

Reproducing and Attributing IASI Radiance Trends with EC-Earth Climate Model Simulations

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1 **Reproducing and Attributing IASI Radiance Trends with EC-Earth Climate**

2 **Model Simulations**

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10 ABSTRACT: The evolution of spectrally resolved outgoing longwave radiation measured at the top
11 of the atmosphere (TOA) reflects the fingerprints of key geophysical variables, serving as a powerful
12 tool for studying climate change. In this work, trends in TOA brightness temperature (BT) in the
13 mid-infrared spectral range observed by the Infrared Atmospheric Sounding Interferometer (IASI)
14 are compared with trends in synthetic BTs generated from a set of atmosphere-only simulations
15 with the EC-Earth3 climate model (v3.3.3), over the period 2008-2019. Despite the presence
16 of spectral biases, the model simulations effectively reproduce the IASI trends in the thermal
17 infrared. A spectral kernel analysis is then applied to the synthetic radiances to quantify the
18 contributions of temperature, surface temperature, water vapor, clouds, and greenhouse gases to
19 these trends. The negative trend found in the core of the CO₂ band is attributed to the stratospheric
20 cooling, which is overestimated in the climate model simulations. In the wing of the CO₂ band,
21 the negative trend in radiance results from the combined effect of a positive contribution from
22 the increasing tropospheric temperature and a negative contribution driven by rising atmospheric
23 CO₂ concentration. In the atmospheric windows, clouds have a negative impact on the radiance
24 trend and also significantly affect the inter-annual variability of the model's radiance. Lastly,
25 the near-zero trend in the water vapor band reflects a balance between the positive trend driven
26 by temperature increases and the negative trend associated with water vapor changes. This work
27 highlights the utility of spectrally resolved radiances to disentangle forcing and feedback processes,
28 improving climate model evaluation.

29 1. Introduction

30 The present-day evolution of the Earth's climate is primarily driven by the anthropogenically
31 modified concentrations of greenhouse gases (GHGs) and aerosols in the atmosphere, which alter
32 the planet's radiative equilibrium, triggering various feedback mechanisms.

33 In the linear feedback approximation (Gregory et al. 2004), the Earth's energy imbalance (EEI)
34 at the top of the atmosphere (TOA) - defined as the difference between absorbed solar radiation
35 (ASR) and the outgoing longwave radiation (OLR) - is expressed in terms of an external radiative
36 forcing F and the net climate feedback as:

$$EEI = \Delta F + \lambda \Delta T_s \quad (1)$$

37 where ΔF presents the effective radiative forcing, i.e., the change in net energy at TOA caused
38 by an external or internal perturbation; λ , the net feedback parameter, contains all the processes
39 resulting as a response to variations in surface temperature ΔT_s .

40 Over time scales much longer than those affected by internal variability, the EEI at TOA should
41 tend to zero (i.e., the feedbacks completely compensate the forcings):

$$\Delta F = -\lambda \Delta T_s \quad (2)$$

42 However, in recent decades, the sharp increase in GHGs concentration, which drives the increase
43 in ΔF , has exceeded the planet's radiative response ($\lambda \Delta T_s$), leading to a rapid rise in the EEI and
44 pushing the climate system further from equilibrium (Raghuraman et al. 2021). A comprehensive
45 study by von Schuckmann et al. (2020) estimated that, over the period 1971–2018, the planet's
46 energy imbalance was $0.47 \pm 0.10 \text{ Wm}^{-2}$. More recently, for the years 2010–2018, this estimate
47 rose to $0.87 \pm 0.12 \text{ Wm}^{-2}$. Notably, nearly all this surplus of energy (about 93 %) remains trapped
48 in the ocean in the form of heat (Meyssignac et al. 2019).

49 The OLR (Wm^{-2}) represents the infrared energy flux emitted by the planet and plays a pivotal
50 role in regulating its cooling. It is highly sensitive to GHGs concentrations and other key climate-
51 controlling variables. For this reason, long-term OLR measurements from space have become
52 fundamental for climate studies and for assessing the performance of global climate models (GCMs)
53 (Wild 2020). The first mission aimed at measuring and monitoring the planet's longwave, shortwave

54 and total energy fluxes was the Earth Radiation Budget Experiment (ERBE) (Barkstrom 1984)
55 started in the mid-1980s. Since the early 2000s, the Geostationary Earth Radiation Budget (GERB)
56 mission performed measurements of the Earth Radiation Budget (ERB) alongside the energy fluxes
57 provided by the Cloud and Earth Radiant Energy System (CERES) (Wielicki et al. 1996; Loeb
58 et al. 2018). CERES is currently regarded as the standard benchmark for tuning global climate
59 models (Hourdin et al. 2017). Raghuraman et al. (2021) show that the trend of CERES OLR is
60 $0.28 \pm 0.22 \text{ W m}^{-2} \text{ decade}^{-1}$ over the period 2001-2020, resulting from the combined effect of
61 a positive contribution of the feedbacks to the OLR trend (energy release of the system) and a
62 negative contribution of the forcings to the OLR trend (energy trapping within the system). In
63 this context, Loeb et al. (2022) highlighted the substantial regional differences in OLR between
64 CERES observations and the ECMWF Reanalysis v5 (ERA5).

65 Adding to CERES' integrated fluxes, we can also rely on spectrally resolved radiance measure-
66 ments ($\text{Wm}^{-2}(\text{cm}^{-1})^{-1}\text{sr}^{-1}$) in the mid-infrared region of the Earth emission spectrum, ranging
67 from approximately 650 to 2500 cm^{-1} (4 - 15 μm), provided by instruments such as the At-
68 mospheric Infrared Sounder (AIRS, 2002-present, Aumann and Miller 1995), the Infrared At-
69 mospheric Sounding Interferometer (IASI, 2006-present, Hilton et al. 2012) and the Cross-track
70 Infrared Sounder (CrIS, 2011-present, Bloom 2001). IASI Next-Generation (IASI-NG), scheduled
71 for launch in 2025, will continue monitoring the mid-infrared range of the spectrum in the near
72 future (Crevoisier et al. 2014). Moreover, the Polar Radiant Energy in the Far-InfraRed Experi-
73 ment (PREFIRE, from 2024) (Padmanabhan et al. 2019) and the FORUM (Far-Infrared Outgoing
74 Radiation and Monitoring, from 2027) mission (Palchetti et al. 2020), will offer unique spectrally
75 resolved measurements of the far-infrared (FIR) spectral range, from 100 to 667 cm^{-1} (15 - 100
76 μm). These missions will address the current observational gap in Earth's emission spectrum from
77 space.

78 Despite their potentiality, spectral measurements are still under-exploited for the study of the
79 EEI and the assessment of climate forcing and feedbacks. Furthermore, while integrated fluxes are
80 commonly used to tune climate models and evaluate their accuracy in representing the ERB, they
81 can obscure compensating spectral errors within the models, as noted by Huang et al. (2006) and
82 Huang et al. (2007). For instance, Della Fera et al. (2023) found that although the integrated fluxes
83 from the EC-Earth3 GCM showed good agreement with CERES broadband fluxes, a comparison

84 of spectral radiances with IASI revealed several biases in the model, some of which were opposite
85 in sign.

86 The causes of biases in spectrally resolved OLR ($\text{Wm}^{-2}(\text{cm}^{-1})^{-1}$) can be identified more readily
87 compared to biases in broadband OLR, as spectrally resolved quantities carry distinct signatures
88 of key climate variables, including temperature, water vapor, gas concentrations, and clouds. For
89 this reason, the spectral dimension of climate feedbacks plays a pivotal role in understanding the
90 processes shaping the climate system and constraining climate models.

91 In this perspective, Raghuraman et al. (2023) analyzed the spectrally resolved OLR trends derived
92 from AIRS data (2003–2021) and the experiments conducted with the Geophysical Fluid Dynamics
93 Laboratory GCM, quantifying the impact of GHGs on spectral radiation by disentangling the forcing
94 and feedback components in the OLR. Along the same line, Roemer et al. (2023) demonstrated
95 the feasibility of utilizing IASI satellite observations (2007-2020) to directly infer spectral climate
96 feedbacks from inter-annual and seasonal variability.

97 Whitburn et al. (2021) analyzed the spectrally resolved OLR trends of IASI clear-sky measure-
98 ments over the period 2008-2017, identifying key indicators of recent climate change. In the same
99 context, Huang et al. (2022) used 17 years of AIRS-observed radiances and simulated radiances
100 to estimate spectral trends in clear-sky conditions and to isolate the contributions of individual
101 variables to these trends. Also using AIRS data, Pan et al. (2015) analyzed the evolution of
102 stratospheric temperatures through spectral kernel analysis (Huang et al. 2014). Furthermore, by
103 incorporating data from Advanced Microwave Sounding Unit A (AMSU-A) and climate model
104 simulations, Pan et al. (2017) distinguished between the impacts of natural variability and external
105 forcings on stratospheric temperatures.

106 In line with previous studies, we analyze trends in IASI spectrally resolved radiances under
107 all-sky conditions for the period 2008 to 2019 and compare them to trends in synthetic radiances
108 generated by a IASI simulator implemented in the EC-Earth global climate model. The primary
109 goal of this analysis is to assess whether the trends in spectral radiances observed over this relatively
110 short period are statistically significant, and to evaluate the ability of a single climate model to
111 accurately reproduce these trends. By doing so, the study demonstrates how the combined use of
112 climate models and observations can provide a robust assessment of model performance, while
113 also offering insights into recent climate evolution on decadal timescales.

114 In addition to comparing simulated and observed trends, we apply a spectral kernel analysis
115 (Soden et al. 2008; Huang et al. 2014) to the trends in synthetic radiances to attribute them to
116 individual climate variables. This approach also enables us to distinguish between stratospheric
117 and tropospheric contributions, which exhibit distinct behaviours in their influence on the OLR
118 trend. Moreover, the analysis allows us to separate between external forcing, driven by the impact
119 of GHGs on radiation, and the feedback mechanisms characterizing the climate system's response.

120 The structure of the paper is as follows: Section 2 describes the observed and synthetic datasets
121 utilized in this study and provides an overview of the updated version of the IASI simulator
122 employed for the climate model simulations. The results are presented in Sections 3 and 4.
123 Section 3 focuses on the comparison of trends in simulated and observed radiances, while Section
124 4 attributes the origin of these trends through a decomposition of the radiances using a kernel
125 analysis. Finally, a discussion and the conclusions are provided.

126 **2. Data and Methods**

127 *a. IASI all sky radiances over the period 2008 - 2019*

128 IASI is a Fourier Transform Spectrometer developed at the Centre national d'études spatiales
129 (CNES) in cooperation with the European Organisation for the Exploitation of Meteorological
130 Satellites (EUMETSAT). It was launched in October 2006 onboard the MetOp-A (Meteorological
131 Operational Satellites) satellite and it was followed by two other identical instruments (IASI-B
132 and IASI-C) onboard MetOp-B (launched in 2012) and MetOp-C (launched in 2019) (Edwards
133 and Pawlak 2000). All the three IASI instruments provide measurements of spectrally resolved
134 radiances covering the spectral range from 645 to 2760 cm^{-1} , commonly known as the mid-infrared
135 range. This range encompasses absorption lines of a wide set of atmospheric gases, including CO_2 ,
136 CH_4 , O_3 , N_2O , CO , SO_2 , NH_3 , CFC-11, CFC-12, and others (Harries et al. 2008).

137 The IASI instruments sample the spectrum with a step of 0.25 cm^{-1} , providing data across 8461
138 channels. The spectral resolution is of 0.5 cm^{-1} . The MetOp satellites follow a sun-synchronous
139 polar orbit with the equatorial crossing time of the ascending node at 9:30 AM (local time) and
140 descending node of the orbit at 9:30 PM (local time). The satellite repeat cycle is of 29 days but
141 IASI measurements achieve the global Earth coverage every 2 days because the instrument's line
142 of sight is scanned in the across-track direction, with a swath of $\pm 48^\circ$ on either side of the orbit

143 track. Each across-track swath is composed of 30 field of regards (FORs), each of them containing
144 4 Field of Views (FOVs) with a ground pixel diameter of about 12 km.

145 In this work, we collected 12 years of IASI (MetOp-A) data for the period 2008 - 2019. Data
146 from 2008 to 2016, taken from the Fundamental Climate Data Record (FCDR) of reprocessed
147 Metop-A Level 1c product (EUMETSAT 2018), are extended with operational data of the same
148 instrument until the 2019. All these IASI data were provided by the European Weather Cloud
149 (EWC) service.

150 To build the all-sky IASI climatology, we followed the approach outlined in Della Fera et al.
151 (2023). While in that study only daytime measurements were used, here we include both daytime
152 and nighttime near-nadir spectra. i.e., for each swath, we considered only the spectra corresponding
153 to the 8 ground pixels closest to the satellite ground track. To mitigate any bias that may arise
154 from an un-even sampling of the measurements of a given area during day- and night- times,
155 we first averaged the daytime and nighttime measurements separately, then combining the two
156 averages with equal weights to get a monthly average. Finally, to limit the spatial mismatch
157 between observations and simulations, IASI spectra were averaged into $2^{\circ} \times 2^{\circ}$ cells centered on the
158 gridboxes of the climate model where the synthetic measurements are actually simulated.

159 *b. Synthetic IASI radiances from the EC-Earth3 climate model*

160 The EC-Earth3 climate model (v 3.3.3), in the rest of the paper referred as EC-Earth3, is a
161 state-of-the-art Earth-system model developed by a European consortium, which participated in
162 the last intercomparison project (CMIP6, (Eyring et al. 2016)). The atmospheric component of
163 the climate model is represented by the Integrated Forecast System (IFS cy36r4) of the European
164 Centre for Medium-Range Weather Forecasts (ECMWF) (Haarsma et al. 2020), while the oceanic
165 component is represented by NEMO 3.6 (Madec 2015). For the other components of the model
166 (sea ice, land, etc.) and more detailed information about the model structure, we refer to Döscher
167 et al. (2021). Similar to other CMIP6 models, EC-Earth3 has been tuned on the basis of the
168 observed CERES fluxes (Wild 2020; Döscher et al. 2021).

169 1) UPDATE OF THE IASI SIMULATOR INSIDE EC-EARTH3: EXTENSION TO ALL-SKY CONDITIONS

170 Della Fera et al. (2023) implemented in EC-Earth3 a IASI simulator based on the $\sigma - IASI$
171 radiative transfer model (Amato et al. 2002; Serio et al. 2023; Masiello et al. 2022, 2024). In that
172 work, the radiative transfer model was integrated in the COSP (v1.4.1) module (Bodas-Salcedo
173 et al. 2011) in order to perform online calculations of the clear-sky spectrally resolved radiances
174 starting from the instantaneous climate model fields. Specifically, prognostic variables from the
175 model (such as pressure, surface emissivity and temperature, air temperature, water vapor, and
176 ozone) are directly supplied to $\sigma - IASI$ through COSP. Additionally, GHGs concentrations for
177 carbon dioxide, methane, and nitrous oxide are sourced from the standard forcing dataset used
178 for historical CMIP6 runs (Meinshausen et al. 2020). The vertical concentration profiles of the
179 other trace gases required by $\sigma - IASI$ (SO_2 , HNO_3 , NH_3 , OCS , HDO , and CF_4) are kept fixed
180 and are taken from the U.S. Standard Atmosphere of the Atmospheric Constituent Profiles dataset
181 (Anderson et al. 1986), as they are not included in this version of EC-Earth3.

182 In this work, the IASI simulator has been extended to operate under all-sky conditions. While
183 cloud cover and the profiles of cloud ice and liquid water content are prognostic variables pro-
184 vided by the IFS model within EC-Earth3, the effective radii of cloud particles are parameterized
185 following the schemes of Martin et al. (1994) and Ou and Liou (1995). These variables—cloud
186 cover, cloud ice and liquid water content profiles, and the effective radii of ice crystals and water
187 droplets—are then passed to the radiative transfer model to simulate TOA radiances under cloudy
188 conditions. In σ -IASI, the treatment of cloud multiple scattering follows the parameterization
189 described by Chou et al. (1999).

190 When comparing observed and simulated radiances, the most critical aspect lies in the choice of
191 an accurate approach to account for the cloud distribution across the very different spatial scales
192 represented by the EC-Earth3 gridbox (an area of approximately 6000 km^2) and the IASI FOV (an
193 area of about 100 km^2). This issue is also crucial within the built-in radiative scheme of the climate
194 model, since assuming homogeneous cloud fields inside the large EC-Earth3 gridbox results in
195 a poor approximation. In order to simulate the sub-grid cloud variability, some assumptions are
196 made on how clouds are distributed horizontally and vertically, and how clouds at different altitudes
197 overlap. For instance, the Rapid Radiative Transfer Model (RRTM, (Mlawer et al. 1997)) integrated
198 in EC-Earth3 computes OLR in a limited number of sub-intervals of the spectrum handling the

199 subgrid-scale cloud variability by generating a set of subcolumns based on an overlap assumption
 200 to which the Monte Carlo Independent Column Approximation (MCICA) algorithm (Pincus et al.
 201 2003) is applied. Therefore, rather than computing the total flux F_{tot} as the average of fluxes
 202 calculated for each subcolumn F_n :

$$F_{tot} = \frac{1}{N} \sum_{n=1}^N F_n \quad (3)$$

203 MCICA uses stochastic sampling to efficiently estimate the impact of subgrid cloud variability on
 204 radiative fluxes

$$F_{McICA} \approx \sum_{k=1}^K F_{n_k,k} \quad (4)$$

205 where $F_{n_k,k}$ is the monochromatic flux computed in K spectral intervals for a single randomly
 206 selected sub-column n_k .

207 The most common assumption, also used in EC-Earth3, is the maximum-random overlap, though
 208 more accurate assumptions can be derived from observations (Hogan and Illingworth 2000). The
 209 subcolumns are stochastically generated using the maximum-random overlap assumption and are
 210 identified by binary values (0 clear, 1 cloudy) at each layer. Then, the vertical profiles of liquid
 211 and water cloud content in the gridbox are multiplied by the binary profile for each subcolumn.
 212 The overall set of subcolumn profiles is generated based on a random probability distribution
 213 function, with the constraint that its integral equals the average gridbox value. In this work, we
 214 follow the same approach integrated in the RRTM model by exploiting the Subgrid Cloud Overlap
 215 Profile Sampler (SCOPS) (Räisänen et al. 2004), already contained in the COSP package present
 216 in the EC-Earth3 model. More in detail, we provide the cloud fraction of the EC-Earth3 model
 217 at each of the 91 IFS layers to SCOPS, which produces a fixed number of subcolumns for each
 218 gridbox. SCOPS can provide an arbitrary number of subcolumns on the basis of three overlap
 219 assumptions: maximum, random and maximum-random. We selected the maximum-random
 220 overlap assumption and 50 sub-columns. This number of sub-columns ensures that the size of a
 221 sub-column is comparable to the size of the IASI instrument's FOV. Then, the online radiative
 222 transfer computation is performed by $\sigma - IASI$ on the basis of the subcolumns profiles and not

223 using the mean gridbox profile information. To replicate an IASI measurement, a single subcolumn
 224 is randomly selected from each model grid box at each time step. In this way, we adopt an approach
 225 analogous to the McICA approximation. Instead of computing the temporal average of the radiance
 226 R_{tot} by considering radiances from all subcolumns in a model grid cell:

$$R_{tot} = \frac{1}{N} \frac{1}{T} \sum_{n=1}^N \sum_{t=1}^T R_{n,t} \quad (5)$$

227 where $R_{n,t}$ is the radiance computed for the n -th subcolumn at each time step t of the time range T ,
 228 we randomly pick only one subcolumn n in each grid cell for each time step t :

$$R_{tot} \approx \frac{1}{T} \sum_{t=1}^T R_{n_t} \quad (6)$$

229 Here R_{n_t} is the radiance computed at time step t for a randomly selected subcolumn n . This
 230 approach significantly mitigates the prohibitive computational costs associated with simulating
 231 radiances for all the 50 subcolumns generated per grid box.

232 2) OUTPUT OF THE IASI SIMULATOR

233 The Earth's emission spectrum is simulated at nadir-view by the $\sigma - IASI$ integrated in the
 234 EC-Earth3 model from 100 to 2600 cm^{-1} . However, the analysis conducted in Section 3 focuses
 235 specifically on the MIR range, which is the range measured by IASI, and it is limited to 2250 cm^{-1} ,
 236 to avoid contamination from solar radiation. The indicative ranges of the main absorption bands
 237 are presented in Table 1. In order to reduce the data storage, the high-resolution output of $\sigma - IASI$
 238 is convolved with a 10 cm^{-1} wide box function. We also convolve the high-resolution radiances
 239 with the IASI instrumental response function (a Gaussian with a Full Width at Half Maximum
 240 of 0.5 cm^{-1}) to get the simulated radiance at 14 spectral channels (listed in Table 2), specifically
 241 chosen for their relevance in capturing the evolution of some key climate variables. The selection
 242 of these high-resolution channels is based on the analysis of the weighting functions, defined as
 243 the derivatives of the transmittance of an atmospheric layer extending from a given height to the
 244 TOA, with respect to the bottom height of the layer itself. This method ensures that channels are

245 selected from various absorption bands, providing sensitivity to key climate variables at different
 246 atmospheric layers.

247 Weighting functions are computed for both clear- and cloudy-sky conditions using the climato-
 248 logical profiles of the U.S. standard atmosphere of the Atmospheric Constituent Profiles dataset
 249 (Anderson et al. 1986).

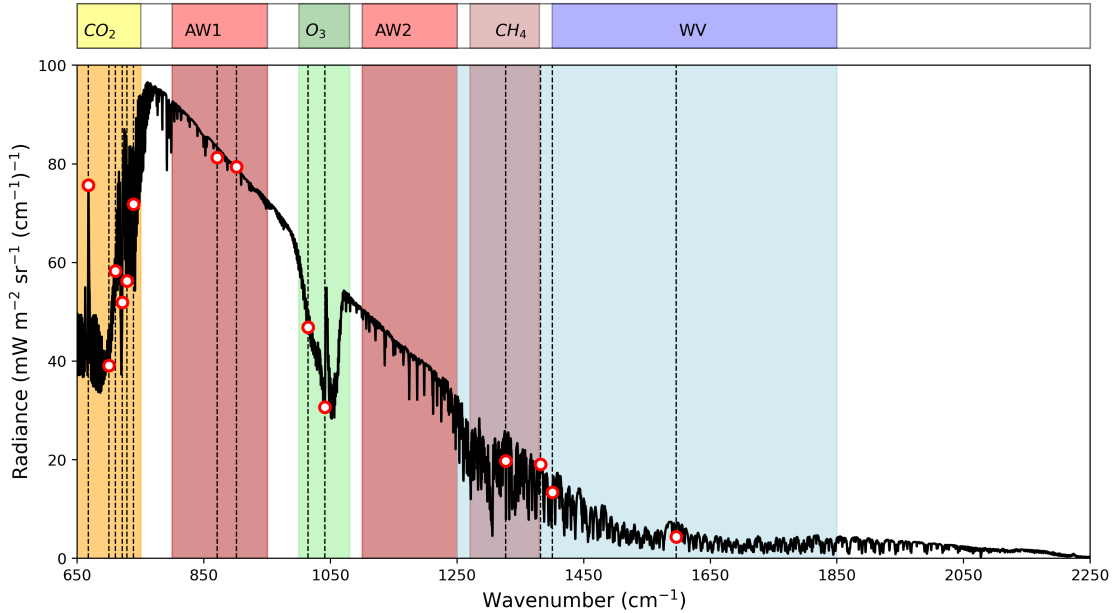
Acronym	Band Details	Spectral Range (cm ⁻¹)
CO ₂	Carbon Dioxide	650 - 750
AW1	Atmospheric Window (1)	800 - 950
O ₃	Ozone	980 - 1080
AW2	Atmospheric Window (2)	1100 - 1250
CH ₄	Methane	1200 - 1400
N ₂ O	Nitrous Oxide	1250 - 1350
WV	Water vapor	1200 - 1850

TABLE 1. Spectral intervals of the atmospheric windows and of the main absorption bands highlighted in Fig. 1.

250 The first column of Table 2 shows the wavenumbers of the selected channels; the second column
 251 indicates the main variables influencing radiances at TOA at that wavenumber and the third column
 252 shows the altitude range where the weighting function peaks (in clear-sky conditions). It is worth
 253 noting that clouds affect the computation of the transmittance and weighting functions, so the
 254 altitudes listed in Table 2 are only indicative, particularly in spectral ranges where the radiance
 255 is heavily influenced by clouds (e.g., atmospheric windows, water vapor bands). The 14 selected
 256 channels are also highlighted in Figure 1, which shows a simulated Earth emission spectrum over
 257 the MIR spectral range, generated using the U.S. Standard Atmosphere from the Atmospheric
 258 Constituent Profiles dataset (Anderson et al. 1986), with the main absorption bands highlighted
 259 (see also Table 1).

267 3) CONFIGURATION OF THE CLIMATE MODEL SIMULATIONS

268 We conduct three atmosphere-only historical simulations for the period 2008-2019, each with
 269 different initial conditions, with the IASI simulator activated. The sea surface temperature (SST)
 270 and sea ice concentration (SIC) are constrained by observations following the Atmospheric Model
 271 Intercomparison Project (AMIP) protocol configuration for CMIP6. The horizontal resolution of
 272 the EC-Earth3 climate model grid is about 80 km (TL255L91-ORCA1) but, to save some computing



260 FIG. 1. Simulated spectrum with red points marking the selected channels listed in Table 2. The key spectral
 261 bands of Table 1 are highlighted with different colors and labeled at the top of the figure. Note that the shaded
 262 area representing the water vapor band overlaps with that of CH₄. Additionally, the N₂O spectral band is not
 263 shown, as it is entirely overlapped by the CH₄ absorption band.

273 time, the IASI spectra are simulated every four latitude and every four longitude grid points of the
 274 model, as in the clear-sky case (Della Fera et al. 2023). Unlike in the clear-sky analysis of Della Fera
 275 et al. 2023, here, the temporal resolution of the climate model output spectra is increased from 6
 276 hours to 3 hours. This adjustment was made to better capture cloud variability and, consequently,
 277 improve the representation of the interaction of clouds with the infrared radiation. The cost of the
 278 simulations is significantly higher compared to clear-sky conditions. The overall computational
 279 cost of the all-sky climate model simulations increases from approximately 4000 core hours per
 280 simulated year (CHPSY) for the clear-sky case to around 9000 CHPSY, 18 times more expensive
 281 than a standard simulation without the IASI simulator (about 500 CHPSY).

282 3. Mean state and trends in observed and simulated radiances

283 Here, we present the results of the comparison between the radiance trends observed by IASI
 284 and those obtained with EC-Earth3 and the IASI simulator. The analysis has been conducted using

Channel (cm ⁻¹)	Variables	Altitude
667.75	T, CO ₂	middle stratosphere
700.25	T, CO ₂	lower stratosphere and upper troposphere
710.25	T, CO ₂	upper troposphere and lower stratosphere
721.25	T, CO ₂	middle troposphere
728.50	T, CO ₂	low troposphere
739.00	T, CO ₂	low troposphere
871.25	T, H ₂ O	surface and low troposphere
901.50	T, H ₂ O	surface and low troposphere
1014.50	T, O ₃	stratosphere and troposphere
1041.00	T, O ₃	stratosphere and troposphere
1326.75	T, H ₂ O	low troposphere
1381.75	T, H ₂ O	middle troposphere
1400.50	T, H ₂ O, CH ₄ , N ₂ O	middle troposphere
1596.25	T, H ₂ O	upper troposphere

264 TABLE 2. High-resolution channels selected for the analysis. The first column shows the wavenumbers of the
265 channels. The second column identifies the variables influencing the radiance in each channel, while the third
266 column indicates the atmospheric layers to which the channel is most sensitive.

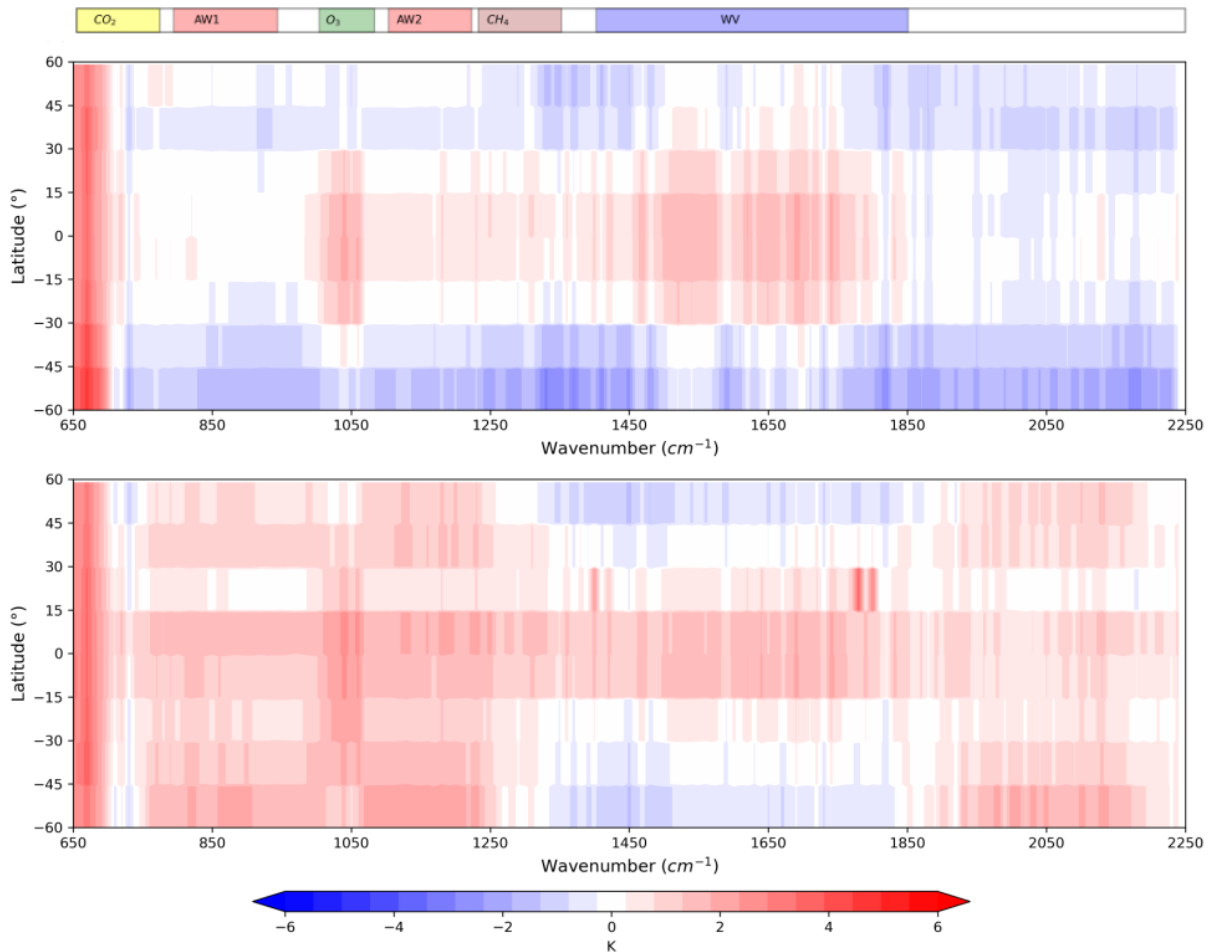
285 the spectral radiances, or, alternatively, the Brightness Temperature (BT), i.e. the temperature a
286 black body should have to emit that specific radiance.

287 To have an overview of the model spectral biases, we first compare the time-average of observed
288 and simulated radiances over the entire period in latitude and spectral bins (Subsection 1). We then
289 present the procedure used to compute the radiance trends (Subsection 2) and finally, in Subsection
290 3, we show and discuss the results of the comparison.

291 Note that, to avoid the still large uncertainties existing on the land surface emissivity models,
292 the analyses are limited to geographical areas over the ocean. The comparison strategy adopted to
293 assess synthetic versus observed spectral radiances may not be appropriate over land, where spatial
294 and temporal mismatches can introduce significant biases, particularly in channels sensitive to the
295 surface and lower atmosphere (Whitburn et al. 2021).

296 1) MEAN STATE BIASES

297 Figure 2 shows the differences between the synthetic BTs generated with EC-Earth3 + IASI
 298 simulator and the observed BTs from IASI measurements, with a spectral sampling of 10 cm^{-1} for
 299 latitudes between 60°N and 60°S (ocean only). The top panel, adapted from Figure 3 of Della Fera
 300 et al. (2023), shows the BT differences between EC-Earth3 and IASI in clear-sky conditions,
 301 while the bottom panel refers to all-sky conditions (using the set of simulations and observations
 302 described above). This comparison is limited to the period 2008–2016, for which both sets of clear-
 303 and all-sky EC-Earth3 simulations (clear and cloudy) are available.



304 FIG. 2. Brightness temperature (BT) differences (model–observations) over ocean, in clear sky conditions (top
 305 panel) and in all-sky conditions (bottom panel) over the period 2008–2016. The top panel is an adaptation from
 306 Fig. 3 of Della Fera et al. (2023).

307 The biases present in the CO₂ band [650-750 cm⁻¹] are nearly identical in clear-sky and all-sky
308 conditions. Since the CO₂ concentration is prescribed by observations in the model simulations,
309 the biases in this spectral range can be primarily attributed to temperature biases in the model. In
310 the core of the band [650 – 690 cm⁻¹], CO₂ molecules show their maximum absorption and, as a
311 consequence, the atmosphere is almost completely opaque. Consequently, the radiation measured
312 in this spectral region is primarily emitted from the stratosphere and upper troposphere, making
313 it generally unaffected by the presence of clouds. The difference between EC-Earth3 and IASI
314 BTs reaches a peak of about 3.5 K in the core of the CO₂ band and gradually decreases towards
315 the band's wing, which is sensitive to different altitudes from upper to lower troposphere. The
316 stratospheric warm bias in the IFS model is well documented, and various improvements to the
317 model physics have been successfully tested since cycle 36 (the IFS version inside EC-Earth3),
318 including enhancements in ozone representation, radiative transfer approximations, and a more
319 accurate representation of the solar spectrum (Hogan et al. 2017).

320 The most evident difference between the two panels in Figure 2 appears in the atmospheric
321 windows (AW1, AW2), regions that are extremely sensitive to surface temperature and to the
322 temperature and water vapor of the first atmospheric layers. In clear-sky conditions the bias is
323 close to zero, in particular in the tropics and subtropics, because the model SST are prescribed by
324 observations. In all-sky conditions, however, a consistent bias of approximately 1 K is observed
325 across all latitudes, with a more pronounced effect in the tropics. This bias is most likely attributable
326 to the representation of clouds in the model. Indeed, it is important to note that, in the presence
327 of clouds, the radiation emitted at altitudes below the clouds does not reach the TOA, making the
328 atmospheric windows highly sensitive to the cloud distribution and, if the clouds are particularly
329 thick, to the temperature of cloud tops.

330 The positive bias of the EC-Earth3 BT in the AW1 and AW2 agrees with what Lacagnina
331 and Selten (2014) obtained in their work regarding cloud biases in the model. Their analysis
332 showed that EC-Earth (version 2.3) generally underestimates cloud cover across all latitudes, while
333 overestimating cloud optical thickness. This combination leads to an overestimated cooling effect
334 due to clouds in the model. The positive BT bias (i.e., excessively large radiance values at the TOA)
335 shown in Figure 2 is consistent with this finding. The spectral region between 1900 and 2100 cm⁻¹
336 is primarily sensitive to air temperature and water vapor in the lower troposphere. Although the

337 spectral radiance in this interval is extremely low—as it lies in the far tail of the Planck function—
 338 small variations in radiance result in large changes in BT. This explains why a positive bias is
 339 clearly visible in BT, despite the radiance values being near-zero.

340 The O₃ absorption band is dominated by a positive bias of about 1.5 K across the tropics and
 341 subtropics both in clear and all-sky conditions. However, in the presence of clouds, the positive
 342 bias is also present at mid-latitudes. It is important to note that the ozone band is sensitive not only
 343 to ozone concentration but also to temperature, both in the stratosphere and in lower troposphere.
 344 Thus, it is difficult to fully disentangle the causes of this bias with a simple analysis. A more
 345 comprehensive analysis, as presented in Sect. 4, in this case becomes necessary.

346 In the water vapor band, small differences are observed between clear and cloudy cases: in both
 347 cases a positive bias is present between 30°S and 30°N, while at higher latitudes the sign of the
 348 bias is reversed. In clear-sky conditions, the positive bias has been related to an underestimation of
 349 the water vapor concentration in the EC-Earth3 model (Della Fera et al. 2023). Additional details
 350 for the all-sky case will be provided in the analysis of the trends and the subsequent attribution.

351 2) ASSESSMENT OF BT TRENDS

352 Trends are estimated from the monthly average BTs computed over ocean (latitudes from 60°S
 353 and 60°N) following the approach presented in Whitburn et al. (2021). We fit the following Fourier
 354 series to the monthly averaged brightness temperatures:

$$BT(t, b_0, \mathbf{c}, \mathbf{d}) = a_0 + b_0 t + \sum_{i=1}^4 \left(c_i \cos\left(\frac{2\pi t}{T_i}\right) + d_i \sin\left(\frac{2\pi t}{T_i}\right) \right) \quad (7)$$

355 where a_0 is a constant term, b_0 is the linear trend term and \mathbf{c}, \mathbf{d} are 8 coefficients driving the
 356 intensity of the *sin* and *cos* terms allowing to represent the atmospheric oscillations with periods
 357 T_i : in our case we use annual (12 months), semi-annual (6 months), seasonal (3 months) and also 4
 358 months periodicities. All these terms and coefficients are fitting parameters of our model. We also
 359 verified that the linear trend term b_0 obtained using this approach is compatible to that obtained by
 360 computing the linear trends to the deseasonalized BT time series. We compute the error associated
 361 with the trend b_0 with the bootstrap resampling method presented in Gatz and Smith (1995) and
 362 Gardiner et al. (2008).

363 Once the fitting parameters are determined, the residual deviations—calculated as the difference
364 between the fitted function and the data—are interpreted as the random effects present in the
365 dataset. Thus, the residuals are randomly sampled and added to the initial fit function to generate
366 a new dataset, which is then used to estimate new fitting parameters. The operation is repeated a
367 large number of times in order to have a distribution of the fitting parameters.

368 The computed errors on the basis of this distribution represent the 95% confidence interval. For
369 each wavenumber, if the trend error bar overlaps the zero value, then the trend is considered not
370 statistically significant.

371 3) RESULTS

372 Figure 3 shows the trends calculated with a spectral step of 10 cm^{-1} for EC-Earth3 (red) and IASI
373 (black) brightness temperature (top) and spectral fluxes (bottom) averaged over ocean, between
374 60°S and 60°N and for all-sky conditions. It is important to note that, to compute the fluxes, here
375 the radiance is assumed to be isotropic, thus, the angular integration is simplified by multiplying
376 the radiance by a factor of π . We acknowledge that this approximation is not entirely accurate, and
377 specific algorithms have been developed to convert spectral radiance into spectral fluxes (Huang
378 et al. 2008; Whitburn et al. 2020). However, as the error introduced by assuming isotropic radiance
379 is systematic, it is unlikely to affect the magnitude of the trends. Providing an accurate estimation
380 of OLR lies beyond the scope of this study; here we limit to solely comparing simulated flux trends
381 with IASI trends across specific spectral bands and with CERES trends over the entire infrared
382 spectrum.

383 The BT trends (top panel in Figure 3) exhibit positive values across the MIR spectral range starting
384 from 750 cm^{-1} . The peak trend, approximately $0.3 \text{ K decade}^{-1}$, is observed in the atmospheric
385 window regions, while in the water vapor band trends are generally around $0.2 \text{ K decade}^{-1}$. In
386 contrast, negative trends are observed in the CO_2 band, ranging from 650 to 750 cm^{-1} , with values
387 reaching $-0.4 \text{ K decade}^{-1}$.

388 The trends are statistically significant across nearly all wavenumbers, as indicated by the associ-
389 ated error band (shadowed areas in the figure indicate the 95% confidence level). Exceptions are
390 observed in the core of the CO_2 band for IASI and in the CH_4 band for both IASI and EC-Earth3.

391 Note that the uncertainty of the model trend is generally smaller than that of IASI, as it reflects the
392 error associated with the average of the trends from the three EC-Earth3 simulations.

393 We have to consider that the trends shown in Figure 3 represent the combined effects of both
394 forcings and feedback mechanisms. Indeed, over the 12-year period from 2008 to 2019, there has
395 been a reduction in the energy emitted at the TOA within the CO₂ absorption band, which is where
396 the most significant radiative forcing occurs. As a consequence, the Earth system has generally
397 increased its longwave radiative emission at TOA, consistent with rising temperatures driven by
398 the Planck feedback.

399 In general, the climate model successfully reproduces the correct BT and radiance trends.
400 Specifically, in the wing of the CO₂ band and in the atmospheric window (AW1) the trends are
401 well captured by EC-Earth3. The trends are also well represented in the water vapor band and,
402 although here EC-Earth3 slightly overestimates their values, the differences with respect to IASI
403 remain within the error bounds. The most relevant differences in the BT trends of EC-Earth3 and
404 IASI are visible in the core of CO₂ band and in the ozone band where the discrepancies are above
405 0.2 K decade⁻¹. In both cases the cause of this difference is most likely due to the stratosphere,
406 which is cooling too rapidly in the climate model.

407 The spectral integration of trends in spectral fluxes (bottom panel of Figure 3) over the whole
408 MIR region [650-2250 cm⁻¹] yields values of $0.46 \pm 0.14 \text{ W m}^{-2} \text{ decade}^{-1}$ for EC-Earth3 and
409 $0.40 \pm 0.14 \text{ W m}^{-2} \text{ decade}^{-1}$ for IASI. Despite the good agreement of these integrated quantities,
410 significant self-compensating discrepancies exist between model and observations, localized in
411 specific gas absorption bands (see Table 1). Specifically, the EC-Earth3 model overestimates the
412 negative trend in the CO₂ band (-0.098 ± 0.005 vs. $-0.086 \pm 0.006 \text{ W m}^{-2} \text{ decade}^{-1}$), while under-
413 estimating the positive trend in the O₃ band ($+0.078 \pm 0.004$ vs. $+0.096 \pm 0.005 \text{ W m}^{-2} \text{ decade}^{-1}$).
414 Additionally, the model overestimates the trend in the water vapor band ($+0.107 \pm 0.004$ vs.
415 $+0.062 \pm 0.004 \text{ W m}^{-2} \text{ decade}^{-1}$). The model is able to reproduce the trend in OLR within the
416 atmospheric windows, with an integrated value across both regions (AW1+AW2) of 0.323 ± 0.005
417 $\text{W m}^{-2} \text{ decade}^{-1}$ for EC-Earth3 and $0.294 \pm 0.007 \text{ W m}^{-2} \text{ decade}^{-1}$ for IASI, despite the biases
418 observed in the model BT values within these spectral regions.

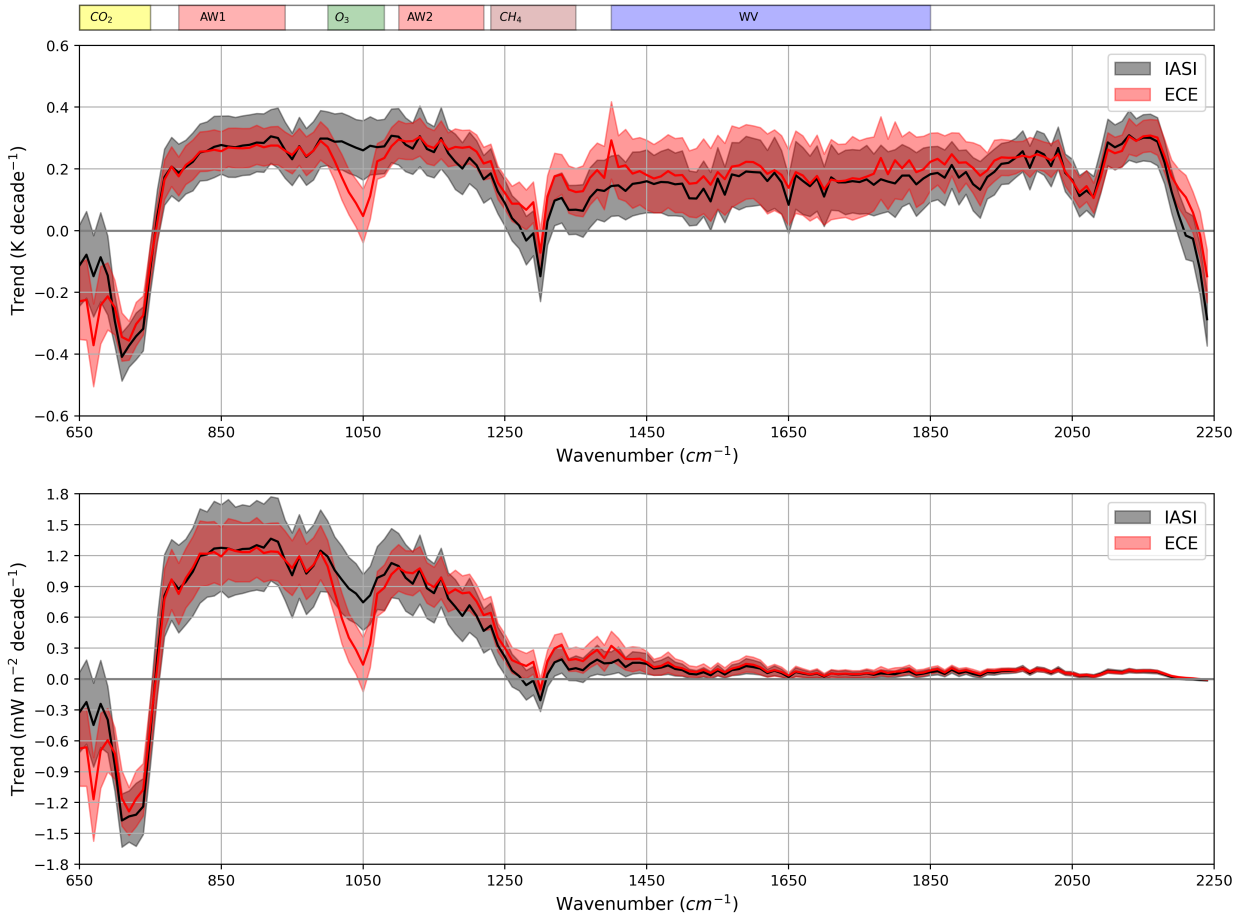
419 Since the EC-Earth3 model provides simulated radiances in both the MIR and FIR regions,
420 we can also estimate the trend in OLR over the entire Earth emission spectrum (from 100 to

421 2600 cm^{-1}) over the ocean, between 60° S and 60° N for the period 2008-2019. The model
422 yields a result of $0.59 \pm 0.12 \text{ W m}^{-2} \text{ decade}^{-1}$, closely matching the OLR trend from CERES of
423 $0.56 \pm 0.14 \text{ W m}^{-2} \text{ decade}^{-1}$, as derived from the EBAF 4.2 dataset.

424 To check whether the spectral integration on 10 cm^{-1} intervals adopted in the analysis presented
425 above hides additional information originally present in the IASI high-resolution spectral mea-
426 surements, we also investigate the trends in the time series of the BT at the 14 high-resolution
427 IASI spectral channels specified in Sect. 2 (see Table 2). Figure 4 summarizes the BT trends
428 (K decade^{-1}) in these channels as derived from the EC-Earth3 model and the IASI observations,
429 including their respective 95% confidence intervals. All the trends are statistically significant
430 except for values of IASI at 1326.75 cm^{-1} (CH_4 band) To complete the high-resolution analysis,
431 Figure 5 presents the time series for a subset of four high-resolution IASI channels, while the full
432 set of time series for all 14 channels is shown in Figure 1 of the Supplementary Material. Here, the
433 three red curves represent the BT time series from the EC-Earth3 simulations, each corresponding
434 to a different initial condition (three ensemble members), while the black line represents the BT
435 time series from IASI observations.

444 Overall, the comparison of the trends in the high-resolution channels confirms the good agreement
445 between model and observations, with the exception of channels that are more sensitive to the
446 stratosphere (667.75 cm^{-1} and 1041 cm^{-1}). The linear BT trend at 667.75 cm^{-1} , shown in Figure
447 4, and the corresponding time series in Figure 5, highlight the significant challenges the model
448 faces in accurately representing stratospheric temperature and its time evolution. In this channel,
449 the trend derived from the EC-Earth3 simulation is $-0.90 \text{ K decade}^{-1}$, to be compared to -0.49
450 K decade^{-1} observed in the IASI data. These values are nearly double as compared to those
451 identified in the low-resolution analysis. This is because the considered channel corresponds to
452 the peak CO_2 absorption. Moving to higher wavenumbers in the wing of the CO_2 , the EC-Earth3
453 performance improves.

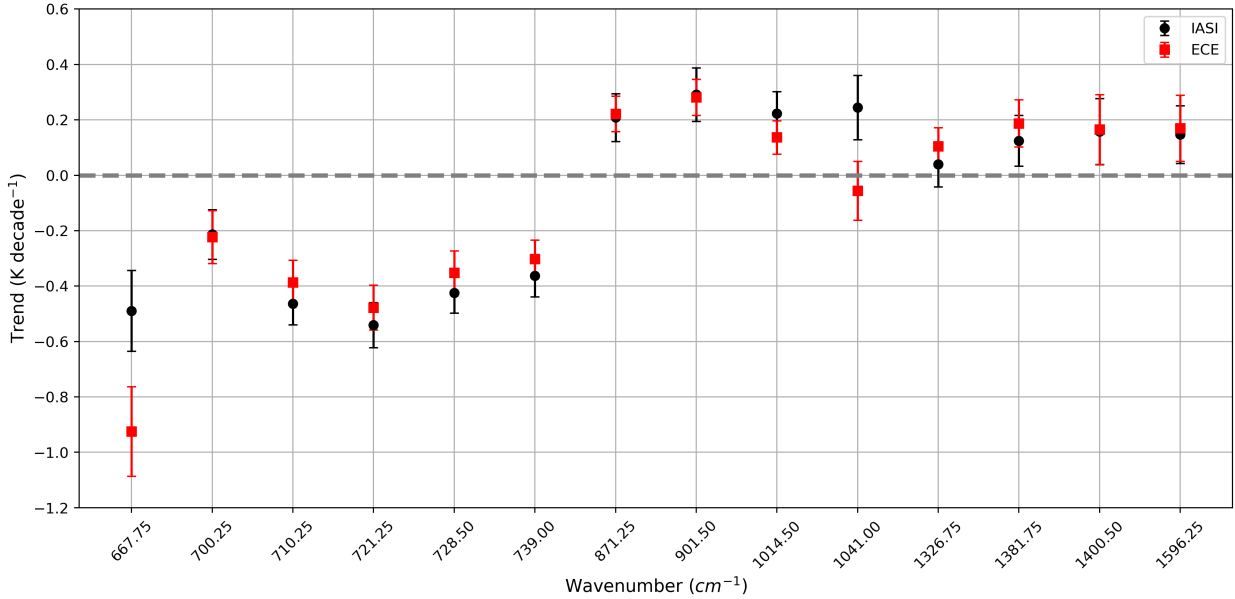
454 As already anticipated, both for the model and IASI at these wavenumbers the BT is decreasing
455 across the analysis period. Of course, this behaviour is not due to a cooling of the troposphere but,
456 as we will better assess in the next section, is actually caused by the combined effect of CO_2 and
457 temperature changes at different altitudes. The channel at 901.50 cm^{-1} , in the atmospheric window,
458 shows a positive trend of $0.31 \text{ K decade}^{-1}$. The slight difference with the channel at 871.25 cm^{-1}



436 FIG. 3. Comparison of all-sky trends for the EC-Earth3 model (label ECE, red) and IASI (black) in terms of
 437 BT (top) and spectral fluxes (bottom) for the period 2008 - 2019. The shaded areas represent the 95% confidence
 438 interval associated with the value of the trend.

459 (see Figure 4), also within the atmospheric window, could be attributed to the different sensitivities
 460 of the two channels to water vapor concentration. Indeed, at 901.50 cm^{-1} , the radiance is less
 461 affected by water vapor amount and the radiation is emitted by atmospheric layers that are closer
 462 to surface. As shown in the time series in Figure 5 panel a), EC-Earth3 overestimates the BT in
 463 this channel by approximately 1 K due to the presence of clouds. Additionally, the amplitude and
 464 the periodicity of the EC-Earth3 BT time series differ substantially from those in the observations.

465 The two selected channels in the ozone band (1014.50 and 1041 cm^{-1}) exhibit contrasting
 466 behaviours in the BT trends estimated from the model (Figure 4): the trend in the first channel
 467 is positive for both EC-Earth3 and IASI, while in the second channel the EC-Earth3 trend has



439 FIG. 4. IASI and EC-Earth3 trends for the high resolution channels selected in Sect. 2. The error bars represent
 440 the 95% confidence intervals.

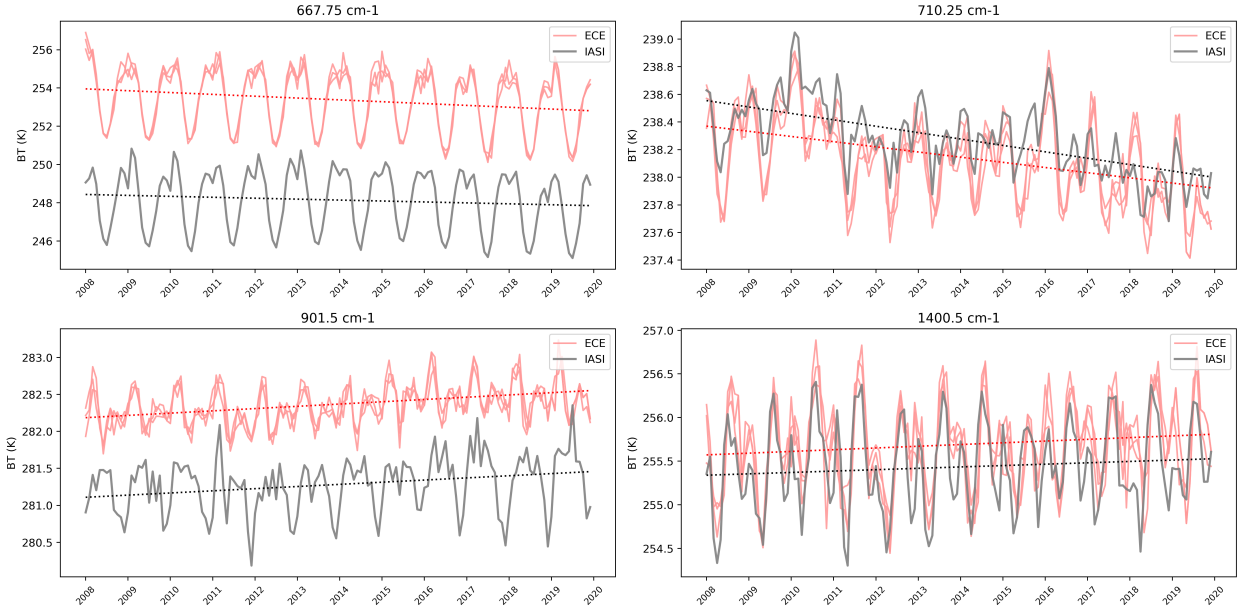
468 opposite sign as compared to IASI. This is because the radiance emitted at 1041 cm⁻¹ primarily
 469 originates from the stratosphere, which cools excessively in the climate model, similar to what is
 470 observed for the channel at 667.5 cm⁻¹ (see also Figure 5 panel a). In contrast, the radiance at
 471 1014.50 cm⁻¹ is more influenced by tropospheric and surface temperatures, leading to a positive
 472 trend and better agreement with IASI observations.

473 The water vapor band is analyzed by selecting four channels (1326.75, 1381.75, 1400.50, and
 474 1596.25 cm⁻¹), with the time series for one of these channels (1400.50 cm⁻¹) presented in Figure 5
 475 panel d).

476 All the channels, despite their sensitivity to water vapor and temperature at different altitudes
 477 (see Table 2), display similar positive trends of approximately 0.2 K decade⁻¹, with the simulated
 478 trends closely matching the observed values. Notably, the channel at 1400.50 cm⁻¹ is influenced
 479 not only by temperature and water vapor in the mid-troposphere but also by methane concentration.

480 4. Decomposition and attribution of trends

481 In Section 3, we identified the main spectral biases in the climate model and assessed its ability
 482 to replicate the observed trends. Here, we employ a kernel analysis on the simulated spectral



441 FIG. 5. Time series of Brightness Temperature in four IASI channels (see plot's key). The three red lines
 442 represent climate model simulations with different initial conditions, while the dotted lines show the linear
 443 component of Equation 7. Note the different vertical scales across the plots

483 radiances to trace the origins of these trends back to the evolution of key climate variables. The
 484 application of spectral kernels enables the separation of forcings and feedbacks. Moreover, given
 485 the good agreement between the model and the observations, lessons learnt from the synthetic
 486 radiances can facilitate the attribution of the radiance trends observed by IASI.

487 In Subsection 1, we describe the kernel technique. Subsection 2 presents the results.

488 1) COMPUTATION OF SPECTRAL KERNELS

489 To decompose the trends of spectrally resolved radiances, we use the following linear approxi-
 490 mation:

$$\Delta \mathbf{L}_\nu(t_i) = \mathbf{K}_\nu(t_i) \Delta \mathbf{x}(t_i) + \epsilon_\nu(t_i). \quad (8)$$

491 In this expression, $\Delta \mathbf{L}_\nu(t_i)$ is a vector whose elements represent the spectral (ν) anomalies of the
 492 radiances of the month t_i with respect to the monthly climatology computed over the period 2008-
 493 2019. $\mathbf{K}_\nu(t_i)$ is the spectral kernels matrix. Each column of this matrix contains the derivative of

494 the spectral radiance with respect to a relevant climate variable (element of vector \mathbf{x}) to which the
 495 radiance is sensitive. Radiance derivatives are evaluated at the monthly mean atmospheric state
 496 for each month t_i during the 2008–2010 period, and subsequently averaged to obtain representative
 497 monthly mean kernels. $\Delta\mathbf{x}(t_i)$ is a vector containing the anomalies of the mean climate variables
 498 at month t_i , with respect to monthly climatology of the whole period 2008–2019. Finally, $\epsilon_v(t_i)$ is
 499 a residual contribution term.

500 We compute the spectral kernels with the radiative transfer model RTTOV (Radiative Transfer
 501 for Tiros-N Operational Vertical Sounder (TOVS) (Matricardi 2009; Hocking et al. 2021) both in
 502 clear- ($\mathbf{K}_{v,\text{clear}}$) and all-sky ($\mathbf{K}_{v,\text{cloudy}}$) conditions (Soden et al. 2008; Huang et al. 2014). Initially
 503 developed to simulate the Tiros-N Operational Vertical Sounder (TOVS) observations, RTTOV is
 504 now able to perform simulations of a large variety of sensors working in different spectral ranges,
 505 from visible to microwaves. RTTOV is based on a set of pre-computed transmittances already
 506 convolved with the instrumental response functions. This aspect makes RTTOV extremely fast and
 507 particularly suitable for simulations based on large set of atmospheric profiles. We use a specific
 508 RTTOV routine, called RTTOV-K, to compute the derivatives of the IASI radiances with respect
 509 to the following climate variables:

$$\mathbf{x} = \begin{pmatrix} \mathbf{T}(p) \\ T_s \\ \mathbf{x}_{\text{H}_2\text{O}}(p) \\ \mathbf{x}_{\text{CO}_2}(p) \\ \mathbf{x}_{\text{O}_3}(p) \\ \mathbf{x}_{\text{CH}_4}(p) \\ \mathbf{x}_{\text{N}_2\text{O}}(p) \end{pmatrix} \quad (9)$$

510 This symbology indicates that our state vector \mathbf{x} contains the temperature profile ($\mathbf{T}(p)$), the
 511 surface temperature T_s , and the vertical concentration profiles of the following gases: water vapor
 512 (H_2O), ozone (O_3), carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O).

513 The anomalies $\Delta\mathbf{x}(t_i)$ are computed from the EC-Earth3 atmospheric profiles. Regarding the
 514 derivatives in $\mathbf{K}_v(t_i)$, for each month of the year, for this analysis they are computed with RTTOV
 515 at the average atmosphere of the actual month in the first three years (2008, 2009, 2010) of the

516 considered period, from the ERA-5 reanalysis, preliminarily interpolated to an horizontal grid of
 517 $2.5^\circ \times 2.5^\circ$ and 17 vertical pressure levels from 1000 hPa to 10 hPa.

518 The effect of clouds on radiances is computed as shown in Huang et al. (2024). First, the
 519 unexplained part of the radiance in clear-sky conditions is computed:

$$\epsilon_{v,\text{clear}}(t_i) = \Delta \mathbf{L}_{v,\text{clear}}(t_i) - \mathbf{K}_{v,\text{clear}}(t_i) \Delta \mathbf{x}(t_i) \quad (10)$$

520 Then, for each month t_i , the radiance anomalies due to clouds ($\delta \mathbf{c}_v(t_i)$) are obtained as a corrected
 521 residual term, adjusted by removing from the all-sky radiances the residual term obtained in clear-
 522 sky conditions. Formally:

$$\delta \mathbf{c}_v(t_i) = \Delta \mathbf{L}_{v,\text{cloudy}}(t_i) - \mathbf{K}_{v,\text{cloudy}}(t_i) \Delta \mathbf{x}(t_i) - \epsilon_{v,\text{clear}}(t_i) \quad (11)$$

523 2) RESULTS

524 The top panel of Figure 6 illustrates the trend of the radiance anomaly for the spectral interval
 525 from 650 to 2250 cm^{-1} , integrated over the global ocean between 60° S and 60° N . It presents
 526 the mean of the trends obtained from the set of the EC-Earth3 model simulations (red), the trend
 527 derived from the observed IASI radiances (black), and the reconstruction obtained from the kernel
 528 analysis (green). This reconstruction is achieved by summing the radiative contributions from the
 529 different variables shown in the bottom panel of Figure 6, which are calculated as the product of the
 530 spectral kernels $\mathbf{K}_{v,\text{cloudy}}$ and the trends of the corresponding variable anomalies $\Delta \mathbf{x}$. The influence
 531 of clouds on radiance anomalies is taken into account as described in Equation 11.

532 The trend reconstructed using the kernel analysis closely matches the radiance trend simulated
 533 by EC-Earth3, including under clear-sky conditions (see Figure 2 in the Supplementary Material).
 534 Since the climate model profiles are used to reconstruct the trend with the kernels, this confirms
 535 that the linear approximation of Equation 8 can reproduce the original trends, even if it does not
 536 accurately reproduce the individual monthly radiance anomalies. In particular, there is an excellent
 537 match of EC-Earth3 and kernel-derived trends in the wing of the CO_2 band and in the O_3 band,
 538 as well as in the atmospheric window regions. The largest discrepancies are observed in the core
 539 of the CO_2 band, in the water vapor band and in the methane absorption band, where the trends
 540 estimated by the kernel analysis are lower than that resulting from EC-Earth3 simulations. Across

541 the entire water vapor band, the contributions of temperature and water vapor to the trend nearly
542 offset each other, resulting in an almost zero net trend. This behaviour can be explained on the basis
543 of the "Simpson's Law", which states that, within the water vapor band, the OLR remains largely
544 unaffected by variations in surface temperature under the assumption of fixed relative humidity
545 (RH) (Jeevanjee et al. 2021). Since RH is not expected to vary significantly under climate change
546 (Ingram 2010), and given that Simpson's Law is a first-order approximation, the anti-correlation
547 between temperature and water vapor may be more pronounced in the kernel analysis, which is
548 also based on a linear approximation. Note that, within our 'Simpsonian' framework, we also
549 expect a near-perfect cancellation between temperature and water vapor contributions in the FIR,
550 which is dominated by the rotational water vapor absorption band and is excluded from our
551 analysis. However, recent studies have shown that surface warming leads to increased emission
552 even within water vapor absorption bands, resulting in a critical stabilizing effect on the climate,
553 an effect not captured by traditional 'Simpsonian' models (Raghuraman et al. 2023; Feng et al.
554 2023). Moreover, the clear-sky longwave feedback is primarily governed by the surface response
555 when the near-surface air temperature is low ($T < 270K$), whereas atmospheric processes become
556 increasingly important at higher temperatures (Roemer and Buehler 2025). Non-linear effects
557 could also explain the mismatch between the EC-Earth3 trends and the kernel-derived trends in
558 the core of the CO₂ band.

559 The good agreement between EC-Earth3 and IASI trends, as also highlighted in the previous
560 Section, and the accurate reconstruction of the EC-Earth3 trends achieved through kernel analysis,
561 enable a reliable attribution of the underlying causes of these trends. For the sake of clarity, in the
562 bottom panel of Figure 6, a negative trend in spectral radiances signifies a reduction in the emitted
563 OLR at the TOA, indicating a positive forcing or a positive (de-stabilizing) climate feedback.
564 Conversely, a positive trend in spectral radiances represents an increase in emitted energy toward
565 the TOA, signifying a negative forcing or a negative (stabilizing) climate feedback.

566 To give a synthetic picture of the individual contributions to the trend, the spectral forcings and
567 feedbacks of Figure 6 have been integrated across the analyzed spectral range ($[650-2250 \text{ cm}^{-1}]$)
568 and converted to fluxes under the approximation of isotropic radiance, and summarized in Table
569 3. The CO₂ forcing (dark red line in Figure 6) represents the most significant forcing impacting
570 the climate system (see left panel in Table 3). This positive forcing is partially offset by a negative

571 component within the core of the CO₂ band. As already discussed, radiance at these frequencies
 572 primarily originates from the stratosphere. The increase in CO₂ concentration raises the emission
 573 level to higher altitudes, enhancing energy emission toward the TOA due to the temperature rise
 574 with altitude in the stratosphere. In the troposphere, the same process - the increase of the emission
 575 level altitude - produces the opposite effect, as temperature decreases with altitude. The estimation
 576 of CO₂ forcing in Table 3 does not account for its total effect, as the FIR spectral range is not
 577 considered. CH₄ (violet line) is the second strongest positive forcing, while the N₂O forcing
 578 (dashed olive line) is approximately half the magnitude of the CH₄ forcing. Unlike the other gases,
 579 the net effect of ozone (green line) on the OLR trend, although minimal, is positive (negative
 580 forcing). This positive trend arises from the influence of ozone concentration changes in the upper
 581 troposphere and stratosphere on radiation (see Figure 3 of the Supplementary Material).

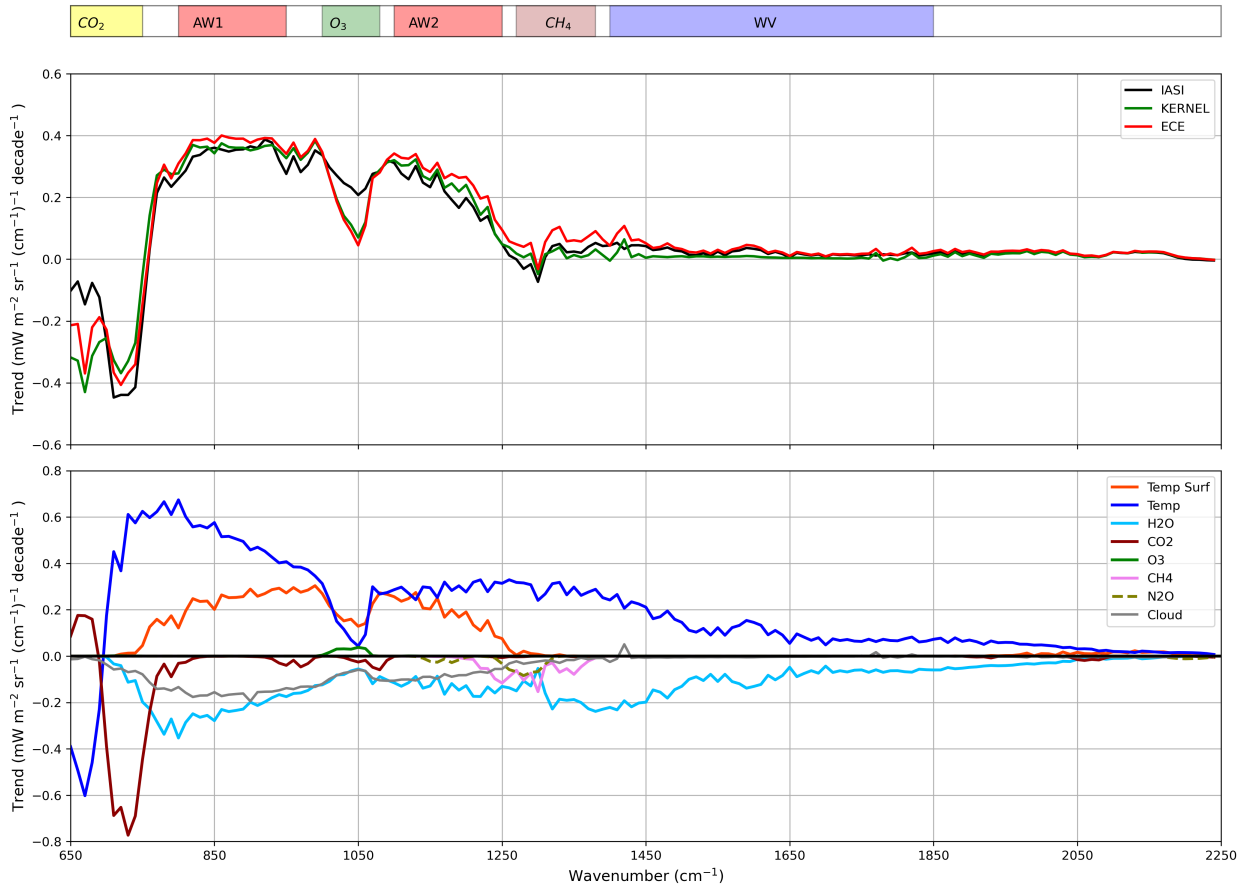
582 As represented in Figure 6 and summarized in Table 3, the planetary feedback is dominated by the
 583 negative Planck feedback, driven by increases in air temperature (blue line) and surface temperature
 584 (orange line). Note that in this analysis, we do not distinguish the lapse rate contribution within
 585 the Planck feedback.

586 The positive water vapor feedback hinders Earth's cooling, as the increased atmospheric water
 587 vapor traps more energy within the system (light blue line). The cloud feedback is also positive,
 588 resulting in a negative influence on the trend (grey line). Although this feedback is primarily
 589 confined to the atmospheric window regions, its magnitude is significant.

Forcing Trend (mW · m ⁻² decade ⁻¹)		Feedback Trend (mW · m ⁻² decade ⁻¹)	
CO ₂	+129.8	T	-946.4
CH ₄	+37.7	T _s	-349.9
O ₃	-6.1	H ₂ O	+537.2
N ₂ O	+19.7	Clouds	+212.6

598 TABLE 3. Trends of integrated spectral forcings (left) and feedbacks (right) across the mid-infrared spectral
 599 range [650-2250 cm⁻¹]. Positive values represent a trend of energy gain for the Earth's system, while negative
 600 values indicate a trend of energy loss.

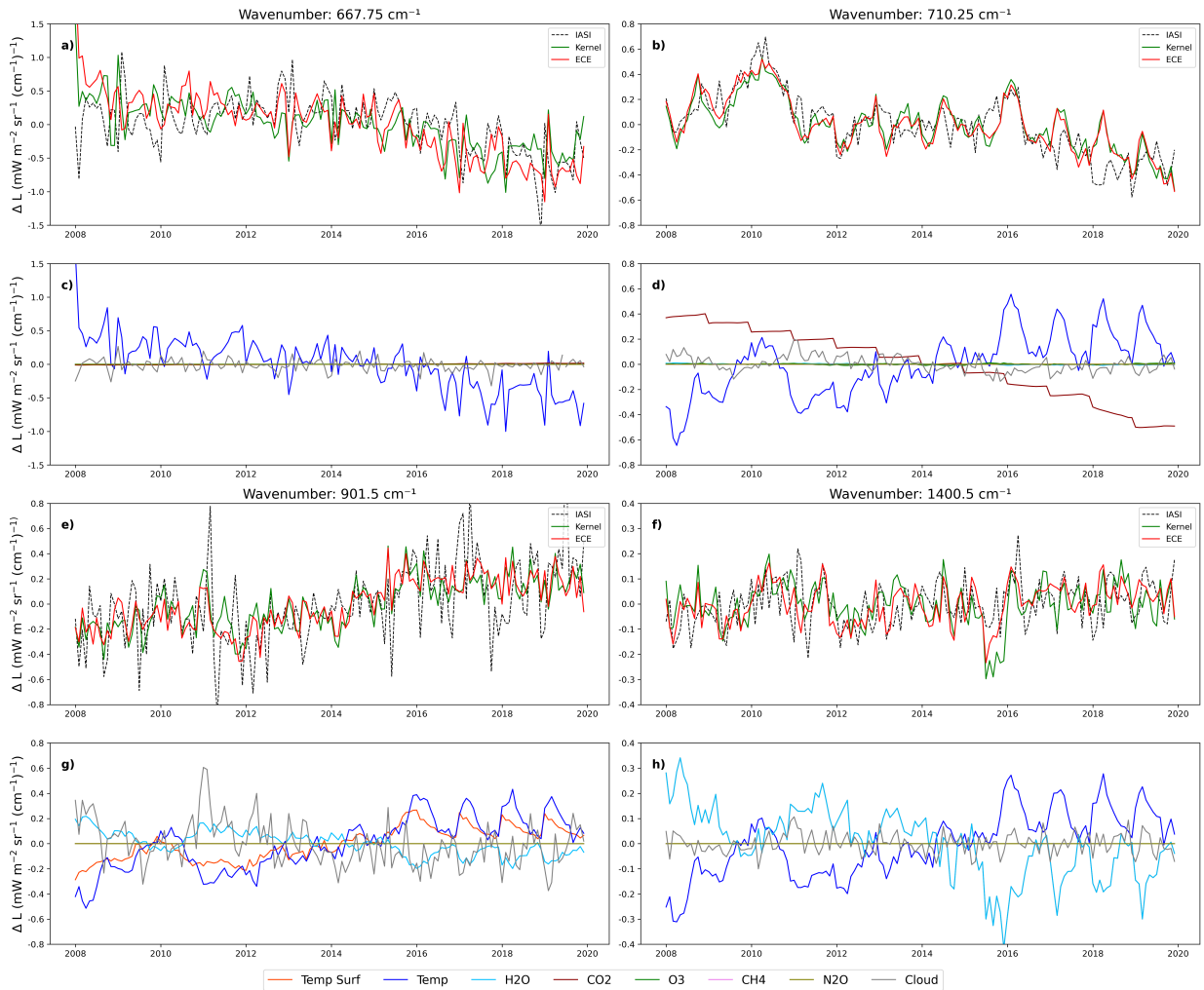
601 To further explore the role of climate variables in the radiation trends, Figure 7 presents the time
 602 series of observed (dashed black lines), simulated (red lines) and kernel-reconstructed (green lines)
 603 radiance anomalies in four of the selected high-resolution IASI channels (see Fig. 7 panels a), b),



590 FIG. 6. Spectral radiance trend computed from model simulations, its reconstruction using spectral kernels
 591 and the observed radiance trend from IASI (top). The various radiative contributions from different variables
 592 are shown (bottom).

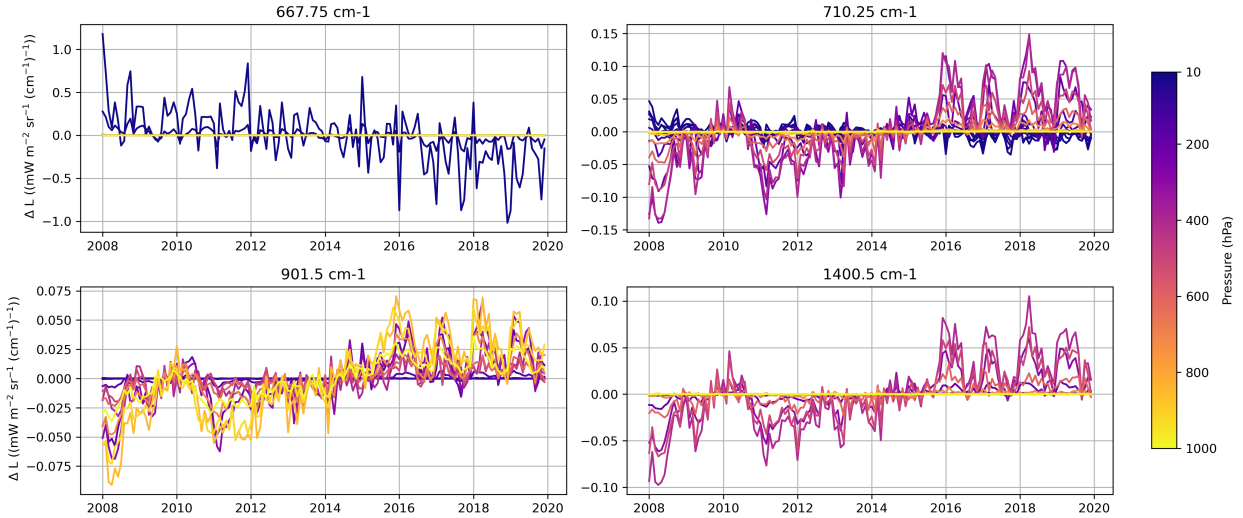
604 e) and f)). Additionally, panels c), d), g) and h) of Fig. 7 show the relevant terms contributing to
 605 the kernel analysis reconstruction. The various terms are identified by the key at the bottom of the
 606 figure. The vertical profiles of temperature and of water vapor give an important contribution to
 607 the radiance anomalies thus, in Figures 8 and 9, we show the breakdown of these contributions by
 608 pressure level (colour code). Figures 8 and 9 refer to temperature and water vapor contributions,
 609 respectively. Each figure panel refers to a specific frequency channel, as indicated in the panel's
 610 key.

614 The linear approximation used in the kernel analysis generally reproduces quite accurately also
 615 the radiance anomalies of the high-resolution channels. The most significant discrepancies between
 616 the climate model simulations and the kernel-reconstructed radiance anomalies are found at 667.75



593 FIG. 7. For each of the 4 considered IASI channels (667.75, 710.25, 901.5 and 1400.5 cm⁻¹) panels a),
 594 b), e) and f) show the radiance anomalies time series from IASI (black), from model simulations (red) and
 595 their reconstruction using spectral kernels (green). For each of the channels, panels c), d), g) and h) show the
 596 contributions to the kernel-reconstructed radiance anomalies from the different variables indicated in the color
 597 code key at the bottom of the figure.

617 and 1400.5 cm⁻¹ (see panels a) and f) of Fig. 7). At 667.75 cm⁻¹, the kernel analysis indicates
 618 that the dominant factor driving the negative trend in spectral radiances anomalies is the air
 619 temperature (blue line) (Figure 7). More in detail, Figure 8 (panel a)) confirms that in this channel
 620 the radiance at TOA is influenced solely by the negative trend in stratospheric temperature. The
 621 cooling of the stratosphere is a well-documented phenomenon in the literature. Over the past
 622 three decades, a continuous decrease in stratospheric temperatures has been observed, primarily



611 FIG. 8. Contributions of temperature at different atmospheric layers (see color code of lines) to radiance
 612 anomalies. The four panels refer to specific channels, as indicated in the panels title. Note the different vertical
 613 scales across the plots.

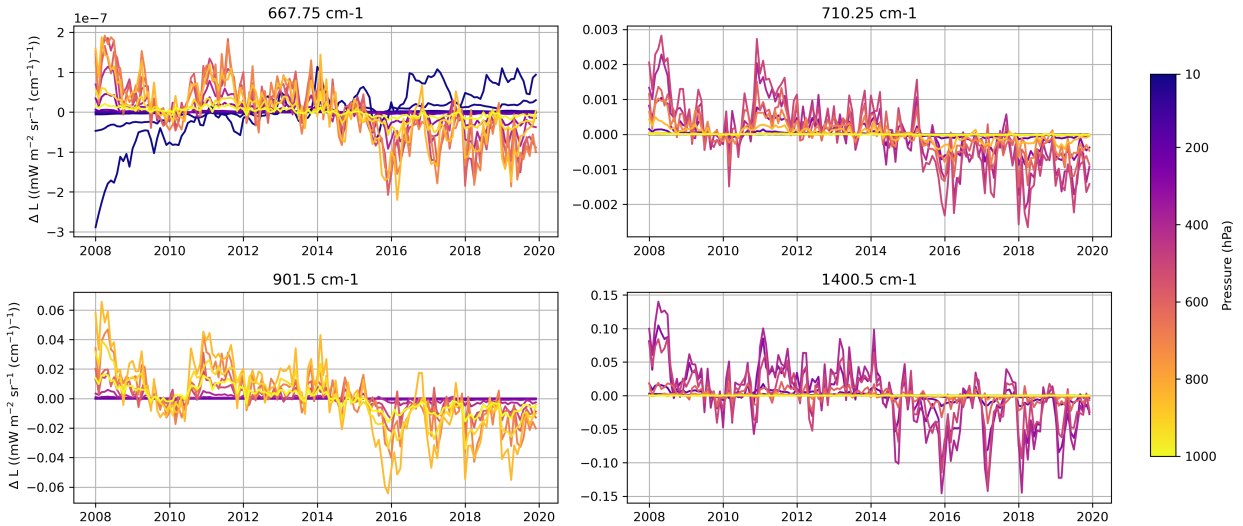


FIG. 9. Same as Fig. 8 but for water vapor. Note the different vertical scales across the plots.

623 attributed to anthropogenic factors, namely ozone loss and increase of other greenhouse gases in
 624 the stratosphere (Ramaswamy et al. 2001, 2006; Pan et al. 2017). As noted in the previous section,
 625 the EC-Earth3 model significantly overestimates the stratospheric cooling, exhibiting a decrease
 626 in BTs nearly twice as steep as the observed values. Additionally, this channel exhibits minimal
 627 sensitivity to water vapor concentration (see Figure 9 panel a). Although the effect of stratospheric

628 water vapor on radiance is about seven orders of magnitude smaller than that of temperature, we see
629 that it is positive, compatible with an increase in water vapor at higher altitudes in the stratosphere.

630 The channel at 710.25 cm^{-1} shows a less pronounced negative trend in spectral radiance as
631 compared to the channel at 667.75 cm^{-1} . Indeed, Figures 7 (panels b) and d)) and 8 (panel b))
632 reveal that in this case the negative radiance trend arises mainly from the positive trend of CO_2
633 concentration. Note that the step-like behaviour of the radiative anomaly due to CO_2 is the result
634 of calculating monthly anomalies of CO_2 concentration that increases almost linearly over the
635 analyzed period. For this channel, the air temperature contribution to the radiance anomaly trend
636 derives both from the negative trend of the stratospheric temperature and from the positive trend
637 of tropospheric temperature (see panel b) of Figure 8). The negative radiance trend driven by CO_2
638 is consistent with the rising concentration of this gas in the troposphere. Indeed, the increase in
639 CO_2 concentration implies more energy trapped in the system, leading to a shift to colder, higher
640 altitudes of the emission level for this channel, causing a decrease in the radiance at TOA. The
641 same effect is determined by the increase of water vapor in the upper troposphere (see panel b)
642 of Figure 9). Finally, the channel at 710.25 cm^{-1} , like the channel at 667.75 cm^{-1} , is minimally
643 affected by clouds.

644 The channel at 901.5 cm^{-1} is within the atmospheric window, where the radiance is very sensitive
645 to both surface temperature and air temperature in the lowest atmospheric layers. The effects of
646 the temperature and water vapor trends on the trend of radiance are opposite in sign. In the
647 atmospheric window, the role of clouds becomes crucial, and for the 901.5 cm^{-1} channel, their
648 effect is comparable to that of all other variables (panels e) and g) of Figure 7). Note that, while
649 in the presence of clouds we see discrepancies both in the amplitude and in the periodicity of the
650 EC-Earth simulated and IASI-measured radiance anomalies, this discrepancy does not show up in
651 the trends comparison.

652 The inverse effect of temperature and water vapor found in the 901.5 cm^{-1} and 710.25 cm^{-1}
653 channels is even more evident in the water vapor band, at 1400 cm^{-1} . Here water vapor and
654 temperature supply contributions to the trend in radiances that are opposite-in-sign and of similar
655 amplitude (see panels f) and h) of Figure 7). The kernel analysis is also applied to the other IASI
656 channels of Table 2. The results of the spectral decomposition are plotted in Figures 4,5 and 6 of
657 the Supplementary Material.

658 5. Discussion and Conclusions

659 In this study, trends in spectrally resolved radiances from the IASI instrument for the period
660 2008–2019 are compared with trends in synthetic outgoing longwave radiances generated by the
661 EC-Earth3 climate model. The synthetic radiances are simulated in runtime using a IASI simulator
662 integrated into the EC-Earth3 climate model (Della Fera et al. 2023), which has been updated and
663 optimized in this work to operate under all-sky conditions.

664 The trend comparison is performed after assessing the main spectral biases in the model-simulated
665 spectra, averaged in 10 cm^{-1} intervals (Figure 3). Additionally, high-resolution synthetic radiances
666 are analyzed at a set of IASI channels selected for being the most sensitive to key climate variables
667 at different altitudes. The EC-Earth3 climate model reproduces quite accurately the observed
668 trends in spectrally resolved radiances measured by IASI across most of the mid-infrared spectral
669 range. Significant discrepancies are observed in the core of the CO_2 band and in the O_3 band,
670 which are attributed to an overestimation of stratospheric cooling in the model. While the BT trend
671 of EC-Earth at 667.75 cm^{-1} is about $-0.9 \text{ K decade}^{-1}$, IASI shows a BT trend of approximately
672 $-0.5 \text{ K decade}^{-1}$. In this channel, IASI BT trend is close to the value found in Pan et al. (2017)
673 from AIRS data ($-0.58 \text{ K decade}^{-1}$) analyzed across the years 2002-2013.

674 Smaller differences between observed and simulated radiance trends are found in the wing of the
675 CO_2 band, in the water vapor band, and in the atmospheric windows. The sign of the bias changes
676 across the OLR spectral range, thus largely self-compensating and giving wavenumber-integrated
677 trends that match well with those obtained from CERES measurements over the same period.

678 We then employ a spectral kernel analysis to quantify the impact of the individual geophysical
679 variables on the radiance trends. The kernel analysis is a linear approximation in which the radiance
680 anomalies are obtained as the product of the spectral kernel—the derivative of the radiances with
681 respect to the climate variables of interest—by the anomalies of the same variables. The good
682 representation of IASI radiance trends by the climate model, along with an understanding of the
683 model’s biases, allows us to decompose and attribute the observed radiance trends to specific
684 variables and quantify the spectral forcing trends and feedbacks over the period considered (2008-
685 2019) (Figure 6). It is important to note that, while the kernel decomposition effectively captures
686 the overall trend, the linear approximation does not accurately reproduce the individual monthly

687 radiance anomalies, meaning that some finer details may not be fully captured by this linear
688 approach.

689 As expected, the main forcing to the system is located within the CO₂ absorption band (650–750
690 cm⁻¹). In the wing of this band (690–750 cm⁻¹), we observe a strong negative BT trend of about
691 -0.4 K decade⁻¹. In agreement with the findings of Raghuraman et al. (2023), this trend arises
692 from the combined effects of reduced radiation escaping to the TOA (an energy gain for the system)
693 caused by the increase in CO₂ concentration, and a compensating positive temperature response,
694 which enhances emission toward the TOA (negative Planck feedback). Conversely, in the core of
695 the CO₂ band (650–690 cm⁻¹), the negative trend is due to the combined effects of stratospheric
696 cooling, which reduces the energy emitted to space, and the increased CO₂ concentration, which
697 enhances the emission in the stratosphere.

698 The Planck feedback, given by the rise in air and surface temperatures, is the strongest stabilizing
699 mechanism for the planet's energy budget. Except for the core of the CO₂ band, this feedback
700 affects the whole mid-infrared wavenumbers determining a positive trend in spectral radiances.
701 This trend reaches its maximum value of approximately +0.3 K decade⁻¹ in the atmospheric
702 windows (800-950 cm⁻¹ and 1100-1250 cm⁻¹). The water vapor feedback, driven by the increased
703 water vapor concentration in the atmosphere and responsible for a negative contribution to the
704 radiance trend, is strongly anti-correlated with the Planck feedback. This is particularly evident
705 in the water vapor absorption band, where the two feedbacks nearly compensate each other. The
706 global ocean comparison conducted in this study likely masks the pronounced latitudinal variations
707 in OLR trends present within the water vapor band, as highlighted in IASI spectral OLR trends
708 presented in Whitburn et al. (2021). Clouds, whose effect is computed here as a residual with
709 respect to the clear-sky radiation, act as a positive feedback in the longwave spectrum by trapping
710 more energy in the system, and their effect on radiation is primarily observed in the atmospheric
711 windows.

712 Other GHGs, such as CH₄ and N₂O, tend to reduce the OLR at TOA in the range 1200-1400
713 cm⁻¹. However, at these frequencies, the radiation trend remains positive due to the dominant effect
714 of the Planck feedback. Finally, although the EC-Earth3 and IASI OLR trends differ significantly
715 within the ozone band ($\approx 1030\text{cm}^{-1}$) due to the excessive stratospheric cooling of the model, in

716 both cases the trend is slightly positive. Thus, unlike other gases, variation of ozone concentration
717 exerts a net positive effect on radiation trend.

718 This comparison highlights the fundamental role of spectral OLR measurements (Level 1 data)
719 in climate studies. Indeed, spectral radiance contains plenty of information about atmospheric and
720 surface properties, providing a new perspective on the study of forcings and feedbacks within the
721 climate system. The main challenge lies in isolating and identifying the individual contributions
722 from various climatic components that are integrated within the spectral signal. While using
723 only Level 2 products (such as temperature, water vapor profiles, etc.) obtained from retrieval
724 procedures might seem like a more efficient approach, these products are always derived with an a
725 priori profile, which can introduce biases into the analysis. In contrast, the combined use of Level
726 1 and Level 2 data allows for a comprehensive study of the evolution of key climate variables.

727 In this context, the study shows how the combined use of radiance trends and their decomposition
728 through spectral kernel analysis provides a complete framework to monitor the evolution of the
729 climate system and to verify the accuracy of climate model projections. While the current study
730 focuses on radiance trends over the global ocean, more detailed analyses could be performed at
731 regional scales to explore specific climate phenomena, which we plan to address in future studies.

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740 *Data availability statement.* Permission to access the EC-Earth3 source code can be requested
741 from the EC-Earth3 community via the EC-Earth3 website (<http://www.EC-Earth3.org/>, EC-
742 Earth3 consortium, 2019a) and may be granted if a corresponding software license agreement is
743 signed with ECMWF.

744 The $\sigma - IASI$ code is available on Zenodo (<https://doi.org/10.5281/zenodo.7019991>)

745 The RTTOV code can be obtained from EUMETSAT NWP-SAF facility
746 (<https://nwp-saf.eumetsat.int/site/software/rttov/download/>).

747 IASI data can be downloaded from EUMETSAT Data Store (<https://data.eumetsat.int/>).

748 The spectral kernels used in this study are publicly available on Zenodo.

749 (<https://doi.org/10.5281/zenodo.15487604>)

750 The tools used to compute the radiance anomalies from the kernels are available in the following
751 GitHub repository : <https://github.com/fedef17/SpectFbCalc>

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