Diagnosing atmospheric heating rate changes using radiative kernels

Han Huang\textsuperscript{1} and Yi Huang\textsuperscript{1}

\textsuperscript{1}Department of Atmospheric and Oceanic Sciences, McGill University

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Han Huang, Yi Huang
Department of Atmospheric and Oceanic Sciences, McGill University, Montreal, Canada

Corresponding Authors:
Han Huang, han.huang2@mail.mcgill.ca (ORCID: 0000-0002-9143-6453),
Yi Huang, yi.huang@mcgill.ca (ORCID: 0000-0002-5065-4198)
Abstract

Atmospheric radiative heating rate, which manifests radiative energy convergence in the atmosphere, is a fundamental factor shaping the Earth’s climate and driving climate change. Compared to the radiative energy budget at the top of atmosphere (TOA) or surface, the atmospheric energy budget and heating rate are less studied and understood due to a lack of observational constraints and of diagnostic tools. Motivated by growing interest in atmospheric energy budget and particularly to facilitate the analysis of atmospheric heating rate, we innovate a set of radiative kernels, which quantitatively measure the sensitivity of atmospheric heating rate to different geophysical variables. When multiplied with the changes in these geophysical variables, these kernels can quantify the contributions of them to the heating rate change. A climate change experiment of Global Climate Models (GCMs) is used to test the application of the heating rate kernels. The results indicate that the radiative heating rate change simulated by the GCMs can be well reproduced by the kernels, which affirms the validity of the kernel method. The decomposition of the heating rate changes reveals rich information of the contributing mechanisms behind the changes. For example, in the tropical upper troposphere, the noticeably enhanced radiative cooling in a warmer climate is found to be dominated by atmospheric temperature and water vapor. Both of them increase the thermal radiation of the atmosphere, and are partially offset by a warming effect of the lifting high-cloud tops in this region. Moreover, we find that compared to the results corrected using the kernels, the cloud effect inferred from the radiative heating difference between clear- and all-skies (using the quantity termed “cloud radiative effect”) has a non-negligible bias, which necessitates the use of kernels to quantify the cloud-induced heating rate changes.

(Plain Language Abstract)

Atmospheric heating rate is a crucial factor shaping the Earth’s climate and its change. To facilitate the understanding of the atmospheric heating rate, we innovated a set of radiative kernels that can be used to isolate the effects of different geophysical variables on the radiative heating rate. The use of the kernels discloses the competitive effects of cloud and non-cloud feedback mechanisms that drive the atmospheric heating rate changes in a warmer climate.

Key Points

1. An innovative set of radiative kernels of heating rate has been generated based on global reanalysis atmospheric profiles
2. The kernels can well explain the major atmospheric radiative heating rate changes in a warming climate
3. The kernels are necessary for correcting the biases when quantifying the heating rate change caused by clouds
1. Introduction

Atmospheric heating rates, also known as temperature tendencies, play an important role in defining the Earth’s climate (Doplick, 1972; Gille & Lyjak, 1986; Johnson & Ciesielski, 2000). As heating rate can be caused by the convergence of both radiative and non-radiative energy fluxes that are controlled by different physical processes, understanding the balance between the heating rate components is crucial to study the interactions between these processes (Zhang et al., 2017). Compared with the well-studied energy fluxes at the top of the atmosphere (TOA) and surface (Soden & Held, 2006; Hu et al., 2019; Zelinka et al., 2020; Huang & Huang, 2023), the heating rates that concern the energy budget inside the atmosphere are much less studied and often treated as the residual. This is due to the lack of observations of the temperature tendencies and also the difficulty to isolate the tendency components driven by different physical processes. Hence, investigating the heating rate and its variation in climate change will not only offer a more complete view on Earth’s energy budget but also provide richer information for the comparisons of climate models.

Based on the energy sources, the atmospheric heating rate can be categorized as radiative, in both longwave (LW) and shortwave (SW), physical and dynamical heating rates, resulting from such physical processes as radiative transfer, convection, advection, turbulence, etc. (e.g., Fueglistaler et al., 2009; Sullivan et al., 2023). For some processes, due to the complexity in their simulation, the corresponding heating rate components are difficult to be directly quantified. For example, diagnosing the dynamical heating rate from gridded analysis data is known to be a challenging task, for example, in conserving the total energy (e.g., Trenberth, 1991; Mayer et al., 2017; Trenberth & Fasullo, 2018). In comparison, the radiative heating rate can be more straightforwardly and self-consistently modelled using either online or offline radiative transfer models (e.g., Li et al., 2015; Zhang et al., 2017; Cesana et al., 2019; Bloxam & Huang, 2023). Leveraging on this advantage, one can, for example, infer vertical motion from radiative heating rate assuming a closed heating budget (e.g., Schoeberl & Dessler, 2011; Wright & Fueglistaler, 2013). Given the needs and benefits of the radiative heating rates, we focus on this heating rate component in this study. To simplify the expression, we refer to the radiative heating rate simply as “heating rate” or “Htr” in short form, if not otherwise stated in the following.

Several previous studies have investigated the Htr distribution in the current climate and made comparisons among different datasets (Fueglistaler et al., 2009; Wright & Fueglistaler, 2013; Zhang et al., 2017). A few geophysical variables, such as temperature, water vapor, clouds, ozone and aerosols, were identified to be the key factors explaining the discrepancies of the Htr values among the datasets (McFarlane et al., 2007; Wright & Fueglistaler, 2013; Turner et al., 2018; Cesana et al., 2019). In addition, one of the fundamental climate questions is how the Htr patterns will evolve during climate change (e.g., Forster & Shine, 1997; Duan & Wu, 2008), such as the heating rate change due to the upshift of cloud tops. It is of great importance and interest to understand how the Htr changes are driven by the controlling geophysical variables and whether their effects are consistently represented in GCMs.

Among the variables controlling the heating rate, cloud, with its diverse microphysical and macrophysical properties, is one of the most significant factors influencing Htr (Chen et al., 2000; Fueglistaler & Fu, 2006; Mather et al., 2007; L’Ecuyer et al., 2008; Crueger & Stevens, 2015; Turner et al., 2018; Cesana et al., 2019). To quantify the cloud effect on Htr, an often-used method is to measure it by the difference of heating rate between all sky and clear sky, which is termed as the “cloud radiative effect” (CRE) (e.g., Johansson et al., 2021; Voigt et al., 2023).
However, it is well known from the cloud feedback studies (Soden & Held, 2006; Huang & Huang, 2021; Huang et al., 2021) that CRE may alias non-cloud effects as cloud effect in quantifying the radiative changes caused by clouds (i.e., the “cloud feedback”), due to the cloud masking issue (for example, see equation (5) and the discussions of Huang et al., 2021 of this issue). Hence, it begs the question: is the CRE-estimate of cloud-caused Htr change also subject to the masking issue?

To answer the questions above and inspired by the radiative kernel technique broadly used for diagnosing the TOA and surface energy flux changes (Shell et al., 2008; Soden et al., 2008), we devise a set of Htr kernels and apply them to diagnosing the Htr changes. In analogy to the flux kernels, the Htr kernels measure the sensitivity of heating rate to geophysical variables and, when multiplied with the changes of these geophysical variables, measure their respective contributions to the total Htr change.

This paper is organized as follows. Section 2 describes the calculation of Htr kernel and how to apply them to decompose heating rate changes. Section 3 shows the distribution of Htr sensitivities as given by the Htr kernels. Section 4 diagnoses the Htr changes in climate change using the kernels and compares the cloud-induced heating rate change using the kernel method and CRE method. Section 5 provides a summary of the major contributions and findings of this work.

2. Method

2.1 Heating rate kernel concept

Analogous to radiative flux kernels, the heating rate kernel measures the sensitivity of heating rate to a unit perturbation of a variable, i.e., \( \frac{\partial H}{\partial X} \) where \( H \) is the atmospheric heating rate profile and \( X \) is a geophysical variable of radiative importance. Here we compute the heating rate kernels of the same non-cloud variables as in the flux kernels (Soden et al. 2008). That means \( X \) represents surface temperature \( (T_s) \), air temperature \( (T_a) \), water vapor \( (WV) \) or surface albedo \( (ALB) \).

We denote the heating rate kernel of variable \( X \) as \( K_X \) and an instantaneous kernel \( K_X^{(i,j)} \) value is calculated as:

\[
K_X^{(i,j)} = \frac{\Delta H_i^o}{\Delta X_j^o}
\]  

(1)

Here the superscripts \( i \) and \( j \) denotes the vertical levels associated with heating rate value (corresponding to the \( i^{th} \) layer of the \( H \) profile) and the geophysical variable perturbation (corresponding to the \( j^{th} \) layer of the \( X \) profile), respectively. \( \Delta X_j^o \) represents a small perturbation of variable \( X \) in the \( j^{th} \) layer. \( \Delta H_i^o \) is the heating rate change in response in the \( i^{th} \) layer. Hence, \( K_X^{(i,j)} \) is a matrix, representing the sensitivity of the heating rate value in the \( i^{th} \) layer to the perturbation of \( X \) in the \( j^{th} \) layer.

To calculate the instantaneous heating rate kernel in equation (1), the partial radiative perturbation method (Wetherald & Manabe, 1988) is used. Radiative transfer calculations are conducted twice, once with no perturbation (the control) and another time with a perturbation of the \( X \) value in the \( j^{th} \) layer (by the amount of \( \Delta X_j^o \)) while keeping all other variables unchanged (the same as the control). In both calculations, the heating rate profile is computed and saved at
each time instance and each location. Then, the heating rate change in each layer \( \Delta H_{i,j}^l \) is obtained by differencing the heating rate profiles calculated from the perturbed and control profiles. Such perturbation calculations are applied to all the other layers of \( X \), one layer by one layer, which generates a heating rate kernel matrix of \( n \) layer by \( n \) layer, where the first dimension denotes the vertical location of the heating rate change (heating rate sensitivity) and the second dimension denotes the layer where the perturbation is added.

For surface temperature and surface albedo, as there is only one layer in these variables, the corresponding instantaneous heating rate kernels for these two variables are 4D arrays of \( (\text{time}; \text{latitude}; \text{longitude}; \text{Htr layer}) \). For air temperature and water vapor, the instantaneous heating rate kernels are 5D arrays of \( (\text{time}; \text{latitude}; \text{longitude}; \text{Htr layer}; \text{perturbation layer}) \). For water vapor, as it has interactions with both LW and SW radiation, there are water vapor LW and SW heating rate kernels, separately. Here the dimension “Htr layer” indicates the vertical location where the heating rate sensitivity is of concern, and the dimension “perturbation layer” indicates the layer where the perturbation is added. The perturbation schemes of each variable follow Huang and Huang (2023): for air temperature and surface temperature, it is a 1K increase. For water vapor, it is the increase of water vapor concentration to keep the relative humidity unchanged when the air temperature is increased by 1K. For surface albedo, it is a 0.01 increment in the albedo value. Note that for air temperature and water vapor kernels, linear additivity tests have been conducted to verify that the heating rate change due to a whole-column 1K increase can be well reproduced by the vertical integration of the kernel values along the “perturbation layer” dimension (i.e., summing the effect of layer by layer 1K perturbation).

As indicated by the dimensionality of instantaneous heating rate kernel, it should be noted that the \( K_X \) value varies with time, geographic and vertical locations. To ensure a proper representation of the diurnal cycle, we have conducted sensitivity tests to determine the necessary temporal sampling and chosen 6-hourly profiles for LW and 3-hourly profiles for SW radiative transfer calculations. To account for the potential interannual variability in heating rate kernel values, we use 5 years’ data (2011 to 2015) to drive the instantaneous heating rate kernel computation and then obtain the monthly or annual mean heating rate kernels by averaging the instantaneous heating rate kernel values. For example, the annual mean LW heating rate kernel is calculated as 
\[
K = \frac{1}{365 \times 4} \sum_{m=1}^{365 \times 4} K_m \] 
(365 is the number of days in a year and 4 is because 4-times daily instantaneous profiles are used in the LW calculation), where the index \( m \) represents the time instances during a year. Note that the results in the following are based on the 5-year monthly or annual mean if not otherwise stated.

2.2 Radiative transfer model and dataset

In this paper, the GCM version of a rapid radiative transfer model (RRTMG) (Mlawer et al., 1997) is used to conduct the radiative transfer calculations and generate the heating rate kernels according to equation (1). RRTMG adopts the correlated-k method to conduct radiative transfer calculations in 16 LW spectral bands and 14 SW bands, which acquires high computing efficiency and meanwhile shows good accuracy when validated against the line-by-line calculations (e.g., Collins et al., 2006).

To drive the RRTMG simulation, we use the instantaneous profiles of skin temperature, air temperature, water vapor, surface albedo, ozone, cloud cover and cloud liquid and ice water contents from the fifth generation European Center for Medium-Range Weather Forecasts atmospheric reanalysis (ERA5) (Hersbach et al., 2020), with the horizontal resolution of 2.5° by
2.5° and 37 vertical pressure levels centered at 1, 2, 3, 5, 7, 10, 20, 30, 50, 70, 100, 125, 150, 175, 200, 225, 250, 300, 350, 400, 450, 500, 550, 600, 650, 700, 750, 775, 800, 825, 850, 875, 900, 925, 950, 975 and 1000hPa. To ensure the accuracy of radiative transfer calculations in the upper troposphere (Smith et al., 2020), five layers of the US standard profile are patched above the 1hPa for LW calculation. Other required variables such as the CO$_2$, N$_2$O, CO, CH$_4$ and O$_2$ volume mixing ratios are set to fixed values as 380ppm, 316ppb, 150ppb, 1.8ppm and 0.209, respectively. Effective radii of cloud liquid droplets and ice crystals are from the 3-hourly synoptic TOA and surface fluxes and the cloud product of the Clouds and Earth’s Radiant Energy System (CERES SYN) (Doelling et al., 2013), with a horizon resolution of 1° and then interpolated to the same resolution as the ERA5 data. A random overlapping scheme is prescribed in all-sky calculations. Other settings are the same as in Huang and Huang (2023).

Note that for LW calculations five layers of the US standard profile are patched above the 1hPa level, although the corresponding heating rate values for these five layers are not saved, i.e. the LW heating rate profiles are of 37 layers (from 1hPa to 1000hPa), the same as the SW heating rate profiles.

As a sanity check, the climatological heating rates computed here are compared with ERA5 data (Figure S1). The comparison shows that our calculation agrees well with the ERA5 and previous studies (Dopplick, 1972; Wright & Fueglistaler, 2013; Zhang et al., 2017).

2.3 Application of the heating rate kernel

The heating rate changes caused by different non-cloud geophysical variables in a climate change can be calculated as the product of the heating rate kernels and the changes in these variables, i.e.,

$$\Delta H^j_X = \sum_{i=1}^{n} K^{(i,j)}_X * \Delta X^i \quad (2)$$

where $\Delta H^j_X$ is the heating rate change in the $j^{th}$ layer caused by the change of variable $X$ ($\Delta X$, the change in all layers). $\Delta X^i$ is the change of variable $X$ in the $i^{th}$ layer. $K^{(i,j)}_X$, as introduced in equation (1), represents the heating rate sensitivity in the $j^{th}$ layer to the perturbation of $X$ in the $i^{th}$ layer. Hence, the product of $K^{(i,j)}_X$ and $\Delta X^i$ represent the heating rate change in the $j^{th}$ layer caused by $\Delta X^i$. For multi-layer variables such as air temperature and water vapor, to obtain the induced total heating rate change in the $j^{th}$ layer ($\Delta H^j_X$), the contribution of perturbations in each layer should be added, i.e., summing the product terms for all layers. For single-layer variables such as surface temperature and albedo, no vertical summation is needed (as index $n$ in equation (2) equals to 1). Note that $\Delta X$ represents the variable changes in discrete layers of finite thickness as defined above in the fixed pressure profile.

If the sum of heating rate change of different components diagnosed by the kernel method can reproduce the total heating rate change (the truth value, e.g., from model output), then it affirms the validity of this method. To quantify this effect, a residual term in the kernel method is defined as:

$$\Delta H_{res} = \Delta H^{clr} - \Sigma \Delta H^{clr}_X \quad (3)$$

where the superscript $clr$ denotes the results of clear sky, to be distinguished from those of all-sky which has no superscript. $\Delta H^{clr}_X$ is the total heating rate change in clear sky directly from
model output. $\Sigma \Delta H_X^{clr}$ is the total heating rate change in clear sky diagnosed and added from the kernel method (sum of all component contributions). $\Delta H_{res}$ is the residual term in clear sky and assumed to be the same in all sky, which represents the unexplained part of heating rate change by the kernel method. As the kernels are all of non-cloud variables, the cloud contribution cannot be directly computed using equation (2) and we use the adjusted cloud radiative effect method as proposed by Shell et al. (2008) to calculate it:

$$\Delta H_c = (\Delta H - \Sigma \Delta H_X) - \left(\Delta H_X^{clr} - \Sigma \Delta H_X^{clr}\right)$$

$$= (\Delta H - \Delta H^{clr}) + \left(\Sigma \Delta H_X^{clr} - \Sigma \Delta H_X\right)$$

$$= \Delta H_{CRE} + \left(\Sigma \Delta H_X^{clr} - \Sigma \Delta H_X\right)$$

(4)

Here $\Delta H_c$ is the cloud-induced heating rate change and is denoted as the cloud contribution calculated by the kernel method. $\Delta H$ is the total heating rate change from model output (truth value) in all sky. $\Sigma \Delta H_X$ is the sum of non-cloud contributions in heating rate change diagnosed by the kernel method in all sky. $\Delta H_{CRE} = \Delta H - \Delta H^{clr}$ is the heating rate change calculated by the CRE method. Equation (4) shows that the difference between $\Delta H_c$ and $\Delta H_{CRE}$ is caused by the difference of non-cloud contributions between clear sky and all sky, i.e., a cloud masking effect on the non-cloud contributions. The existence of this term $\left(\Sigma \Delta H_X^{clr} - \Sigma \Delta H_X\right)$ means that the CRE method ($\Delta H_{CRE}$) may be a biased estimate of the cloud-induced heating rate change ($\Delta H_c$).

3. Kernel characteristics

As explained in Section 2, the heating rate kernels are of multiple dimensionalities (time; latitude; longitude; Htr layer; perturbation layer). To illustrate their values, we first select one location to show vertical distribution of the annual mean heating rate kernels in all sky (Figure 1) and then present the all-sky zonally and vertically averaged annual mean kernels in Figure 2. The corresponding clear-sky results are provided in the Supplementary Information (Figure S2 and S3).

3.1 One representative location

The selected location is 0N, 180E and the primary features in Figure 1 as discussed below are representative of most locations. As there is only one perturbation layer in surface temperature and albedo kernels, these kernels are shown as the line plots in Figure 1a and b. An increase of 1K in surface temperature (Figure 1a) emits more energy into the atmosphere and thus leads to positive heating rate changes. This warming effect is mostly confined in the boundary layer (below 900hPa). Similarly, a 0.01 increase in surface albedo (Figure 1b) enhances the reflection of SW radiation into the atmosphere and also leads to a warming effect on the atmosphere. This albedo warming effect shows two peaks in the bottom of the troposphere and in the stratosphere, respectively, due to the abundance of different SW absorbers in these regions (water vapor in the lower troposphere and ozone in the stratosphere).

For the air temperature and water vapor kernels, as they are of multiple perturbation layers, their structures are more complex and are shown by the two-dimensional plots in Figure 1c-f, where the x-axis represents the perturbation layer and y-axis represents the Htr layer.
The air temperature kernel (Figure 1c) shows negative values on the diagonal, as 1K temperature increase in the perturbation layer leads to more emission (energy loss) of the layer. The layers above and below the perturbation layer display a warming effect as the increased LW emission from the perturbation layer leads to more absorption in these layers.

The water vapor LW kernel (Figure 1d) shows negative values on and above the diagonal and positive values below. An increase of the water vapor concentration in the perturbation layer leads to higher emissivity and thus more emission, resulting the cooling effect on the perturbation layer (the negative kernel values on the diagonal). The emissivity increase also means reduced transmission of thermal radiation from the layers below to the layers above the perturbation layer, which tends to override the increased emission by the perturbation layer at this location (0N, 180E) and leads to a cooling effect on the layers above. In contrast, the increased the emission by the perturbation layer heats the layers below.

The water vapor SW kernel (Figure 1e) shows heating rate increases in the perturbation layers owing to enhanced SW absorption by more water vapor. The layers below the perturbation layer show a cooling as the increased water vapor in the perturbation layer absorbs more SW and reduces the SW radiation reaching these layers. For the layers above the perturbation layer, it is also a weak cooling effect as the enhanced water vapor in the perturbation layer reduces surface-reflected SW radiation reaching these layers. The net water vapor kernel (Figure 1f) is dominated by the LW effect.

### 3.2 Zonal and vertical mean

Figure 2 shows the zonally and vertically mass-weighted averaged heating rate kernels. The surface temperature and albedo kernels (Figure 2a and b) show generally similar features to those discussed in Figure 1a and b. The surface temperature kernel value generally decreases with height at all latitudes (Figure 2a) and so does the surface albedo kernel (Figure 2b), although a noticeably stronger warming effect is observed in the lower latitudes and lower troposphere in the case of the surface albedo kernel due to the higher solar insolation in the lower latitudes, as well as the abundance of water vapor in the lower latitudes.

The air temperature and water vapor kernels are shown in Figure 2c-f. Shown here are the mean kernel values averaged along the Htr vertical dimension, i.e., the y-axis in Figure 1. They show the cooling or warming effects of the atmospheric column as a whole, when a perturbation occurs at a certain layer. The air temperature kernel (Figure 2c) shows that the perturbation (increase of air temperature by 1K) in any layer would lead to a cooling effect of the atmosphere. Note that although Figure 1c shows warming above and below the perturbation layers, the absorbed radiation accounting for the warming in these layers is only a fraction of the increased emission by the perturbed layer. This means that the off-diagonal terms in Figure 1c are dominated by the diagonal terms, leading to an overall cooling effect of the whole atmospheric column. This cooling effect is the most prominent when the temperature perturbation occurs in the bottom layer (1000hPa), where the emission increase is the strongest due to higher temperature and higher emissivity there.

The water vapor LW kernel (Figure 2d) shows a distribution pattern with interesting sign changes in the vertical, indicating that the energy gain or loss of the atmospheric column depends on the vertical location of the water vapor perturbation. When the perturbation is added to the mid-to-high troposphere (from about 600hPa to the tropopause), it leads to a warming effect.
Otherwise, a cooling effect. This results from the competing effects discussed above concerning Figure 1d. When water vapor is added to the mid-to-high troposphere, the warming effect due to an enhanced trapping of LW radiation from the surface and lower layers exceeds the cooling effect due to enhanced LW emission from the perturbation layer and this leads to an overall energy gain of the atmospheric column. In other regions, the competition leads to the opposite effect: a loss of energy of the atmospheric column.

The water vapor SW kernel (Figure 2e) shows a stronger warming of the atmospheric column when the moistening perturbation occurs at the lower troposphere, due to the more abundant water vapor concentration there. The water vapor Net kernel (Figure 2f), similar to Figure 1f, is dominated by the LW effect.

Figure 1. Vertical distribution of all-sky heating rate kernel at one location (0N, 180E) of (a) surface temperature ($T_s$), (b) surface albedo ($ALB$), (c) air temperature ($T_a$), (d) water vapor longwave ($WV\ LW$), (e) shortwave (SW) and (f) Net (LW + SW). In panel (c-f), x-axis represents the level where the perturbation is added; y-Axis represents the level of heating rate.
profile. Each column represents the heating rate change given a perturbation at one level as marked by x-axis. Note that a non-linear colorbar is used in panel (c) and that the colorbar range in panel (e) is different from that in panel (d) and (f).

Figure 2. All-sky zonally averaged heating rate kernel. (a) Surface temperature ($T_s$) kernel, units: K (day K)$^{-1}$, (b) surface albedo (ALB) kernel, units: K (day 1%)$^{-1}$, and vertically averaged kernels of (c) air temperature ($T_a$), units: K (day K)$^{-1}$, (d) water vapor ($WV$) LW, units: K (day K)$^{-1}$, (e) water vapor ($WV$) SW, units: K (day K)$^{-1}$, (f) water vapor ($WV$) Net, units: K (day K)$^{-1}$.

The y-axis in panels (c-f) represents the perturbation levels.

4. Kernel application
In this section, we apply the Htr kernels developed here to the GCM simulations from the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Eyring et al., 2016) to decompose and understand the Htr changes during climate change. We use the results from two experiments: one is the AMIP experiment, which uses atmospheric general circulation models to simulate the present climate with prescribed sea surface temperature and sea ice concentration from the observation (Eyring et al., 2016); the other is the AMIP-p4K experiment, which is similar to AMIP but with a uniform 4K increase in sea surface temperature (Webb et al., 2017). Three CMIP6 models as listed in Table 1 are used for analysis. For each experiment, the data from the last 20 years of each model are used and interpolated to the same horizontal and vertical resolutions as the ERA5 heating rate kernel (2.5 degree by 2.5 degree, 37 pressure levels). Then, the differences in the geophysical variables (specific humidity, air temperature, surface temperature and surface albedo inferred from surface SW fluxes) between AMIP-p4K and AMIP (AMIP-p4K minus AMIP) are used to compute the $\Delta X$ in equations 2-4, following the procedure described in Section 2.3. Because the truth total heating rate changes ($\Delta H$ and $\Delta H^{clr}$) required in equations 3-4 are lacking from some models, following Voigt et al. (2023), we use the radiative flux profiles to derive the corresponding heating rate profiles. We validated such inferred heating rate profiles by comparing it with the direct model output available from CNRM-CM6-1 and the consistency between them suggests that the inferred heating rate can be used to represent the truth value. To keep the consistency among all models, all truth values of total heating rate change used below are derived this way and are referred to as GCM output values (to distinguish from kernel-diagnosed ones). For brevity, only the all-sky results are presented in this section and the clear-sky results are included in the Supplementary Information (Figure S4).

Table 1. CMIP6 models used.

<table>
<thead>
<tr>
<th>Model</th>
<th>Horizontal resolution (lat*lon)</th>
<th>Vertical levels</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNRM-CM6-1</td>
<td>1.4*1.4</td>
<td>91 levels</td>
<td>Voldoire et al. (2019)</td>
</tr>
<tr>
<td>MIROC6</td>
<td>1.4*1.4</td>
<td>81 levels</td>
<td>Tatebe et al. (2019)</td>
</tr>
<tr>
<td>MRI-ESM2-0</td>
<td>1.125*1.125</td>
<td>80 levels</td>
<td>Yukimoto et al. (2019)</td>
</tr>
</tbody>
</table>

4.1 Kernel-diagnosed heating rate change

Figure 3 presents a comparison of total heating rate change from GCM output and that diagnosed from the kernel method. The results suggest that the kernel diagnosis can well reproduce the total heating rate change, confirming the validity of the kernel method. A side note is that as the kernel quantification of heating rate change involves the product of two terms ($K_X \cdot \Delta X$, as shown in equation 2), this may generate vertical features of higher wavenumbers that do not exist in either of the multiplying terms ($K_X$ and $\Delta X$). In light of the Nyquist frequency resolvable by the given vertical coordinates, we apply a 3-point filter to smooth the kernel-diagnosed results to remove the spurious high-wavenumber signals resulted from the multiplication. The use of this 3-point smoothing scheme is detailed in the example analysis program published together with the kernel data.

The total LW heating rate change features an arch-like strong cooling in the upper troposphere (right below the tropopause) and a warming in the tropical lower stratosphere (Figure 3a and b). In the SW, the heating rate change mostly shows a similar arch-like warming...
pattern below the tropopause (Figure 3 d and e). Again, the Net heating rate change is dominated by the LW effect (Figure 3g and h).

The total heating rate change is then decomposed into contributions from non-cloud and cloud variables with the aid of kernels (Figure 4). The heating rate change caused by surface albedo is negligible and thus not shown here, as the same sea ice is prescribed in the AMIP and AMIP-p4K experiments. The strong surface warming in AMIP-p4K experiment leads to a strong warming in the lower atmosphere (Figure 4a) by itself, but this warming effect is much compensated by the air temperature increase-induced cooling effect (Figure 4b). The compensation leads to a weak heating rate change in the lower troposphere (Figure 4c). The strong positive heating rate anomaly in the lower stratosphere and negative anomaly in the upper troposphere are driven by the air temperature decrease and increase in the two regions, respectively (Figure 4b and Figure S5).

The water vapor-driven heating rate changes (Figure 4 d-f) show a noticeable positive anomaly in the middle troposphere and a negative anomaly in the Upper Troposphere and Lower Stratosphere (UTLS), which interestingly neutralizes the temperature-driven warming in the extratropical lower stratosphere (Figure 3 a, g). It is worth noting that the heating rate changes caused by water vapor changes display a pattern distinct from the water vapor change itself, which is a ubiquitous moistening in the atmosphere (Figure 4d and Figure S5). This cautions against making simplistic inference of heating rate changes based on radiative drivers ($\Delta X$) alone. It is necessary to use the kernels to properly identify each geophysical variable's effect on the heating rate.

Kernel-diagnosed cloud contributions to heating rate changes are shown in Figure 4 g-i. The patterns generally agree with those reported in Voigt et al. (2023), with noticeable positive anomalies in the deep-tropical upper troposphere and in the extratropical mid-troposphere. This is explained by an upward shift of cloud tops in the deep tropics (Figure S5), which leads to a LW warming effect below the cloud top (Figure 4g) and a SW warming at the cloud top (Figure 4h), a classical heating rate signature of the clouds (e.g., see Goody & Yung, 1995).
Figure 3. Multi-model mean and zonal mean all-sky heating rate changes in the AMIP-p4K experiment. (Left) from GCM output (truth value), (middle) diagnosed by the kernel method and (right) the residual term defined in equation 3, for (a-c) LW, (d-f) SW and (g-i) Net effects, respectively. In the middle column, $\Sigma \Delta H_X$ is the sum of kernel diagnosed non-cloud contributions, $\Delta H_c$ is the cloud contribution and the sum of these two is the total heating rate change reproduced from the kernel method. Units: K/day.
Figure 4. Kernel-diagnosed multi-model mean and zonal mean all-sky heating rate changes in the AMIP-p4K experiment, due to (a) surface temperature ($T_s$), (b) air temperature ($T_a$), (c) total temperature effect (sum of panels a and b), and (d-f) water vapor ($WV$) LW, SW and Net effects, and (g-i) cloud (C) LW, SW and Net effects. Contour lines represents the changes in (b-c) air temperature (ranging from -5K to 5K by 1K), (d-f) water vapor concentration (in natural logarithmic scale, ranging from -0.5 to 0.5 by 0.1) and (g-i) cloud cover (ranging from -10% to 10% by 1%), with solid line of positive sign and dashed line of negative sign. Units: K/day.

Figure 5 zooms into the deep tropics (10N to 10S), where we noticed the most vertically variable heating rate changes, to show the heating rate profile changes more clearly. The decomposition again shows a dominant LW effect (Figure 5a). The overall LW heating rate change is in turn dominated by contributions from the air temperature in the upper troposphere and from the water vapor in the middle troposphere (Figure 5b). Interestingly, in the tropopause region (upward from about 200hPa), the increase of air temperature and water vapor both cause a cooling effect, which is partly compensated by the effect of clouds. The net effect is a warming in the tropopause region above 100hPa, which may have profound impacts, for example, on the troposphere-stratosphere exchange and stratospheric water vapor budget (e.g., Fueglistaler et al., 2009).
Figure 5. Deep-tropical mean (10N-10S) all-sky heating rate changes. (a) Net (black), LW (red) and SW (blue) changes diagnosed from the kernel method (solid line) and from GCM output (dashed line). (b) Kernel-diagnosed total LW heating rate changes contributed by surface temperature ($T_s$), air temperature ($T_a$), water vapor ($WV$) and cloud ($C$). (c) Similar to panel b, but for the SW decomposition. Units: K/day.

4.2 Cloud masking issue

Equation 4 suggests that the CRE-estimate of the cloud-induced heating rate change may alias in the non-cloud contributions due to the cloud masking terms. Figure 6 shows a comparison of the estimates of the kernel method and CRE method. Although the CRE-estimated cloud contributions generally resemble the distribution pattern of the cloud contribution to the heating rate change (Figure 4g-i and Figure 6a-c), the difference plots in Figure 6(d-f) clearly evidence the quantitative biases, which are especially strong in the LW. Based on Equation 4, the cloud masking effect can be further decomposed into contributions from surface temperature, air temperature and water vapor, as shown in Figure 6(g-i). This discloses strong biases of aliasing some of the air temperature effects as the cloud effect at the regions of high cloud occurrence (lower and upper troposphere). This is because given the existence of clouds in these regions, the temperature changes result in strong thermal emission changes and thus heating rate changes. However, this effect is only manifested in the all-sky as in the clear-sky there is no emitters to substantiate this temperature effect. Without correcting this effect, the CRE-estimate is apparently biased.

Figure 6 suggests that although the CRE-method can capture the general features of cloud-induced heating rate changes, the magnitude and details can be biased. This cautions against the quantitative use of the CRE and necessitates the use of the kernels in the heating rate diagnosis.
Figure 6. Multi-model mean and zonal mean cloud-induced heating rate changes estimated by (a-c) the CRE method, in the Net, longwave (LW) and shortwave (SW), respectively, and (d-f) the biases against the kernel method. The cloud masking effect is further decomposed to (g) surface temperature, (h) air temperature and (i) water vapor LW contributions. CRE = cloud radiative effect. Units: K/day.

5. Conclusions and discussions

In this work, we innovate a set of heating rate kernels for diagnosing atmospheric heating rate changes and isolating the effects of radiatively important geophysical variables, such as surface temperature, air temperature, water vapor, surface albedo and cloud. These heating rate kernels are computed according to the partial radiative perturbation concept using global instantaneous atmospheric profiles from the ERA5 reanalysis dataset to sample diverse atmospheric conditions and then averaged over 5 years for different calendar months to obtain the representative values of the sensitivities of the atmospheric heating rate to the geophysical variables.

The kernels show distinct and interesting radiative sensitivity patterns (Figure 1 and Figure 2). The features in these distribution patterns can be explained by the emission and/or absorption processes affected by the geophysical variables. For example, the air temperature kernel (Figure 1c) renders negative values in the diagonal and positive values off diagonal, indicating that a warming (+1K) temperature perturbation leads to cooling and warming effects on the perturbed layer and the layers around, respectively. For the water vapor longwave kernel, the sign of the sensitivity varies because of the compensating absorption and emission effects incurred by water vapor perturbation at the same time. This signifies that the atmospheric heating
rate (energy change) response to the radiative gas perturbation is non-local and not simple. This is why we need the aid of the kernels to understand its impacts on the heating rate profile.

The use of the heating rate kernels is demonstrated by applying them to diagnosing the heating rate change simulated by CMIP6 GCMs in a climate change experiment (AMIP-p4K). We find that the kernels can well reproduce the total heating rate change from the GCM output (Figure 3), affirming the validity of heating rate decomposition. The decomposition discloses interesting and otherwise not-known effects of different geophysical variables on heating rate change. For example, the air temperature, water vapor and cloud effects jointly control the tropospheric heating rate change and are characterized by distinct global patterns (Figures 3 and 4). In the deep tropics, the heating rate change is dominated by air temperature and water vapor contributions in the troposphere (Figure 5b), resulting in an interesting dipole pattern across the tropopause. Such rich information of the heating rate effects of different geophysical variables would not be available without the kernel decomposition.

Another important finding here is that the cloud masking issue (equation 4) could lead to considerable biases (Figure 6), if the cloud-induced heating rate change were estimated from the "cloud radiative effect" (the difference between all- and clear-sky heating rates), which does not distinguish the effects due to cloud existence and due to cloud change. Because of this issue, the kernel decomposition is recommended for accurate quantification of cloud feedback effect on the atmospheric heating rate.

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Data Availability Statement

The ERA5 datasets can be accessed through the ECMWF website (https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset). The RRTM code can be downloaded at http://rtweb.aer.com/rrtm_frame.html. The heating rate kernels computed in this work can be obtained from Huang and Huang (2024).
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