearly be identified as the main
source of the interconfiguration spread in climate feedbacks, especially in the tropics. The SW component of $\lambda_k$ makes a larger contribution to this spread than its LW counterpart. Perturbation, within physical uncertainties, of a number of tunable parameters can alter the SW $\lambda_c$ by 60%, pointing to the existence of many degrees of freedom in this feedback.

A surprising result is that the change in the radiative feedbacks in response to the parameter perturbations does not scale linearly with the perturbation. This highlights the importance of nonlinear interactions between the different processes determining the response of the climate to an external forcing. Furthermore, the total feedback parameter ($\lambda$) exhibits small variations within 10% of its reference value, indicative of its robustness in EC-Earth. This is a relatively modest change compared to the CMIP5 intermodel differences [Andrews et al., 2012] and to studies centered around perturbed physics ensembles in a single GCM [Sanderson et al., 2010; Klöcke et al., 2011]. These are based on future climate projections with changing concentrations of greenhouse gases in coupled GCMs, unlike the AMIP4K simulations considered here. When SSTs are allowed to adjust to the model settings, more degrees of freedom can affect $\lambda$. Therefore, AMIP4K sensitivity experiments are likely to underestimate the spread in the diagnosed feedback parameters. Sensitivity experiments with the fully coupled EC-Earth model and different warming scenarios should be carried out in the future to unravel this discrepancy.

Moreover, it should be noticed that feedbacks calculated in this study for AMIP4K experiments can be different in magnitude with respect to feedbacks diagnosed with other types of climate perturbations. We have performed two additional simulations with the fully coupled EC-Earth reference configuration forced once with preindustrial levels of CO2 and once with an abrupt quadrupling of atmospheric CO2. These experiments are run for 150 years and global-annual means of TOA fluxes and surface-air temperatures are used to derive the climate sensitivity, similarly to Andrews et al. [2012]. The equilibrium climate sensitivity is 3.4 K and $\lambda \approx -1.1 \, \text{W m}^{-2} / \text{K}$ in EC-Earth, values that are similar to the multimodel average [see Andrews et al., 2012 for a comparison]. In contrast, $\lambda \approx -1.7 \, \text{W m}^{-2} / \text{K}$ in the AMIP4K experiments used in this study. This supports the findings of Block and Mauritsen [2013], who have shown that $\lambda$ depends on the type and strength of the forcings applied to the model climate.

Finally, this study reaches compelling conclusions that are of interest to the general GCM community. An important question that is relevant in tuning models to observations is whether a systematic link exists between how models perform in present-day climate and the strength of the cloud feedbacks. One might expect that with the continuing improvement of GCMs over time, models would converge in the simulation of the various climate feedbacks, but this has not proved true yet [Klöcke et al., 2011]. However, consistent with Brierton and Bony [2012], we find that the strength of the low-cloud SWCRE response to climate change is strongly correlated with the strength of the low-cloud SWCRE simulated in the current climate. In addition to Brierton and Bony [2012], we find that this correlation holds for stratocumulus regimes only and not for trade-cumulus. We also find that much of this correlation for stratocumulus regimes is contributed by reduction in the low-cloud amount, rather than changes in the low-cloud optical thickness. These results suggest that any model development, aiming to improve the representation of stratocumuli in the current climate, affects the SW low-cloud feedback by a factor that is proportional to the change in the stratocumulus biases. The reference EC-Earth configuration underestimates the SWCRE response by about 35% in these cloud regimes, compared to configurations closer to the observations. Therefore, biases in the representation of stratocumuli may contribute to the small cloud feedback diagnosed in EC-Earth.

An additional link between model bias and cloud feedbacks is also discussed. We find that certain sensitivity experiments simulate high clouds lower in altitude in present-day conditions compared to the other experiments and this altitude difference increases in a warmer climate. This can impact the LW cloud feedback, since the sensitivity of OLR to a given cloud fraction increases with increasing cloud altitude [Zelinka et al., 2012a]. However, the correlation between present-day cloud-top altitude and LW cloud feedback is not systematic, implying that cloud amount and optical depth changes are not negligible in determining this feedback.

The results presented in this study provide guidance for future model developments and emphasize links between model fidelity and cloud feedbacks, suggesting that observational constraints may be used to assess the credibility of these feedbacks in GCMs. Further analyses that expand these findings are warranted, such as investigating the reasons for the robust response of the total feedback to model setting.
changes in EC-Earth and the connection between high-cloud top altitude simulated in the present-day climate and the LW cloud feedback. Analysing this latter in other models with the appropriate framework [e.g., the partitioning technique in Zelinka et al., 2012b] would help to assess the robustness of this correlation.

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