

# Comparing gravity waves in a kilometre-scale run of the IFS to AIRS satellite observations and ERA5

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1 **Comparing Gravity Waves in a Kilometre-Scale Run of**  
2 **the IFS to AIRS Satellite Observations and ERA5**

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8 **Key Points:**

- 9 • A kilometre-scale IFS run is resampled as AIRS using two different methods to  
10 allow for comparison of gravity wave properties  
11 • Gravity waves can be seen in the resampled IFS run and AIRS at similar times  
12 and locations  
13 • Mean amplitudes in the resampled IFS run are found to be significantly lower than  
14 in the observations by a factor of  $\sim 2.77$

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## 15 Abstract

16 Atmospheric gravity waves (GWs) impact the circulation and variability of the at-  
 17 mosphere. Sub-grid scale GWs, which are too small to be resolved, are parameterized  
 18 in weather and climate models. However, some models are now available at resolutions  
 19 at which these waves become resolved and it is important to test whether these mod-  
 20 els do this correctly. In this study, a GW resolving run of the ECMWF (European Cen-  
 21 tre for Medium-Range Weather Forecasts) IFS (Integrated Forecasting System), run with  
 22 a 1.4 km average grid spacing (TCO7999 resolution), is compared to observations from  
 23 the Atmospheric Infrared Sounder (AIRS) instrument, on NASA's Aqua satellite, to test  
 24 how well the model resolves GWs that AIRS can observe. In this analysis, nighttime data  
 25 are used from the first 10 days of November 2018 over part of Asia and surrounding re-  
 26 gions. The IFS run is resampled with AIRS's observational filter using two different meth-  
 27 ods for comparison. The ECMWF ERA5 reanalysis is also resampled as AIRS, to allow  
 28 for comparison of how the high resolution IFS run resolves GWs compared to a lower  
 29 resolution model that uses GW drag parametrizations. Wave properties are found in AIRS  
 30 and the resampled models using a multi-dimensional S-Transform method. Orographic  
 31 GWs can be seen in similar locations at similar times in all three data sets. However,  
 32 wave amplitudes and momentum fluxes in the resampled IFS run are found to be sig-  
 33 nificantly lower than in the observations. This could be a result of horizontal and ver-  
 34 tical wavelengths in the IFS run being underestimated.

## 35 Plain Language Summary

36 Small-scale atmospheric waves, known as gravity waves, transport energy and mo-  
 37 mentum and affect the dynamics of the atmosphere. Gravity waves in a high resolution  
 38 run of the European Centre for Medium Range Weather Forecasts Integrated Forecast-  
 39 ing System (IFS) weather model are compared to those in observations from the AIRS  
 40 (Atmospheric Infrared Sounder) instrument on NASA's Aqua satellite, to test how well  
 41 these waves are resolved in the model. Nighttime data is compared over part of Asia and  
 42 surrounding regions, during the first 10 days of November 2018. Since the high resolu-  
 43 tion IFS run has a higher vertical resolution, and a significantly higher horizontal res-  
 44 olution than the satellite observations, the model is resampled as if the satellite was view-  
 45 ing the model atmosphere. This removes gravity waves with horizontal and vertical wave-  
 46 lengths outside of the ranges that can be seen in the observations, allowing the data sets  
 47 to be compared. Gravity waves formed by wind flowing over mountain ranges, can be  
 48 seen at similar times and in similar locations in the IFS run and observations, but wave  
 49 amplitudes in the resampled IFS run are found to be significantly lower.

## 50 1 Introduction

51 Atmospheric gravity waves (GWs) are small-scale waves which transport energy  
 52 and momentum throughout the atmosphere (M. J. Alexander et al., 2010; Fritts & Alexan-  
 53 der, 2003). These waves have both direct and indirect effects on the atmosphere: to take  
 54 just a few examples, GWs act as a major cause of clear-air turbulence affecting aircraft  
 55 (Lane et al., 2009), contribute to ozone depletion in the polar stratosphere (Carslaw et  
 56 al., 1998), affect the formation of sudden stratospheric warmings in winter by precon-  
 57 ditioning the polar vortex (Albers & Birner, 2014) and affect the timing of the polar vor-  
 58 tex breakdown in spring (Polichtchouk et al., 2018). GWs in the stratosphere have also  
 59 been shown to impact the Brewer-Dobson Circulation (e.g. Sato & Hirano, 2019). Sources  
 60 of GWs include orographic sources (wind flowing over topography) and non-orographic  
 61 sources, such as convection and wind shear (Fritts & Alexander, 2003; M. J. Alexander  
 62 et al., 2010).

63 Despite their importance for achieving realistic atmospheric circulations, GWs and  
 64 their impacts remain notoriously difficult to represent in numerical models. One reason  
 65 for this is that large portions of the GW spectrum occur at scales below the grid size of  
 66 the model, and are therefore unresolved. Instead, the acceleration (or deceleration) of  
 67 the background flow at different altitudes due to GW propagation and breaking is rep-  
 68 resented by parameterizations, which can be tuned to correct for the unknown momen-  
 69 tum forcing due to GWs not resolved by the model. However, these parameterizations  
 70 are poorly constrained by observations and contain simplifying assumptions that can lead  
 71 to major circulation biases (Butchart et al., 2011; Harvey et al., 2019). Due to compu-  
 72 tational constraints, this reliance on GW parameterizations is still widespread in the vast  
 73 majority of operational models used for numerical weather prediction (NWP), atmospheric  
 74 research and long-term dynamical climate simulations (M. J. Alexander et al., 2010; Plougonven  
 75 et al., 2020).

76 In recent decades, ever-increasing computational power has allowed models to be  
 77 developed with sufficient spatial resolution to resolve ever-larger portions of the GW spec-  
 78 trum. In some of these specialist non-operational configurations, the resolution is suf-  
 79 ficiently high that GW parameterizations are no longer required (Sato et al., 2012; Vosper,  
 80 2015; Watanabe & Miyahara, 2009; Lund et al., 2020; Wedi et al., 2020). While these  
 81 simulations are still prohibitively expensive for operational use, it is likely that this trend  
 82 will continue and models will be able to resolve an increasingly large portion of the GW  
 83 spectrum. This then raises a question: how realistic are the resolved waves in these high  
 84 resolution simulations compared to observations?

85 Here this question is investigated for one such model: a high-resolution “kilometre-  
 86 scale” configuration of the Integrated Forecasting System (IFS) model developed by the  
 87 European Centre for Medium Range Weather Forecasts (ECMWF), as described by Wedi  
 88 et al. (2020). This configuration was run at TCo7999 resolution (Wedi et al., 2020), which  
 89 is equivalent to an average horizontal grid spacing of around 1.4 km globally, and no GW  
 90 parameterizations were used. In this study, the amplitudes, wavelengths and momen-  
 91 tum fluxes of resolved GWs in the model stratosphere are compared to 3-D satellite ob-  
 92 servations from the Atmospheric Infrared Sounder (AIRS) instrument using the retrieval  
 93 of Hoffmann and Alexander (2009). For further comparison, we also investigate resolved  
 94 GWs in the ECMWF ERA5 reanalysis, with a horizontal resolution of 31 km, to under-  
 95 stand the impact of the increased resolution of the km-scale IFS on resolved GW prop-  
 96 erties compared to operational configurations. Unlike the kilometre-scale run of the IFS,  
 97 ERA5 is generated using data assimilation.

98 The ECMWF IFS, run at different resolutions, has been validated by comparisons  
 99 to observations in previous work. In Kruse et al. (2022), four numerical weather predic-  
 100 tion models, including the IFS run with an average grid spacing of  $\sim 9$  km, were com-  
 101 pared to AIRS data, which showed that the models reproduced mountain waves in the  
 102 observations well, near to the Drake Passage, but wave amplitudes were lower than those  
 103 observed. Temperature variances in the IFS run at resolutions of 9 km and 4 km were  
 104 also compared to AIRS observations globally in August 2016 (Stephan et al., 2019). The  
 105 results of this study showed that the spatial structure of these temperature variances was  
 106 similar for the model and observations in the mid- to high latitudes of the Southern Hemi-  
 107 sphere. GW potential energy was found to be underestimated in the middle atmosphere  
 108 in three IFS versions run at  $\sim 9$  km resolution, compared to data from the Compact Rayleigh  
 109 Autonomous Lidar (CORAL) at Río Grande in the lee of the Southern Andes (Gisinger  
 110 et al., 2022). GW momentum fluxes in the ECMWF operational analysis, produced us-  
 111 ing the IFS and 4D variational data assimilation, at a grid spacing of approximately 16  
 112 km (T1279 resolution) with 91 model levels, were found to be a factor of 5 lower than  
 113 in Concordiasi balloon observations (Jewtoukoff et al., 2015). The ECMWF operational  
 114 analysis was also found to have lower wave amplitudes by a factor of 2–3 compared to  
 115 AIRS observations, using data from 2003 to 2012 (Hoffmann et al., 2017).

116 However, making comparisons between observed and simulated GWs is not straight-  
117 forward. This is because no instrument can observe the full GW spectrum. The sam-  
118 pling and resolution characteristics of a particular observing instrument (such as AIRS  
119 as used here) limit the range of observable GW horizontal and vertical wavelengths, a  
120 phenomenon known as the “observational filter” of the instrument (Preusse et al., 2002;  
121 M. J. Alexander & Barnett, 2007). Likewise, the spatial resolution of a model can limit  
122 its ability to simulate all GW wavelengths. Therefore, to make a fair comparison between  
123 observations of GWs and resolved GWs in a model, we must first sample the model as  
124 if it were observed by the instrument by applying the instrument’s sampling pattern and  
125 horizontal and vertical resolutions to the model output fields (Wright & Hindley, 2018;  
126 Hindley et al., 2021). This model-sampled-as-observations data set can then be analysed  
127 in exactly the same way as the observations and a fair comparison between the measured  
128 GW properties can be made. The approach taken to perform this sampling method how-  
129 ever can vary between studies, so here two different sampling methods are investigated  
130 to create this data set: one using a simplified approach described by Hindley et al. (2021)  
131 and the second using the more rigorous, but more computationally-expensive, approach  
132 of Wright and Hindley (2018).

133 A further issue with model and observation comparisons of GWs is instrument noise.  
134 Sources of noise include instrument radiometric noise, planetary waves that are not fully  
135 removed by detrending to find the perturbations from the background atmosphere, mesoscale  
136 convective systems and turbulence. Gravity waves with amplitudes too far below the noise  
137 level to be distinguished from the noise cannot be compared to models and the noise can-  
138 not be removed from the observations. In this study, noise is added to the resampled model  
139 data, to avoid comparing low amplitude waves that could not be observed by the AIRS  
140 satellite instrument.

141 The km-scale configuration of the IFS was run globally for the period of Novem-  
142 ber 2018. During this time, significant stratospheric GW activity was observed in the  
143 model, AIRS observations and the ERA5 reanalysis over part of continental Asia and  
144 surrounding regions, so this region is selected to perform the comparison (see Figure 1).  
145 The region is likely to contain numerous sources of orographic GW activity generated  
146 by surface flow over mountain ranges, such as the Abakanski Khrebet Mountain range,  
147 the Ural mountains, the Pamir mountains and other hotspots as observed by Hoffmann  
148 et al. (2013) and Hindley et al. (2020). GWs in this region have previously been shown  
149 to be strongly visible in AIRS (Hindley et al., 2020) and aircraft (Wright & Banyard,  
150 2020) observations, but not in limb sounder observations (Geller et al., 2013; Ern et al.,  
151 2018). This may suggest a strong role for the GWs with long vertical and short horizon-  
152 tal wavelengths that this model should be well configured to accurately resolve. The re-  
153 gion is also likely to contain non-orographic GW activity from jets, fronts and sponta-  
154 neous geostrophic adjustment processes around the edge of the wintertime stratospheric  
155 polar vortex. This region and time period therefore presents an ideal opportunity to in-  
156 vestigate the realism of resolved GWs in the high resolution IFS simulation compared  
157 to observations and to the lower resolution reanalyses.

158 The data sets used in this study are described in Section 2. In Section 3, the meth-  
159 ods for resampling the models as AIRS and calculating the GW properties are described.  
160 The results of the comparison between the resampled models and AIRS observations are  
161 presented in Section 4. These results are then discussed in Section 5, and the summary  
162 and conclusions are presented in Section 6.

## 2 Data

### 2.1 AIRS

Stratospheric temperature data are used from the AIRS instrument on NASA’s Aqua satellite (Hoffmann & Alexander, 2009). Aqua’s orbit is sun-synchronous and near-polar, with a period of 98.8 minutes. This allows AIRS to obtain data with near daily global coverage. AIRS has 2378 channels which measure infrared radiation in the wavelength range of 3.7–15.4  $\mu\text{m}$  and 4 channels that measure near-infrared and visible radiation with a range of 0.4–0.94  $\mu\text{m}$  (Parkinson, 2003). AIRS scans from a viewing angle of  $+49.5^\circ$  to  $-49.5^\circ$  across track, with 90 elements and a swath width of  $\sim 1780$  km and has a horizontal resolution of  $\sim 13.5$  km  $\times$  13.5 km at nadir which reduces to 41 km  $\times$  21.4 km at the track edge (Chahine et al., 2006). The data are stored in granules containing 6 minutes of data, with 240 granules for each day (Aumann et al., 2003).

The 3D temperature data used in this study are calculated from AIRS radiance measurements using the retrieval scheme described by Hoffmann and Alexander (2009). This retrieval has an improved horizontal resolution by a factor of 3 in comparison with AIRS operational data in both the along- and across-track directions, allowing more GW features to be seen in the data. The retrieval uses 12 AIRS CO<sub>2</sub> emission channels near 15  $\mu\text{m}$  for daytime and nighttime, and an additional 23 channels near 4  $\mu\text{m}$  for nighttime. In daytime, the radiance measurements for the 4  $\mu\text{m}$  channels are affected by non-LTE (local thermodynamic equilibrium) effects due to solar excitation, so these channels are not used. In the middle and upper stratosphere, few of the 15  $\mu\text{m}$  channels are sensitive to temperature perturbations and therefore, GWs, compared to the 4  $\mu\text{m}$  channels. The estimated retrieval error of the temperature measurements is 1.6–3.0 K for altitudes from 20 to 60 km. The retrieved temperatures have a vertical resolution of  $\sim 7$ –15 km (Hoffmann & Alexander, 2009). Figure 2a–c of Hindley et al. (2019) show estimated AIRS temperature retrieval errors due to noise and vertical resolution with altitude.

### 2.2 High Resolution IFS Simulation (TCO7999)

The high resolution run of the ECMWF IFS used in this study is a global, hydrostatic simulation, based on version CY45R1 of the IFS atmospheric model (ECMWF, 2023), and run at a TCO7999 resolution (Wedi et al., 2020; Polichtchouk et al., 2022). This resolution has a horizontal grid spacing of 1.25 km at the equator, with an average of 1.4 km globally. In this paper, the simulation is referred to as the 1 km IFS run. ECMWF’s operational 10 day forecasts, at the time of writing, use the IFS at a resolution of 9 km with deep convection parameterization.

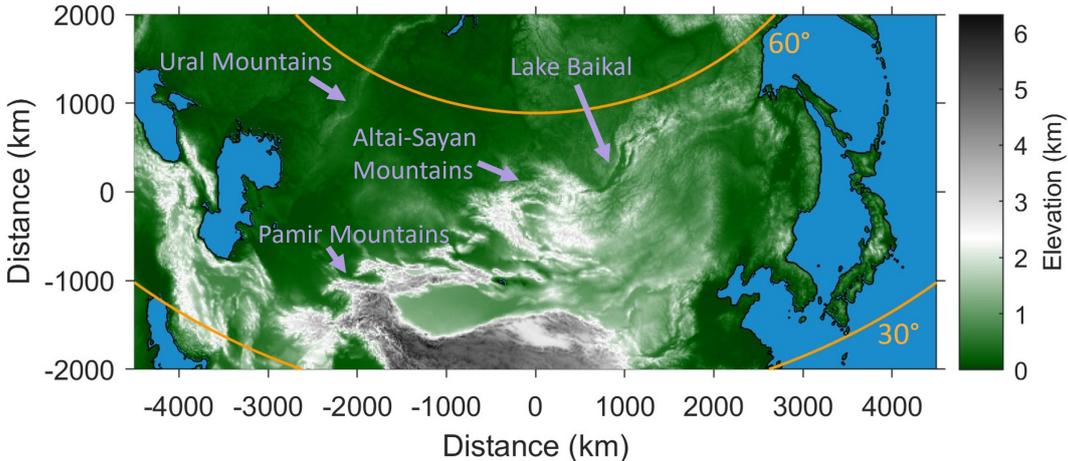
The CY45R1 version of the IFS has 137 hybrid sigma/pressure (model) levels, from 0.01 hPa down to the surface and the spacing between the levels increases with altitude (Wedi et al., 2020). GWs with the smallest wavelengths are likely to be strongly damped by numerical diffusion in the IFS (Polichtchouk et al., 2023). To prevent wave reflection at the top of the model, the IFS has a weak sponge layer from 10 hPa to the model top, which only has a small effect on resolved waves, and a very strong sponge layer above 1 hPa. The contribution of the GW drag parameterizations is designed to reduce as the horizontal resolution of the model is increased, and is zero at an average grid spacing of 1.4 km. The simulation did not use deep convection parameterizations. The 1 km IFS simulation was initialised on 1<sup>st</sup> November 2018 00:00 UTC, integrated for 4 months, and ran with a time step of 60 s and a model output frequency of 3 hours. The temperature structure and background flow of the 1 km IFS remain similar to IFS simulations run for the same time period at 3.9 km and 7.8 km horizontal resolutions during the first 15 days of the simulation (Polichtchouk et al., 2022). Polichtchouk et al. (2022, 2023) investigated the effect of the increase in horizontal resolution from  $\sim 9$  to  $\sim 1$  km and the deep convection parameterization and found GWs are still under-resolved at a grid spacing of  $\sim 9$  km, compared to GWs at the  $\sim 1$  km resolution.

214 In this study, 3 hourly 1 km IFS temperature data are interpolated onto a regu-  
 215 lar longitude-latitude grid, with a resolution of  $0.1^\circ \times 0.1^\circ$ , with a regular distance spac-  
 216 ing of  $\sim 11.1$  km at the equator. This reduced resolution is chosen to make the data eas-  
 217 ier to use and does not affect the results, as this is still a significantly higher than the  
 218 horizontal resolution of the AIRS retrieval in the region investigated.

219 **2.3 ERA5**

220 The ECMWF ERA5 atmospheric reanalysis is global and is run from 1940 to the  
 221 present (Copernicus Climate Change Service, 2023) at a horizontal resolution of 31 km.  
 222 ERA5 uses 4D-Var data assimilation which combines observations, including AIRS data,  
 223 and hindcasts (past weather forecasts). The observations and hindcasts are combined  
 224 in space and time within 12 hour assimilation windows (ECMWF, 2021). The hindcasts  
 225 used in the data assimilation are from the ECMWF IFS CY41R2 (ECMWF, 2023), im-  
 226 plemented in 2016, at TCo1279 resolution (9 km average horizontal grid spacing glob-  
 227 ally). ERA5 has the same model levels and sponge layers as in the CY45R1 version of  
 228 the IFS (ECMWF, 2021, 2020). The ERA5 temperature data used have been regridded  
 229 to a regular latitude-longitude grid with a resolution of  $0.25^\circ$  (Copernicus Climate Change  
 230 Service, 2023). This data is hourly, but since the 1 km IFS run is 3 hourly, ERA5 data  
 231 is only used at every 3 hours during the time period investigated, to avoid time differ-  
 232 ences between the two models affecting the results.

233 **3 Methods**



**Figure 1.** Map of topography in the region investigated on a regular distance grid centred at  $52^\circ$  latitude with a 15 km grid-spacing,  $94^\circ$  longitude. Coastlines are shown in black. Yellow-orange lines show the location of  $30^\circ\text{N}$  and  $60^\circ\text{N}$  latitude on the regular distance plot. Regions with mountain ranges are labelled with light purple arrows. The longitude and latitude ranges of the data shown are  $22.9^\circ\text{E} - 165.2^\circ\text{E}$  and  $23.0^\circ\text{N} - 70.0^\circ\text{N}$ , respectively. The elevation data used to plot this map are from the ETOPO Global Relief Model (NOAA National Centers for Environmental Information, 2022) at a resolution of 60 arc-seconds.

234 Data from the first 10 days of November 2018 for AIRS, the 1 km IFS run and the  
 235 ERA5 reanalysis are used, as the 1 km IFS run was initialized on the 1<sup>st</sup> of this month  
 236 at 00:00 UTC. This time period is selected, due to the expectation that the 1 km IFS's  
 237 background temperature and wind structure, which affect the generation and propaga-

238 tion of GWs, will remain similar to observations in this period (Polichtchouk et al., 2022).  
 239 This assumption is investigated in section 3.1.3.

240 Where higher magnitude temperature perturbations, indicating GWs, are present,  
 241 the data are expected to have a greater variance in general. During this time period, the  
 242 AIRS granules with the highest variances are located in a part of Asia and surrounding  
 243 areas, suggesting stronger GW activity. Hence, this study focuses on data from this re-  
 244 gion (shown in Figure 1). Variances of AIRS temperature perturbations are also used  
 245 in Hoffmann et al. (2013) to identify individual GW events. AIRS granules with any data  
 246 points located in the region shown, are selected for this study and the models are resam-  
 247 pled as these AIRS granules, but only data points which are within the region are in-  
 248 cluded in the results.

249 In this study, all results use data at 39 km altitude in AIRS and the resampled mod-  
 250 els as this is at the centre of the AIRS usable height range (see Figure 2 of Hindley et  
 251 al. (2019)). This is also in the altitude range where the AIRS retrieval vertical resolu-  
 252 tion is greater (from around 21–54 km) and the noise is lower (from around 21–39 km)  
 253 for nighttime data in polar winter, mid latitudes and the tropics, in comparison with al-  
 254 titudes outside of these ranges. The results are presented only for nighttime data, due  
 255 to the the higher vertical resolution and lower retrieval error of the nighttime AIRS re-  
 256 trieval compared to the daytime retrieval.

### 257 3.1 Resampling Methods

258 In this study, the observational filter of the AIRS retrieval is applied to the 1 km  
 259 IFS run and ERA5, to remove GWs outside of the horizontal and vertical wavelength  
 260 ranges in which these waves can be seen in the observations. Data are selected from the  
 261 3 hourly 1 km IFS run at the closest time to the measurement time of each AIRS gran-  
 262 ule, and are resampled as that granule. ERA5 data are 1 hourly, but are selected at the  
 263 same 3 hourly time as the 1 km IFS run for resampling as each AIRS granule, so that  
 264 comparison between the results for the resampled models are not affected by time dif-  
 265 ferences. The models are not interpolated to the AIRS measurement times as this would  
 266 smooth out small scale structures such as GWs (Wright & Hindley, 2018). Two differ-  
 267 ent methods are used to resample the 1 km IFS run as AIRS. As the vertical resolution  
 268 of the AIRS retrieval varies with latitude, different values are used to smooth to AIRS  
 269 vertical resolution depending on whether most of the data points in the model, interpo-  
 270 lated to an AIRS granule location, are in the tropics ( $<30^\circ$  latitude), mid-latitudes ( $30^\circ$ –  
 271  $60^\circ$  latitude) or polar region ( $>60^\circ$  latitude). The yellow-orange lines in Figure 1 are at  
 272 the boundaries of these regions. The first resampling method is run on a desktop com-  
 273 puter, whereas the second is more computationally expensive (Wright & Hindley, 2018)  
 274 and requires the use of high performance computing.

#### 275 3.1.1 Method 1

276 The first method, referred to as method 1 in this paper and applied to both the  
 277 1 km IFS run and ERA5, is described by Hindley et al. (2021). The 1 km IFS data, which  
 278 were previously interpolated onto a regular longitude-latitude grid with a spacing of  $0.1^\circ$ ,  
 279 are selected at the closest 3 hourly time to each AIRS granule. These 1 km IFS data are  
 280 interpolated onto a regular distance grid in the horizontal with a point spacing of 2.7 km,  
 281 which is a higher resolution than any part of the original  $0.1^\circ$  longitude-latitude grid spac-  
 282 ing in the region investigated. The data are then smoothed to the approximate horizon-  
 283 tal resolution of AIRS at track-centre, using a Gaussian with a FWHM (full width at  
 284 half maximum) of  $13.5 \text{ km} \times 13.5 \text{ km}$ . Following this, the data are interpolated onto the  
 285 location of the AIRS granule. The data are then interpolated to a regular distance spac-  
 286 ing in the vertical of 0.1 km from 26 to 55 km altitude, so they could be smoothed to  
 287 the vertical resolution of the AIRS retrieval. As the vertical resolution of the retrieval

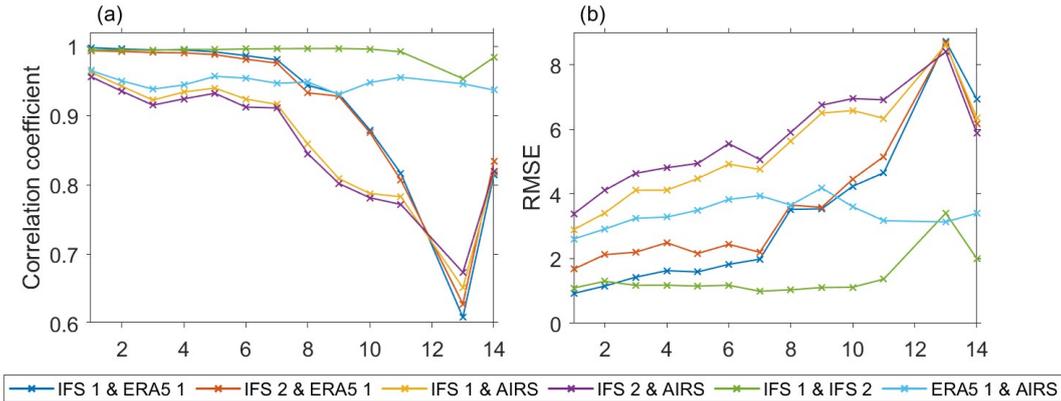
288 varies with altitude, the whole volume of data is smoothed in the vertical using a Gaussian  
 289 function with a different FWHM for each AIRS altitude, from 27 to 54 km, with  
 290 a 3 km point spacing. Different arrays of values for the FWHM at each altitude are used  
 291 (shown in Figure 2, of Hindley et al. (2019)) for each of the granules, depending on whether  
 292 they are located mostly in the tropics, mid-latitudes or polar region. The nearest hor-  
 293 izontal levels to each altitude are then found and stored.

294 ERA5 is also resampled using this method, but since these data have a lower hor-  
 295 izontal resolution than AIRS, they are not interpolated to a regular distance grid and  
 296 smoothed to the horizontal resolution of AIRS before they are interpolated to the AIRS  
 297 granule location. The 1 km IFS run and ERA5 resampled using this method are referred  
 298 to as IFS 1 and ERA5 1 in this paper.

299 **3.1.2 Method 2**

300 The second method used to resample the 1 km IFS run as AIRS is described by  
 301 Wright and Hindley (2018) and referred to as method 2 in this paper. This involves over-  
 302 sampling the model data onto a grid with a spacing of 1 km in the along- and across-  
 303 track directions and 1/20 of a decade of pressure in the vertical. These values were se-  
 304 lected based on sensitivity testing discussed in Appendix B of Wright and Hindley (2018).  
 305 Each oversampled point is then weighted by the estimated instrument sensitivity at each  
 306 point and summed to produce a sample corresponding to each AIRS measurement. This  
 307 aims to improve the accuracy in comparison with interpolating the model to the centre  
 308 of the satellite measurement volume. Compared to interpolating to a single point, Wright  
 309 and Hindley (2018) showed that this method leads to improvements in brightness tem-  
 310 perature measurements derived from AIRS Level 1 data which are significant for small-  
 311 scale temperature perturbations caused by GWs. The 1 km IFS data resampled as AIRS  
 312 using this method are referred to as IFS 2.

313 **3.1.3 Temperature Divergence of the Resampled Models and AIRS**



**Figure 2.** Point-wise correlation coefficients and RMSE (Root-Mean-Square Error) between the temperature at 39 km altitude in AIRS, and the 1 km IFS run and ERA5 resampled as AIRS, for each night during the first 14 days of November 2018, within the region shown in Figure 1. The x-axes show the day in November 2018 (UTC) of the start of each night. Lines between the data points are not used to imply linearity and are shown to make it clearer to see where all the correlation and RMSE points are for each pair of data sets.

Figure 2 shows the point-wise correlation (Figure 2a) and RMSE (Root-Mean-Square Error) (Figure 2b) between the temperature at 39 km altitude in AIRS and the resampled models. These are plotted for each night during the first 14 days of November 2018. The data for the 12<sup>th</sup> night is missing, because AIRS data were not recorded for most of the region studied during this night.

The point-wise correlation (Figure 2a) between IFS 1 and 2 and AIRS decreases over time up to the 11<sup>th</sup> night, which is expected since the free-running 1 km IFS run diverges from the ‘truth’. On night 13, the correlation is lower due to a single large anomalous wave covering a large fraction of the region investigated in the raw 1 km IFS data. The correlation then increases on the 14<sup>th</sup> night. As ERA5 assimilates data from observations, including AIRS, the resampled ERA5 data do not have a decreasing correlation with the AIRS retrieval. Since IFS 1 and 2 are the same data resampled as AIRS using different methods, the correlation coefficient between these data sets remains very high, but is lowest on the 13<sup>th</sup> night.

The RMSE (Figure 2b) is greatest between IFS 1 and 2 and AIRS and increases up to night 11. The RMSE also increases between IFS 1 and 2 and ERA5 1 up to night 11. On the 13<sup>th</sup> night there is a peak in the RMSE between the 1 km IFS run resampled using both methods and the other data sets, and between IFS 1 and 2, as a result of the large anomalous wave in the 1 km IFS run data for this night. Due to the correlations and RMSE’s shown in Figure 2, data are only used from the 1<sup>st</sup> – 10<sup>th</sup> November 2018 for the results presented in Section 4.

### 3.2 Regridding the Data to a Regular Distance Grid and Finding Temperature Perturbations

The AIRS and resampled model data are regridded onto regular 3D distance grids, as this is required for 3D spectral analysis. The grids have a horizontal point spacing of  $\sim 20$  km in the across track direction and  $\sim 18$  km in the along-track direction, so that the number of across-track and along-track points remain the same after the data have been regridded, and a vertical spacing of 3 km. Following this, the background is removed from AIRS and the resampled models using a 4<sup>th</sup> order polynomial fit in the cross track direction (Wu, 2004; M. J. Alexander & Barnet, 2007). There is no background removal in the along-track direction as AIRS is travelling meridionally, so there are large differences in temperature in this direction.

Separately, temperature perturbations are also found for the 1 km IFS run and ERA5 before resampling as AIRS to allow for comparison to the resampled models and observations (see Section 4.3). The 1 km IFS run and ERA5 are interpolated to a regular distance grids with a point spacing of 1 km in the vertical and a horizontal point spacing of 15 km for the 1 km IFS run, and 30 km for ERA5. The background is found by smoothing both data sets using a Gaussian filter with a convolution kernel size of  $11 \times 11$  points and a standard deviation of 7.15 points. This is then subtracted from the temperature data to find the perturbations.

### 3.3 Adding AIRS Retrieval Noise to the Resampled Models

Since the signal in the AIRS retrieval data cannot be separated from the noise, AIRS noise is added to the temperature perturbations found for the resampled models (ERA5 1, IFS 1 and IFS 2), so that only waves that can still be seen with AIRS noise added are compared. To find granules containing only noise, the granules are sorted from lowest to highest variance of the temperature perturbations, and checked in this order to find granules without subjectively clearly visible waves.

In previous studies, noise has been added to model data resampled as AIRS to reduce the effect of noise on the comparison. However, there were some issues with the noise

363 addition method used highlighted in these studies. In Hindley et al. (2021), tempera-  
 364 ture perturbations were found for an AIRS overpass containing 2 granules with no waves,  
 365 which were then randomised at each altitude, and added to the temperature perturba-  
 366 tions found for the model resampled as AIRS. This method was also used in Okui et al.  
 367 (2023), but using one AIRS granule containing no visible waves. However, since the noise  
 368 added in these studies is uncorrelated pixel-scale noise, any noise structures larger than  
 369 around 30–50 km in the AIRS retrieval data would not be included. Okui et al. (2023)  
 370 found that adding noise using this method resulted in lower background amplitudes in  
 371 the resampled model than in AIRS. They suggest that this is mainly due to lower noise  
 372 amplitudes in the added noise, and therefore the method used may not be suitable for  
 373 adding AIRS retrieval noise at global scales. As a result of these problems, a different  
 374 noise addition method is used in this study, in which the AIRS perturbations are not ran-  
 375 domized at each altitude, so the structure of the noise is not lost and the variation of  
 376 noise with latitude is also taken into account.

377 30 nighttime AIRS granules containing no subjectively visible waves are selected  
 378 in total, with 10 granules with >50% of the data points mostly in the tropics (<30° lat-  
 379 itude), mid-latitudes (30°–60° latitude) and polar region (>60° latitude), respectively.  
 380 The boundary lines for these regions are shown in Figure 1. Granules are chosen with  
 381 over 10% of the data points in the region investigated. This percentage is chosen to al-  
 382 low at least 10 AIRS granules clearly containing only noise during the first 14 days of  
 383 November 2018 for the mid-latitudes and tropics to be found. As there are not enough  
 384 nighttime polar AIRS granules containing only noise in the first two weeks of Novem-  
 385 ber 2018, granules are chosen during the first 2 weeks of November in years from 2016  
 386 to 2020 for the polar region. The AIRS noise should vary mostly meridionally, so the noise  
 387 granules are selected for the latitude regions described, and any noise granules selected  
 388 that contain data points mostly outside the region investigated should have little effect  
 389 on the results. The temperature perturbations of each of the AIRS noise granules (shown  
 390 in Supplementary Figures S1–S3) are found using the method described above. The data  
 391 in the arrays of noise temperature perturbations are reversed in the along- and across-  
 392 track directions separately, and saved so that there are 30 arrays of noise in total for each  
 393 group, to increase the number that can be selected.

394 Before adding the noise to the resampled models, the magnitudes of the AIRS noise  
 395 temperature perturbations are rescaled, due to the gravity wave amplitudes being sig-  
 396 nificantly lower in the resampled models than in the observations. Scaling factors are found  
 397 by calculating the 95<sup>th</sup> percentile for each of the resampled model data sets without added  
 398 noise and dividing these values by the 95<sup>th</sup> percentile of the AIRS observations in the  
 399 first 10 days of November 2018. The scaling factors calculated for the 1 km IFS run, re-  
 400 sampled using methods 1 and 2 (IFS 1 and IFS 2), are averaged so that noise added to  
 401 IFS 1 and IFS 2 is scaled by the same factor (0.32) and this does not lead to differences  
 402 in the results using these methods. A scaling factor of 0.28 is used for ERA5. For each  
 403 granule of model data resampled as AIRS, a noise temperature perturbation array is cho-  
 404 sen randomly from the corresponding group, multiplied by the scaling factor, and added  
 405 to the resampled model temperature perturbations. If the magnitudes of the noise tem-  
 406 perature perturbations are not rescaled before being added to the resampled models, waves  
 407 with lower amplitudes that may also be observable in the observations, but with higher  
 408 amplitudes may be too far below the added noise level in the resampled models to be  
 409 clearly identified.

### 410 3.4 2D+1 S-Transform

411 The S-Transform (ST) is a spectral analysis method commonly used for the anal-  
 412 ysis of GWs (e.g. Fritts et al., 1998; M. J. Alexander et al., 2008). The 2D+1 ST is based  
 413 on the 2D ST (Hindley et al., 2016) and the 3D ST (Wright et al., 2017), which are ex-  
 414 tensions of the 1D ST (Stockwell et al., 1996).

415 The 2D+1 ST calculates vertical wavelengths using vertical phase shifts between  
 416 spectral features, which allows it to measure waves more effectively for 3D data with low  
 417 resolution in one dimension. Nadir-sensing instruments, such as AIRS have high hori-  
 418 zontal resolution, but low vertical resolution. This means there are a low number of ver-  
 419 tical points, for the data from these instruments, in the stratosphere in comparison with  
 420 the point numbers in the horizontal, limiting estimates of the vertical wavelengths of GWs.  
 421 For the 2D+1 ST, 2D S-Transforms are found for the horizontal data levels and the ver-  
 422 tical phase differences between them are calculated (Wright et al., 2021). The vertical  
 423 wavelengths between the levels can then be found using these phase differences. Unlike  
 424 the 3D ST, the 2D+1 ST does not quantize vertical wavelengths to Fourier modes, so  
 425 these wavelengths vary smoothly in the output.

426 The 2D+1 ST is used to find wave properties for the resampled 1 km IFS run and  
 427 ERA5 reanalysis, both models before being resampled, and each AIRS granule. The wave  
 428 amplitude is an output of the 2D+1 ST. The horizontal and vertical wavelengths are cal-  
 429 culated using the wave frequencies, in the coordinate frame of the granule, from the 2D+1  
 430 ST. The zonal  $M_x$  and meridional  $M_y$  components of the momentum flux are calculated  
 431 using the following equation derived in Ern et al. (2004),

$$M_x, M_y = -\frac{\rho}{2} \left( \frac{k}{m}, \frac{l}{m} \right) \left( \frac{g}{N_B} \right)^2 \left( \frac{|T'|}{\bar{T}} \right)^2 \quad (1)$$

432 where  $\rho$  is the atmospheric density,  $k$ ,  $l$  and  $m$  are the wavenumbers in the zonal,  
 433 meridional and vertical directions respectively,  $g$  is the acceleration due to gravity and  
 434  $N_B$  is the buoyancy frequency.  $\bar{T}$  is the local background temperature and  $|T'|$  is the am-  
 435 plitude. The wavenumbers are signed to preserve the sign (direction) of the zonal and  
 436 meridional momentum flux components (P. Alexander et al., 2018).

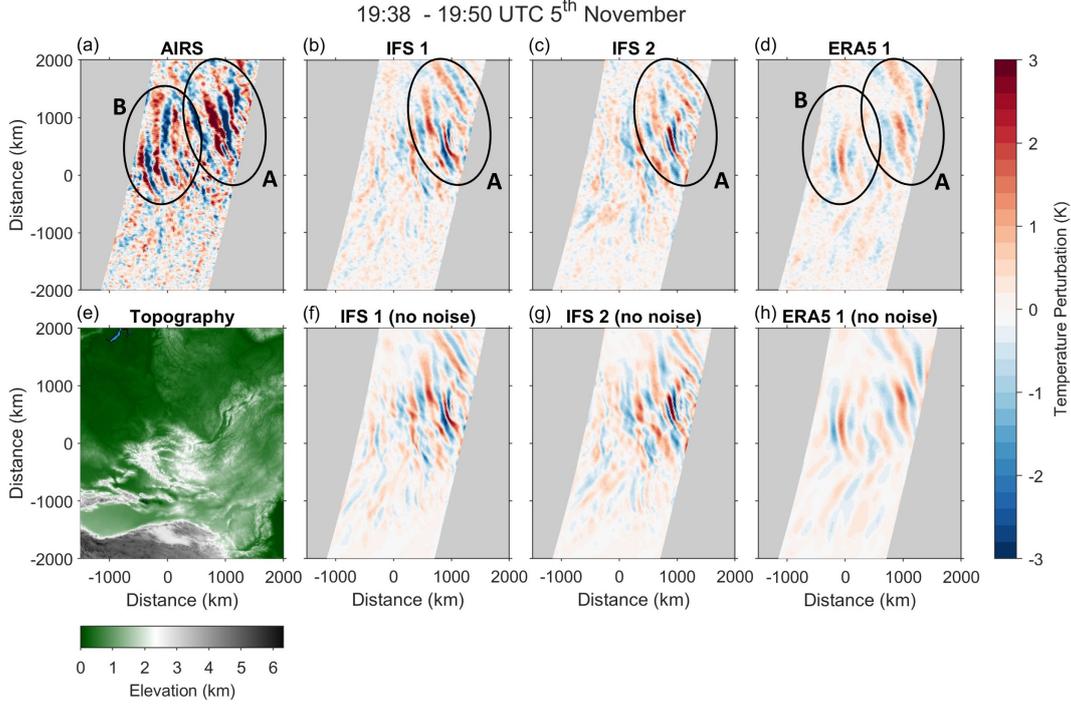
437  $N_B$  is calculated using ERA5 temperature data resampled at each AIRS granule  
 438 location at the closest 3 hourly time, assuming land surface pressure is equal to 1000 hPa.  
 439 The values for  $N_B$  are then interpolated to the altitudes of AIRS and the resampled mod-  
 440 els (IFS 1, IFS 2 and ERA5 1). These new values for  $N_B$  are used to calculate the mo-  
 441 mentum flux for all the resampled model datasets and AIRS observations. However, since  
 442 calculating the  $N_B$  values was found to have little effect on the results, the buoyancy fre-  
 443 quency is set  $0.02 \text{ s}^{-1}$  in this study for the models not resampled as AIRS to reduce com-  
 444 putational time.

445 The altitude range selected of the model data resampled as AIRS and of the AIRS  
 446 data used for the 2D+1 ST analysis is 27–54 km. Including altitudes outside of this range  
 447 with higher noise would affect the wave properties calculated using the 2D+1 ST. The  
 448 2D+1 ST is restricted to select waves with horizontal wavelengths ranging from 60 to  
 449 800 km. These values are chosen as 60 is approximately twice the Nyquist frequency and  
 450 800 km is below half the track width of each AIRS granule. Data points where the ver-  
 451 tical wavelength is below 6 km (twice the vertical spacing) or above 45 km are removed  
 452 from the data for the wave properties calculated. The 45 km upper limit is selected as  
 453 this is the approximate height of the stratosphere.

## 454 4 Results

### 455 4.1 GW Structures and Properties in two Case Studies

456 Two case studies, in a sub region of the area shown in Figure 1 at 39 km altitude,  
 457 are presented in order to compare the resampled models and AIRS. These case studies  
 458 are chosen to show an example with better agreement between the AIRS observations  
 459 and the resampled IFS (Figures 3 and 4), and an example with worse agreement between  
 460 the resampled IFS and the observations, further in time from when the IFS was initialised



**Figure 3.** Temperature perturbations at 39 km altitude for granules in a sub region of the area shown in Figure 1, with mean times of 19:38–19:50 UTC for AIRS (a) and at the closest time for the resampled models. Panels (b–d) show the resampled models after adding AIRS noise, with the resampled models before adding noise below them (no noise, panels f–h). The section of the topography from Figure 1 for the sub region is shown in panel (e), with (0,0) at 52° latitude, 94° longitude.

461 (Figures 5 and 6). The case studies also show examples of the difference in the wave struc-  
 462 tures in the resampled model data compared to the observations and the temperature  
 463 perturbations for the resampled models with and without added scaled noise (Figures  
 464 3 and 5).

465 The first case study includes data from AIRS granules with mean times of 19:38–  
 466 19:50 UTC on the 5<sup>th</sup> November and the resampled model granules at the closest 3 hourly  
 467 times to the observations. The temperature perturbations for this example are shown  
 468 in Figure 3. The top row shows the AIRS swath (Figure 3a) and resampled models with  
 469 AIRS noise added (Figure 3b–d). The topography of the area is shown in Figure 3e as  
 470 well as the resampled model swaths before adding noise (Figure 3f–h). 8  $\mu$ m AIRS bright-  
 471 ness temperatures and ERA5 winds are shown for both case studies in Supplementary  
 472 Figures S4 and S5.

473 The large wave on the right, labelled A, is seen in AIRS and the resampled mod-  
 474 els (Figure 3a–d) is likely to be orographic, as it is close to a region of higher topogra-  
 475 phy, near Lake Baikal (labelled in Figure 1). A curved wave can be seen on the left in  
 476 AIRS (labelled B, in Figure 3a), which could be convective as it is located close to a re-  
 477 gion with a brightness temperature lower than 220 K, indicating deep convection (Hoffmann  
 478 & Alexander, 2010) (see Supplementary Figure S4a). This wave cannot be clearly seen  
 479 in the resampled IFS (IFS 1 & 2, Figure 3b and c), which suggests that the convective  
 480 source is missing or significantly reduced in strength in the 1 km IFS run. In ERA5, wave  
 481 (B) can be seen but at a lower amplitude, suggesting the convective source may have been

482 correctly assimilated in the reanalysis or this source could have been correctly simulated  
483 in ERA5 due to the atmospheric flow remaining closer to that of the real atmosphere.

484 Figure 4 shows the wave properties, derived from the 2D+1 S-Transform, for the  
485 AIRS and resampled model granules shown in Figure 3a–d. Discontinuities can be seen  
486 in the figure (and Figure 6, which shows the wave properties for the 2<sup>nd</sup> case study) at  
487 the granule edges, as the 2D+1 S-Transform output was found separately for each AIRS  
488 or model resampled as AIRS granule. Areas of higher amplitude in Figure 4a–d are seen  
489 in similar locations in each data set, but are highest in AIRS (Figure 4a) and lowest in  
490 ERA5 1 (Figure 4d). These regions can also be clearly seen for larger areas in AIRS than  
491 in the resampled models. In ERA5 1, an area of higher amplitude can be seen at the left  
492 of the granule stripe, near the centre of the y axis which is also seen in AIRS, but is not  
493 as clearly seen in IFS 1 and 2 (Figure 4b and c). Longer horizontal and vertical wave-  
494 lengths can be seen in IFS 2 (Figure 4g and k), than in IFS 1 (Figure 4f and j), and in  
495 areas of noise the horizontal wavelengths are lower for all the data sets (Figure 4e–h).  
496 The magnitudes of the zonal and meridional momentum fluxes are highest in AIRS (Fig-  
497 ure 4m and q), and lowest in ERA5 1 (Figure 4p and t). In IFS 1, there is a patch in  
498 the zonal and meridional momentum fluxes (Figure 6n and r), in a location where the  
499 amplitude is higher, where the direction of these fluxes is reversed compared to the other  
500 datasets. This could be a result of a wave in this dataset close to vertical, so the 2D+1  
501 S-Transform is less effective at finding the wave direction.

502 The second case study is shown for AIRS granules with mean times of 19:14–19:26  
503 UTC on the 9<sup>th</sup> November 2018, and the resampled model granules at the closest 3 hourly  
504 times. Temperature perturbations for this case study are shown in Figure 5. As in Fig-  
505 ure 3, the resampled model temperature perturbations are shown with AIRS noise (Fig-  
506 ure 5b–d) and before adding AIRS noise (Figure 5f–h). The GWs shown in Figure 5a–  
507 d are likely to have orographic sources as they are close to regions of higher topography,  
508 such as near Lake Baikal and the Altai-Sayan mountains (labelled in Figure 1, and not  
509 located near a region of deep convection (shown in Supplementary Figure S4b).

510 In Figure 6, the wave properties are shown for the second case study (the AIRS  
511 swath, and models resampled as the swath in Figure 5a–d). The wave properties found  
512 for the resampled 1 km IFS run appear to agree less well with the AIRS observations,  
513 compared to the first case study in Figure 4. By the 9<sup>th</sup> November, the 1 km IFS run  
514 would have diverged further from reality compared to the first case study on the 5<sup>th</sup> Novem-  
515 ber, which is closer to the time the simulation was initialised. The amplitudes in ERA5  
516 1 (Figure 6d) are higher than in the example shown in Figure 4 and are higher over a  
517 larger area than for IFS 1 and 2 (Figure 6b and c) in a similar location to where the AIRS  
518 amplitudes are highest (Figure 6a). This is expected as ERA5 assimilates observations,  
519 unlike the 1 km IFS run. In the areas where the amplitude is higher in IFS 1 and 2 (Fig-  
520 ure 6b and c), the horizontal wavelengths (Figure 6f and g) are longer than in AIRS (Fig-  
521 ure 6e) for the same locations. The horizontal wavelengths in the area with greater am-  
522 plitudes in ERA5 1 (Figure 6h) appear to also be longer than in AIRS (Figure 6e).

523 The vertical wavelengths in IFS 1 and 2 (Figure 6j and k) are shorter than in AIRS  
524 (Figure 6i) for the areas where GWs can be seen. In the areas with higher amplitude in  
525 ERA5 1 (Figure 6d), the vertical wavelengths are generally longer (Figure 6l) than in  
526 the same locations for AIRS (Figure 6i). The magnitudes of the zonal and meridional  
527 momentum fluxes are also highest in AIRS for this case study (Figure 6m and q), due  
528 to the higher wave amplitudes, but they are lower in the resampled 1 km IFS run (IFS  
529 1 and 2 in Figure 6n, o, r and s) than in ERA5 1 (Figure 6p and t). In both case stud-  
530 ies, (Figures 4m–t and 6m–t) the zonal and meridional momentum flux is generally neg-  
531 ative in areas where the amplitude is highest for all the data sets.

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## 4.2 Mean GW Properties in Days 1–10 of November 2018

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Figure 7a–d shows the mean nighttime amplitudes during the first 10 days of November 2018 at 39 km altitude for the region in Figure 1. AIRS amplitudes (Figure 7a) are divided by a factor of 2 before plotting, so that areas with higher amplitudes in the resampled models can be seen more clearly. These results are also presented Supplementary Figure S6, but without noise added to the resampled models. The mean horizontal wavelengths for nighttime data, with and without scaled AIRS noise added to the resampled models, in the first 10 days of November 2018 are also shown in Supplementary Figures S7 and S9 respectively.

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Areas of higher amplitude in Figures 7a–d are seen in similar locations in AIRS and the resampled models. However, the amplitudes are significantly higher in AIRS than in the resampled 1 km IFS run (Figure 7c and d) and ERA5 1 (Figure 7b), and are lower in ERA5 1 than in IFS 1 and 2. The regions of higher amplitude are located near to mountain ranges, shown as areas of higher elevation in Figure 1 including the mountains near Lake Baikal, the Altai-Sayan Mountains, the Pamir Mountains and the Urals, suggesting that the GWs have orographic sources. There is an area of higher amplitude over the Urals (labelled in Figure 1) in Russia which can be seen in AIRS and the resampled IFS (1 and 2), but can only be seen in ERA5 1 at a significantly lower amplitude. The locations of the peaks in amplitude in AIRS and the resampled models are consistent with Hindley et al. (2020) and Wright and Banyard (2020). The maximum mean amplitudes in IFS 1 (Figure 7c) and IFS 2 (Figure 7d) are a factor of 2.72 and 2.81 lower than in AIRS respectively, so the mean of the maximum mean amplitudes for the 1 km IFS run is a factor of 2.77 lower than in AIRS, averaging the results from the two resampling methods. The maximum mean amplitude in ERA5 1 (Figure 7b) is a factor of  $\sim 3.59$  lower than in AIRS. Supplementary Figure S6 shows similar results for the mean amplitudes with no noise added to the resampled models, but Figure 7b–d have higher background amplitudes due to the added noise. The factors lower than in AIRS for the maximum mean amplitudes are similar without noise added to the resampled models, but slightly lower.

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The mean nighttime zonal and meridional momentum fluxes are shown in Figure 7e–h and 7i–l respectively. Like the amplitude, the magnitude of the mean zonal and meridional momentum flux is significantly higher in AIRS (Figure 7e and i) than in the resampled models (Figure 7f–h and j–l). The zonal momentum flux generally has a higher magnitude than the meridional momentum flux, which is expected based on the AIRS retrieval climatology of Hindley et al. (2020) and due to background wind related processing, including wind filtering and refraction. In areas where the amplitude is higher, the zonal momentum flux is negative (westward) and the meridional momentum flux is also negative (southward). This suggests that the highest amplitude GWs are formed by wind flowing over the northeast–southwest aligned topography shown in Figure 1. The maximum mean zonal momentum fluxes for the resampled IFS are a factor of 3.87 and 4.23 lower than in AIRS, for IFS 1 and IFS 2 respectively. In ERA5 1, the maximum mean zonal momentum flux is a factor of 9.74 lower than in the satellite observations. For the maximum mean meridional flux, IFS 1 and 2 are factors of 5.48 and 5.35 lower than in AIRS respectively and ERA5 1 is a factor of 17.6 below AIRS.

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## 4.3 Effect of Adding Randomly Selected Noise to the Resampled Models

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Figure 8 shows time series for the mean amplitude and momentum flux on each night in the first 10 days of 2018. The values for the resampled models with no noise added and AIRS observations are shown as crosses and the mean values for AIRS are divided by 2. The circles show the median values of the means from 100 ensemble members where granules of AIRS noise temperature perturbations are selected randomly and scaled be-

583 fore being added to the resampled model data. The shading behind the lines with cir-  
 584 cles shows the range from the minimum to maximum mean found for each night from  
 585 the 100 noise ensemble members.

586 Before finding the mean values, areas of noise in the AIRS and resampled model  
 587 data are reduced by smoothing the amplitude measurements using a 7 by 7 point box-  
 588 car filter and removing points in the original unsmoothed data where the amplitude of  
 589 the smoothed data is below the 70<sup>th</sup> percentile of the amplitude in nighttime data in the  
 590 first 10 days of November 2018 in each data set ( $\sim 0.31$  for IFS 1 and 2 (no noise),  $\sim 0.28$   
 591 for ERA5 1 (no noise) and  $\sim 1.18$  K for AIRS). For the ensemble members, the 70<sup>th</sup> per-  
 592 centiles of the amplitude were found for each ensemble member separately. The 70<sup>th</sup> per-  
 593 centile is chosen for the amplitude cutoff for each dataset to optimise for reducing the ar-  
 594 eas of noise in the data, while removing as little of the areas with low amplitude GWs  
 595 as possible. The mean values for amplitude and momentum flux are lower for each night  
 596 in the resampled models with no noise added than the mean values calculated for the  
 597 ensemble. The range in mean values from the different ensembles is small for both the  
 598 amplitude and the momentum flux, suggesting that the addition of different random scaled  
 599 AIRS noise temperature perturbations has only a small effect on the results.

600 The 95<sup>th</sup> percentiles of the amplitudes and momentum fluxes are found for the re-  
 601 sampled models in each ensemble member and for the AIRS observations for compar-  
 602 ison. The 95<sup>th</sup> percentile is chosen rather than the 100<sup>th</sup> percentile to avoid including  
 603 spikes in the AIRS data. The 95<sup>th</sup> percentile of the AIRS observations is divided by the  
 604 minimum, median and maximum 95<sup>th</sup> percentiles of the 100 ensemble members. The fac-  
 605 tors lower than the 9<sup>th</sup> percentile for AIRS amplitudes, of the median 95<sup>th</sup> amplitude  
 606 percentiles of the resampled models are found to be 2.87 for IFS 1 (ranging from 2.84–  
 607 2.89 from the maximum to minimum 95<sup>th</sup> percentile), 2.90 for IFS 2 (ranging from 2.88–  
 608 2.93), and 3.30 for ERA5 1 (ranging from 3.26–3.3). The factors of the median 95<sup>th</sup> per-  
 609 centile for the momentum fluxes found are 10.2 for IFS 1 (with a range of 10.1–10.3),  
 610 10.2 for IFS 2 (with a range of 10.0–10.4), and 16.5 for ERA5 1 (with a range of 16.2–  
 611 16.7) lower than in the observations.

#### 612 **4.4 Distributions of GW Properties in AIRS Observations and Mod-** 613 **els Before and After Resampling as AIRS**

614 Kernel distribution functions (KDFs) for the amplitudes, horizontal and vertical  
 615 wavelengths and momentum flux are shown for nighttime data during the first 10 days  
 616 of November 2018 at 39 km altitude in Figure 9. In the first column (Figure 9a, c, e and  
 617 g), the KDFs for AIRS, and ERA5 and the 1 km IFS run (IFS) before resampling as AIRS  
 618 are shown and the second column (Figure 9b, d, f and h) shows the KDFs for AIRS and  
 619 the median from 100 noise ensemble members for the resampled models. The shading  
 620 behind the lines for the median resampled model KDFs, shows the range from the min-  
 621 imum to the maximum probability for the ensemble members. KDFs were chosen to show  
 622 the distributions of the data rather than probability density functions (PDFs), as plot-  
 623 ting PDFs would involve making assumptions about the data distributions and they could  
 624 not properly show the distribution of the data.

625 Areas of noise in the data are reduced using the same method as for the mean am-  
 626 plitude and momentum flux time series (Figure 8), by removing areas in the original data  
 627 where the smoothed amplitude (using a 7 by 7 point boxcar filter) is below the 70<sup>th</sup> per-  
 628 centile for AIRS ( $\sim 1.18$  K) and the 70<sup>th</sup> percentiles found for the resampled models in  
 629 each ensemble member separately. For the KDFs of ERA5 and the 1 km IFS run before  
 630 being resampled as AIRS, the same method as for AIRS and the resampled models, was  
 631 used to remove areas of the data where the smoothed amplitude, using the 7 by 7 point  
 632 boxcar filter, is below the 70<sup>th</sup> percentile of AIRS. The AIRS noise is scaled by the ra-  
 633 tio of amplitudes between the observations and the resampled models without added noise

(see Section 3.3), which have significantly lower wave amplitudes, so lower amplitude cut-offs can be used for the resampled models to avoid removing areas of low amplitude gravity waves.

After being resampled as AIRS, the horizontal and vertical wavelength spectra of the models are more similar to the AIRS data (Figure 9d and f), compared to the spectra before resampling (Figure 9c and e), suggesting that the resampling methods used allow a fairer comparison between the observations and models to be made. There are a higher proportion of points with shorter horizontal wavelengths in AIRS than in the resampled models (Figure 9d), but this could be affected by the higher magnitude noise in the observations. Areas containing only noise with no identifiable wave signals have shorter horizontal wavelengths (shown in Figures 4e–h and 6e–h in areas where the amplitude is low). There is some quantization of the horizontal wavelengths longer than around 200 km, leading to multiple peaks in the KDFs for all data sets in Figure 9c and d, with the highest peaks in ERA5 1. This is a result of these waves being approximated by Fourier modes in the 2D+1 ST, since they are long relative to the data size. For the resampled models, the peaks in the vertical wavelength are offset from the observations by around 2–3 km (Figure 9f). This could be due to the values of the AIRS vertical resolution being overestimated, but this could also be due to the vertical wavelengths in the resampled models could be too short, and the different 70<sup>th</sup> percentile amplitude cutoffs used for each data set could also affect these results. For the horizontal wavelengths, the variation in the resampled model distribution is greatest at the peaks, but very low at shorter horizontal wavelengths (Figure 9d). The range for the ensemble distributions is most visible for the vertical wavelengths in the resampled models (Figure 9f), suggesting the added noise has a greater effect on this wave property, although the range is still low and is largest at the peaks.

Before resampling there are a greater proportion of higher amplitude GWs in the 1 km IFS run, up to  $\sim 17$  K, than in the AIRS observations, where the KDF tails off at  $\sim 15$  K, and significantly higher fraction of lower amplitude waves in ERA5, where the KDF tails off at around  $\sim 9$  K (Figure 9a). After the AIRS observational filter is applied to the models, the wave amplitudes are generally higher in AIRS, and there is a greater fraction of data points with lower amplitudes in ERA5 1, where the KDF decreases to  $\sim 3$  K, than in IFS 1 and 2, which have KDFs that decrease to  $\sim 6$  K and  $\sim 5$  K respectively (Figure 9b). Whilst the horizontal momentum flux KDFs are similar for AIRS and the 1 km IFS run before resampling (Figure 9g), they are generally higher in AIRS than in the resampled models (Figure 9h), as the momentum flux is proportional to vertical wavelengths and the square of the amplitudes. The results shown in Figure 9b, d and f suggest that there are high amplitude GWs with shorter horizontal or vertical wavelengths in the AIRS retrieval data that are not present in the resampled 1 km IFS run. There is no visible shading showing the range of probabilities for the logarithm to base 10 of the amplitude probabilities in Figure 10b, but these ranges were very small before the amplitude probabilities were logged. The range in probability distributions is also low for the momentum flux.

Supplementary Figure S10 shows the kernel distribution functions, as in Figure 9, but with no scaled AIRS noise added to the resampled models. Areas where the smoothed amplitude is below the 70<sup>th</sup> percentile for each resampled model data set, with no added noise, are removed using the same method as for the resampled model data set with added scaled AIRS noise. The differences for the results with and without added noise include that the distributions shift to the left of the panel with no noise added (Figure S10d). This is because areas of noise have lower horizontal wavelengths (see Figures 4e–h and 6e–h). The peaks of the momentum flux distributions are also at lower values without added noise (Figure S10h).

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#### 4.5 Point-wise Comparisons of GW Properties

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Bivariate histograms, plotted using nighttime data from the first 10 days of November 2018 at 39 km altitude, are shown in Figure 10 to compare the wave properties in the resampled models and AIRS. The color bars show the normalised density, i.e. the number of counts in each bin divided by the total number of counts. Areas of noise in the data used for the bivariate histograms are also reduced using the method described in Section 4.3. The number of points can be found in Table S1 in the Supplementary Information. These values vary as points are only included if both data sets do not have a missing value in the point location. Values will be missing if the vertical wavelength in the point location is lower than 6 km or greater than 45 km, or the amplitude at that location is below the 70<sup>th</sup> percentile amplitude cutoff for each data set. Table S1 also shows the fraction of points above (f.a) and below (f.b) the 1:1 line (grey dashed line) in Figure 10. Figure S11 shows the bivariate histograms as in Figure 10, but with no scaled AIRS noise added to the resampled models.

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The amplitudes in nighttime AIRS data are significantly higher than in the resampled models (Figure m, q and u), with f.b ranging from 0.952 (AIRS & IFS 1) to 0.977 (AIRS & ERA5 1) (Table S1). Stripes with no data can be seen in the bivariate histograms of the horizontal wavelengths (Figure 10b, f, j, n, r, and v), as the horizontal wavelengths are quantized at longer wavelengths. There are also more points where the AIRS data have a longer vertical wavelength than in the resampled 1 km IFS run (Figure 10o, s and w) with f.b ranging from 0.632 (AIRS & IFS 1) to 0.627 (AIRS & IFS 2). In ERA5, there are more points with longer vertical wavelengths than in AIRS (f.b of 0.471). The histograms also show higher momentum fluxes in AIRS (Figure 10p, t and x) as a result of the higher GW amplitudes and vertical wavelengths. For the momentum flux (Figure 10d, h, l, p, t and x), the points in the bivariate histograms are very spread out suggesting there is little point-wise correlation between the data sets except between IFS 1 and 2 (Figure 10d). The data points are also quite spread out for the vertical wavelength plots (Figure 10c, g, k, o, s, and w) indicating a low point-wise correlation. Data points are closer to the 1:1 line for IFS 1 and 2 for higher amplitude values (Figure 10a-d) and the other wave properties shown. The fraction of points above and below the 1:1 line for IFS 1 & IFS 2 (Figure 10a-d) are similar for all wave properties shown (see Table S1) with the greatest difference in the fractions for the vertical wavelength where f.a is 0.540 and f.b is 0.460.

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## 5 Discussion

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The methods used in this study have allowed a more observing-system-aware comparison between the models and AIRS observations compared to previous work. However some issues still remain, including how noise is selected and added, AIRS's observational filter and the amplitude cutoffs used.

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The AIRS temperature perturbations containing only noise are selected by ordering the granules from lowest to highest variance and selecting granules manually for different regions in nighttime data, during the same period of the year as the data used in this study. This means the noise added to the resampled models is better correlated to the location of each resampled model granule compared to previous methods used (e.g. in Hindley et al., 2021; Okui et al., 2023) and could include large noise structures that are present in AIRS noise. However this method of selecting noise granules would be too time consuming for a longer data set, so using machine learning, with a training data set selected by eye, to identify whether granules contain only noise or GWs could be a better approach.

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A limitation of this work is that only GWs in the 1 km IFS run with wavelengths in the AIRS's observational filter can be compared to AIRS observations. The AIRS re-

735 retrieval data have a low vertical resolution, and relatively low horizontal resolution com-  
 736 pared to the 1 km IFS run. In future work, data from instruments with different obser-  
 737 vational filters, such as limb sounders or satellites using GPS radio occultation, could  
 738 be used to validate some of the resolved GWs in the 1 km IFS run with wavelength ranges  
 739 outside of AIRS’s observational filter. Limb sounders have a low horizontal resolution,  
 740 but higher vertical resolution than nadir sounders like AIRS.

741 Whilst the location and timing of the GWs agree well in the resampled 1 km IFS  
 742 run and AIRS observations, the mean amplitudes are found to be significantly lower in  
 743 the resampled 1 km IFS run, by a factor of  $\sim 2.77$ , but higher than in the lower resolu-  
 744 tion ERA5 reanalysis. As a result of this, the horizontal momentum flux is also lower  
 745 in the resampled models compared to the observations. Kruse et al. (2022) found that  
 746 GW amplitudes in a lower resolution run of the IFS, with a grid-spacing of  $\sim 9$  km, were  
 747 lower than in AIRS observations. High amplitude GWs, seen in the AIRS observations,  
 748 are not found in the resampled 1 km IFS data (Figure 9), but are present in the 1 km  
 749 IFS run before resampling suggesting these waves have wavelengths outside of AIRS’s  
 750 observational filter.

751 Amplitude cutoffs were used to reduce areas of noise included in the AIRS retrieval  
 752 and resampled model data for the kernel distribution functions (Figure 9) and bivari-  
 753 ate histograms (Figure 10), but this could not remove all areas of noise without also re-  
 754 moving areas of low amplitude GWs. This means that these results will be affected by  
 755 the remaining noise. These cutoffs were chosen by finding the 70<sup>th</sup> percentile of all night-  
 756 time data during the first 10 days of November 2018 for each data set. Due to the lower  
 757 wave amplitudes in the resampled models, the added noise is scaled by the amplitude  
 758 differences (see subsection 3.3 in the Methods section), so lower 70<sup>th</sup> percentiles can be  
 759 used as the amplitude cutoffs without removing areas of low amplitude gravity waves.

760 The two methods used to resample the 1 km IFS lead to quite similar results and  
 761 work effectively to smooth the model data to AIRS’s resolution, resulting in more sim-  
 762 ilar distributions of GW horizontal and vertical wavelengths (Figure 9c–f). However, the  
 763 peaks of the distributions of vertical wavelength for the resampled models are found to  
 764 be around 2–3 km lower than for AIRS (Figure 9f). This could be a result of the AIRS  
 765 resolution values, used to smooth the model data, being overestimated, but could also  
 766 be due to differences in the vertical wavelengths in the resampled models compared to  
 767 the observations. These differences in peaks for the vertical wavelength distributions be-  
 768 tween the resampled models and AIRS are also seen in Supplementary Figure S10, show-  
 769 ing that the added noise has little effect on this result.

770 The results in Figures 7, 9 and 10 are also shown in the Supplementary Informa-  
 771 tion with no noise added to the resampled models in Figures S6, S10 and S11. Compar-  
 772 ison of these suggest that while the added noise has some effect on the results this is not  
 773 large. The largest effect appeared to be on the horizontal wavelength distribution, be-  
 774 cause lower horizontal wavelengths are calculated in areas of noise. Amplitudes and mo-  
 775 mentum fluxes are also slightly lower without added noise. An ensemble of added noise  
 776 with 100 members for each resampled model data set is also analyzed. This analysis shows  
 777 that the effect of randomly selecting AIRS noise temperature perturbations has little ef-  
 778 fect on the distributions of the wave properties and on the mean amplitudes and momen-  
 779 tum fluxes for each day in the first 14 days of November 2018.

## 780 6 Summary and Conclusions

781 In this study, gravity wave (GW) properties in a  $\sim 1.4$  km gravity-wave-resolving  
 782 run (TCO7999 resolution) of the IFS are compared to AIRS observations over a part of  
 783 Asia and surrounding regions, using nighttime data during the first 10 days of Novem-

ber 2018. The results show a good level of fidelity for the model by comparison to the observations, but with important differences, discussed below.

Two different methods were used to resample the 1 km IFS run to facilitate this comparison, the first method by smoothing to AIRS' resolution, followed by interpolating to the measurement location, and the second by oversampling the model and then producing a weighted average of the oversampled points. Although small differences are seen, they generally produce quite similar results. Since method 2 is significantly more computationally expensive, method 1 may be better suited for comparing models to AIRS. This result does not necessarily hold in the general case: the large- and vertically-deep volume of nadir measurements, such as those from AIRS, is likely less sensitive to footprint positioning and morphology than measurements with finer vertical and lower horizontal resolution, such as those from limb sounders, and this will be investigated further in future work.

Based on these results, the output from the ERA5 reanalysis is also resampled as AIRS using method 1, to see how well the 1 km IFS run resolves GWs in comparison to this lower resolution (and slightly chronologically older) model with assimilative capabilities. Noise derived from wave-free AIRS observations was also added to the simulated data to produce a more observing-system-aware comparison with the very noisy observations, following experience in Okui et al. (2023) which showed the significant effect such noise has on 1:1 comparisons. Finally, the 2D+1 S-Transform analysis of Wright et al. (2021) is used to find the wave properties for each data set.

The results of this analysis lead to the following conclusions:

1. GWs in the 1 km IFS run can be seen at similar locations and times, and with similar wave morphology to AIRS, suggesting that the model works well in this regard. ERA5 waves are in general less morphologically consistent with observations, and in particular often have inconsistently long horizontal wavelengths, but do occur at similar locations and times to the observations in many if not most cases.
2. Measured amplitudes and momentum fluxes are significantly lower in both resampled models than in AIRS data, with ERA5 amplitudes slightly lower (and thus less observationally-consistent) than those in the 1 km model. This difference is large, with a long tail of high-amplitude AIRS measurements (Figure 9b) which in turn drives a similar difference in momentum fluxes.
3. Investigation of the raw model data shows that many high-amplitude waves in the 1 km IFS run have wavelengths too horizontally-short for AIRS to observe (see e.g. Figure 9), which are thus not seen in the resampled model. Given that the overall amplitude and momentum flux distributions (Figure 9a,g) in the raw models are broadly similar to AIRS, this may suggest that wave activity in the model has plausible total amplitudes and fluxes, but skewed to much shorter wavelengths than in the true GW spectrum.
4. The effect of adding noise to models resampled as AIRS that is scaled by the differences in amplitudes between the resampled models and observations has also been investigated. The results show that adding this noise does not have a large impact on the results, but this appears to have a larger effect on the results for the horizontal wavelength than for the other wave properties compared. Adding noise leads a higher proportion of shorter horizontal wavelengths in the resampled model data.

Vertical wavelengths in both ERA5 and the 1 km IFS run are found to be significantly shorter than in AIRS observations, even after resampling to match the observational resolution. This difference is typically  $\sim 2-3$  km, i.e. approximately 10-20% of the observed wavelengths. This conclusion is difficult to decouple from the effects of noise

835 in the AIRS observations, and further work is needed to address this question more care-  
 836 fully. However, this result is also shown without noise added to the resampled models,  
 837 suggesting that this added noise has little impact on this result.

838 This work highlights the importance of carefully applying the observational filter  
 839 of the observing platform to models before comparing GWs in simulations to those in  
 840 observations, which is shown to be necessary for producing a meaningful comparison in  
 841 this study. This is important for accurate testing of how well GWs are resolved in high  
 842 resolution models, with further implications for parameterization development, as this  
 843 increasingly frequently uses high-resolution models of this nature as a ‘truth’ for tun-  
 844 ing purposes.

## 845 Open Research

846 The AIRS temperature data used in the study were computed from AIRS radiances  
 847 using the retrieval scheme described in Hoffmann and Alexander (2009). The 3D AIRS  
 848 temperature retrieval can be obtained from [https://datapub.fz-juelich.de/slcs/](https://datapub.fz-juelich.de/slcs/airs/gravity_waves/data/retrieval/)  
 849 [airs/gravity\\_waves/data/retrieval/](https://datapub.fz-juelich.de/slcs/airs/gravity_waves/data/retrieval/) (Hoffmann, Lars, 2021). The ECMWF ERA5  
 850 reanalysis data at 0.25° resolution (Copernicus Climate Change Service, 2023) can be  
 851 downloaded from the Copernicus Climate Data Store at [https://cds.climate.copernicus](https://cds.climate.copernicus.eu/cdsapp#!/dataset/10.24381/cds.bd0915c6?tab=overview)  
 852 [.eu/cdsapp#!/dataset/10.24381/cds.bd0915c6?tab=overview](https://cds.climate.copernicus.eu/cdsapp#!/dataset/10.24381/cds.bd0915c6?tab=overview). For the 1 km IFS run,  
 853 the size of the raw model output on the native grid is a few hundred TB, so it is not pos-  
 854 sible for all of the data to be made available. However, the post processed data will be  
 855 retained and is available on request. Code written in MATLAB (available at [https://](https://uk.mathworks.com/products/matlab.html)  
 856 [uk.mathworks.com/products/matlab.html](https://uk.mathworks.com/products/matlab.html)) was used to resample the models as AIRS,  
 857 analyse the gravity wave properties and produce the figures. The MATLAB code used  
 858 is available at Lear, Emily (2024).

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 870 ness data.

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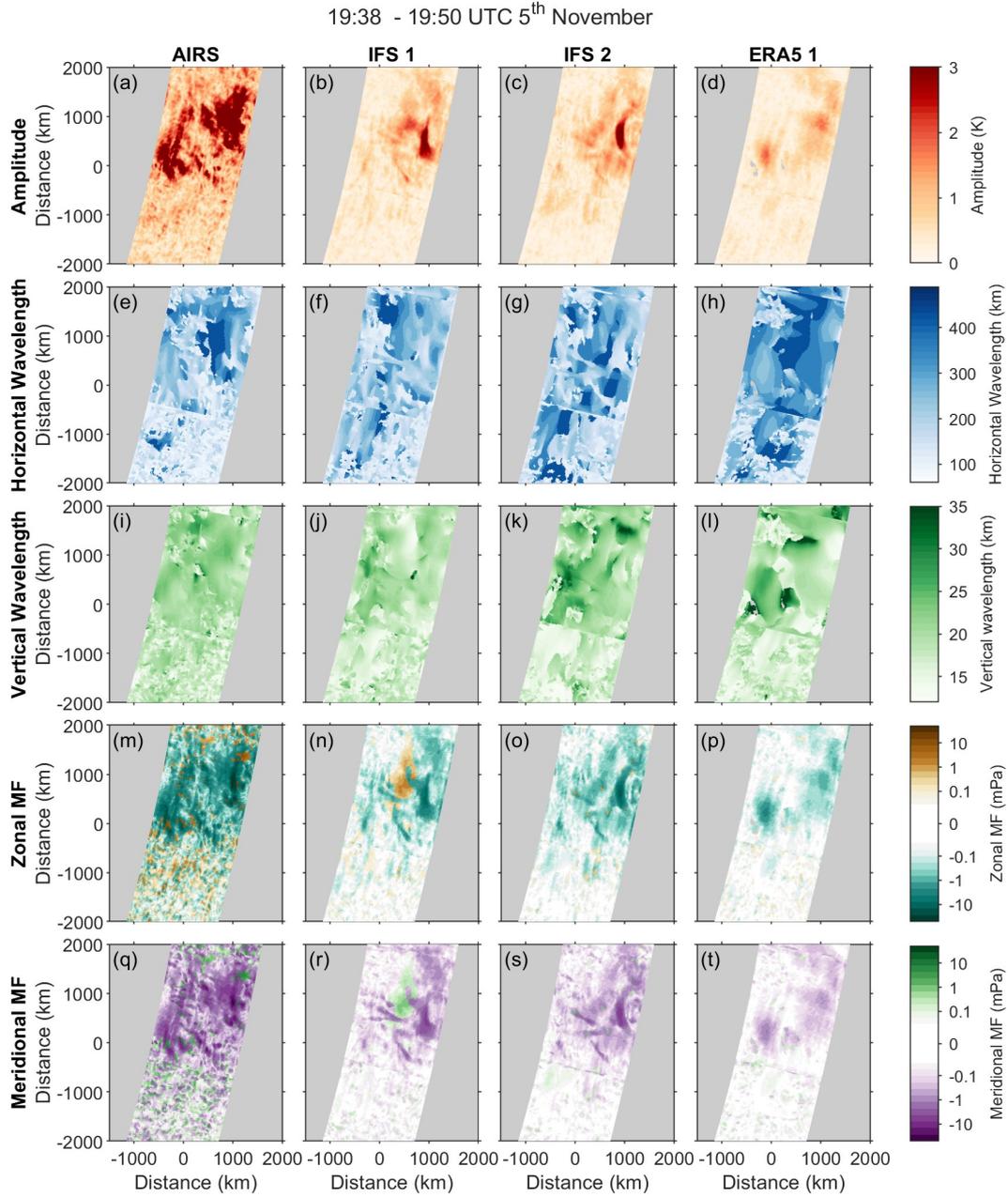
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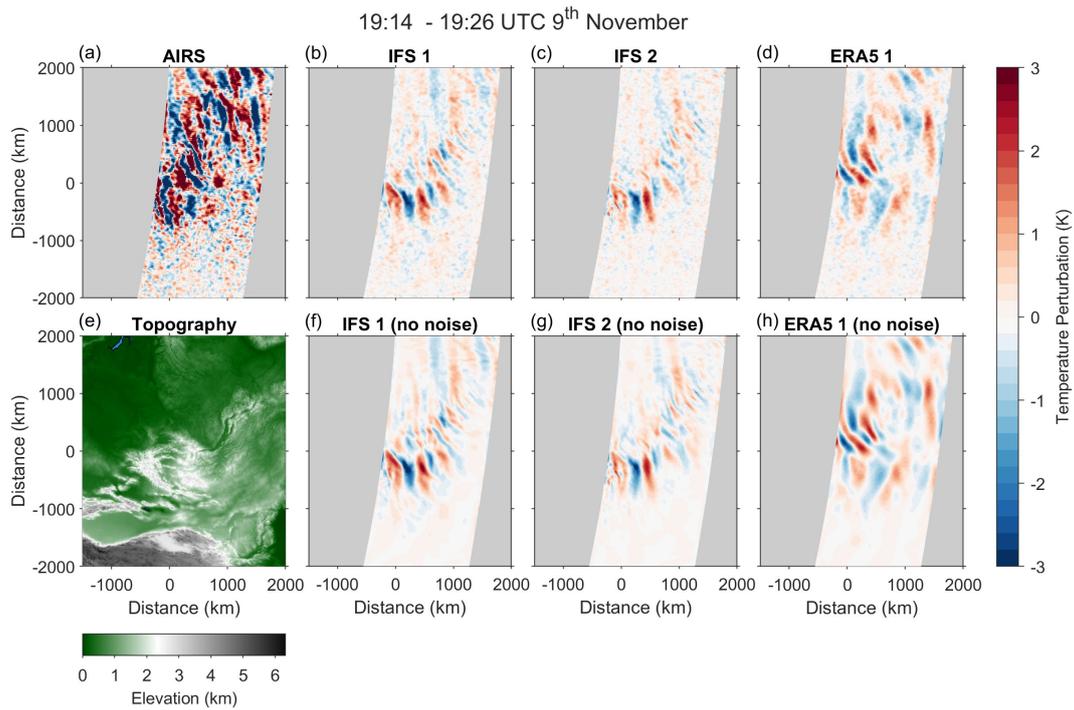
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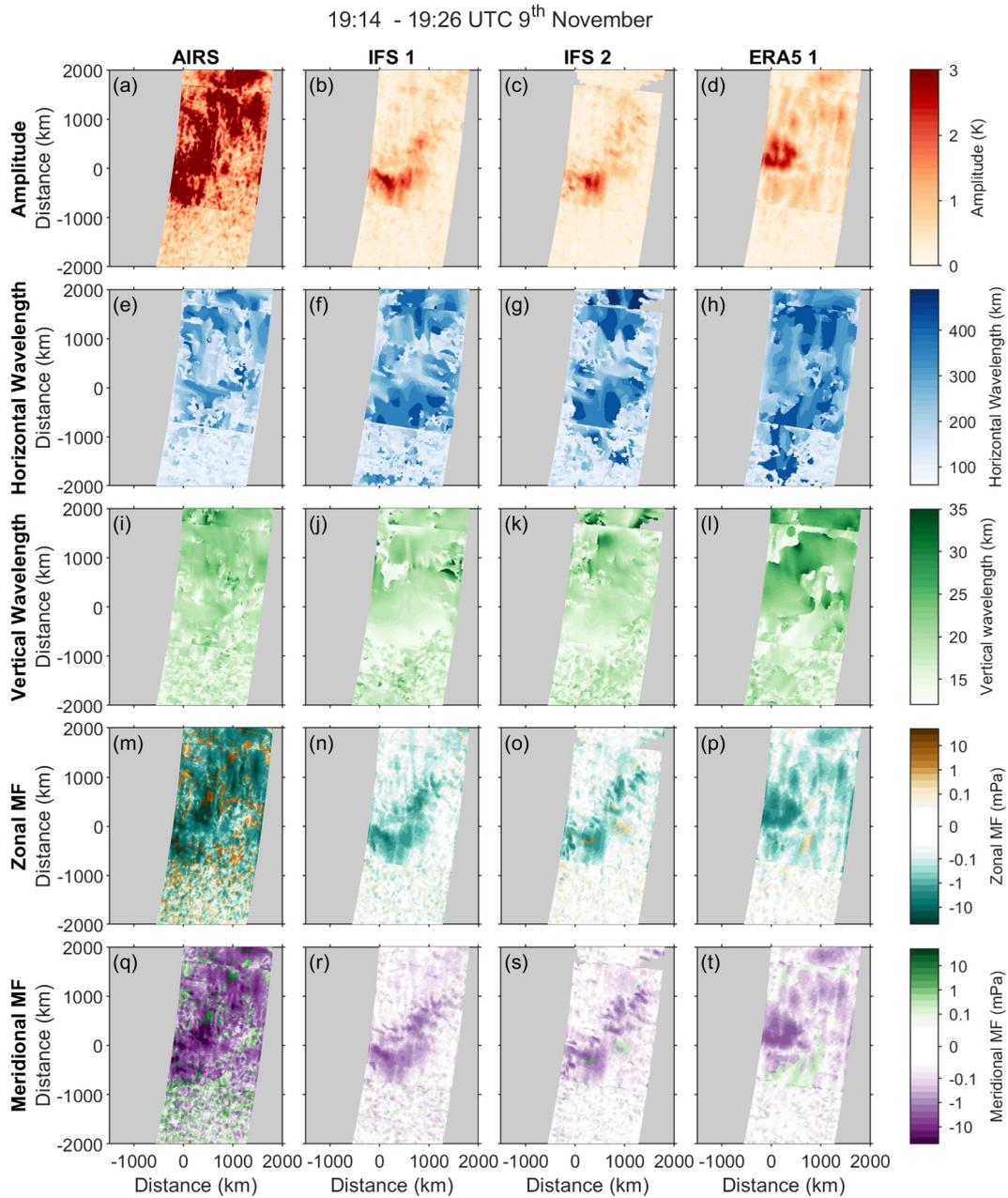
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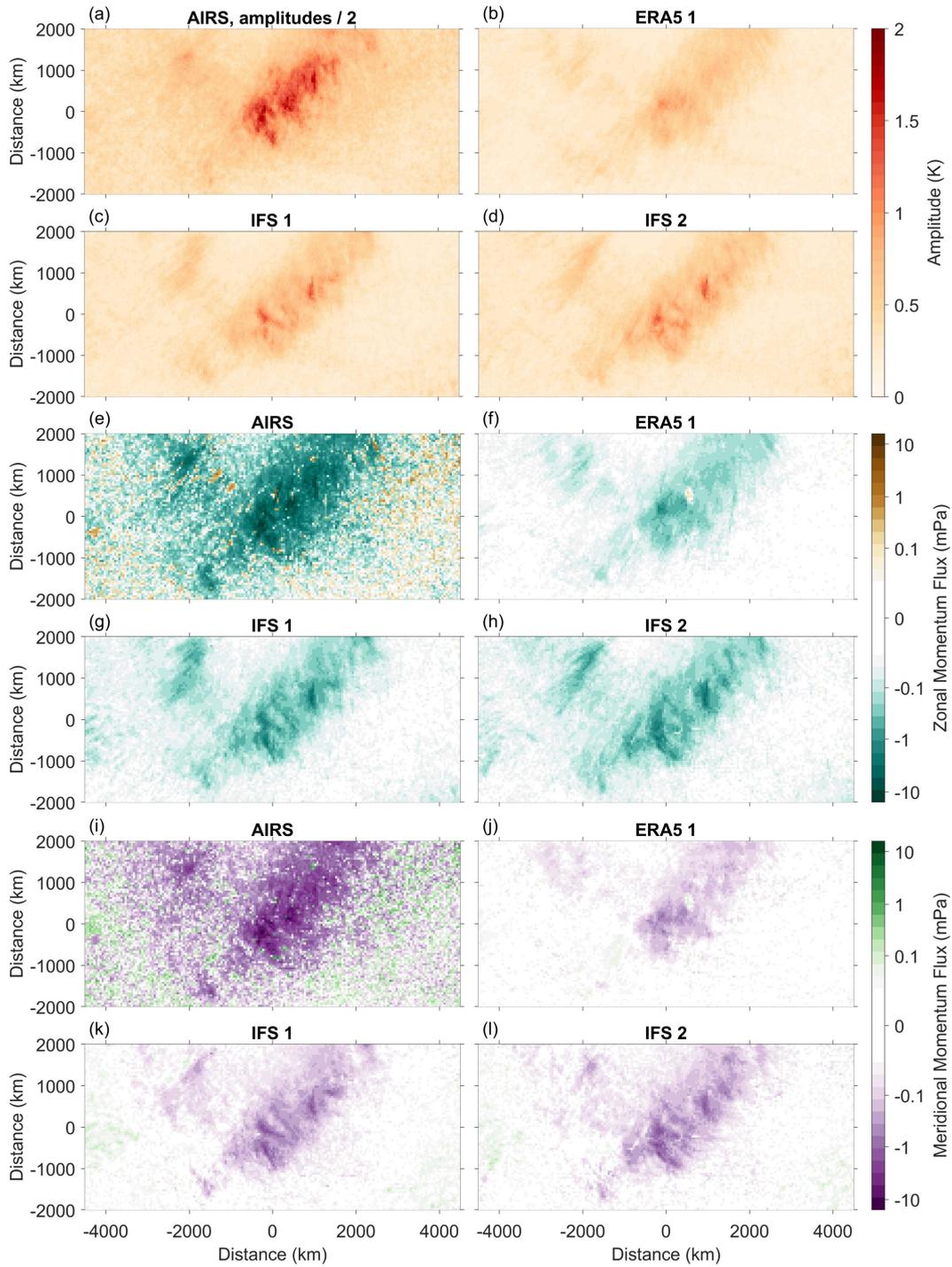
**Figure 4.** Wave properties at 39 km altitude for the granules shown in Figure 3, including the amplitude, horizontal and vertical wavelengths and the zonal, and meridional momentum flux (MF). The zonal and meridional momentum flux are shown on a log color scale. Data points were removed where the vertical wavelength is below 6 km or above 45 km. Wave properties are only significant in regions where the amplitude is higher for each data set.



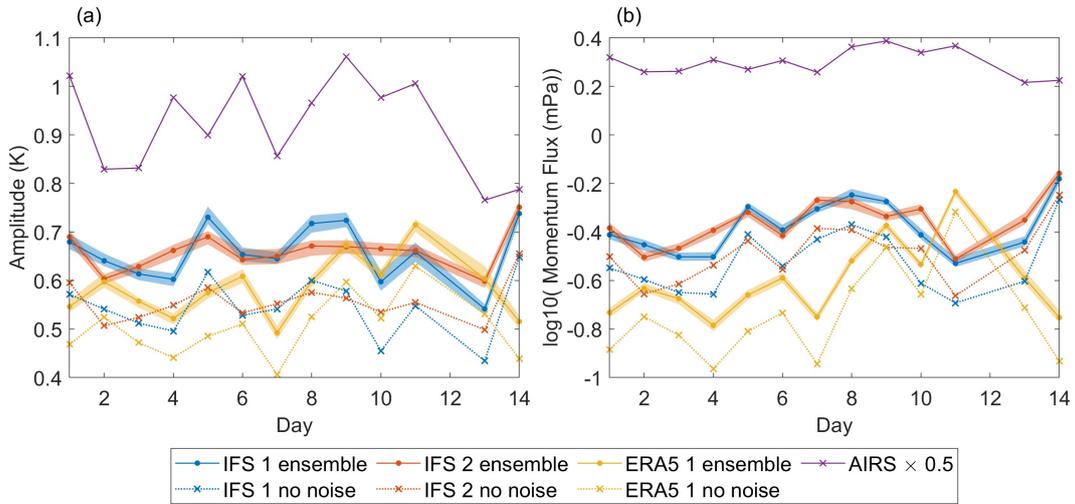
**Figure 5.** As in Figure 3 at 39 km altitude, but for AIRS granules with mean times from 19:14 to 19:26 UTC on the 9<sup>th</sup> November 2018 (a) and the resampled models at the closest times (b–d) with and (f–h) without AIRS noise added.



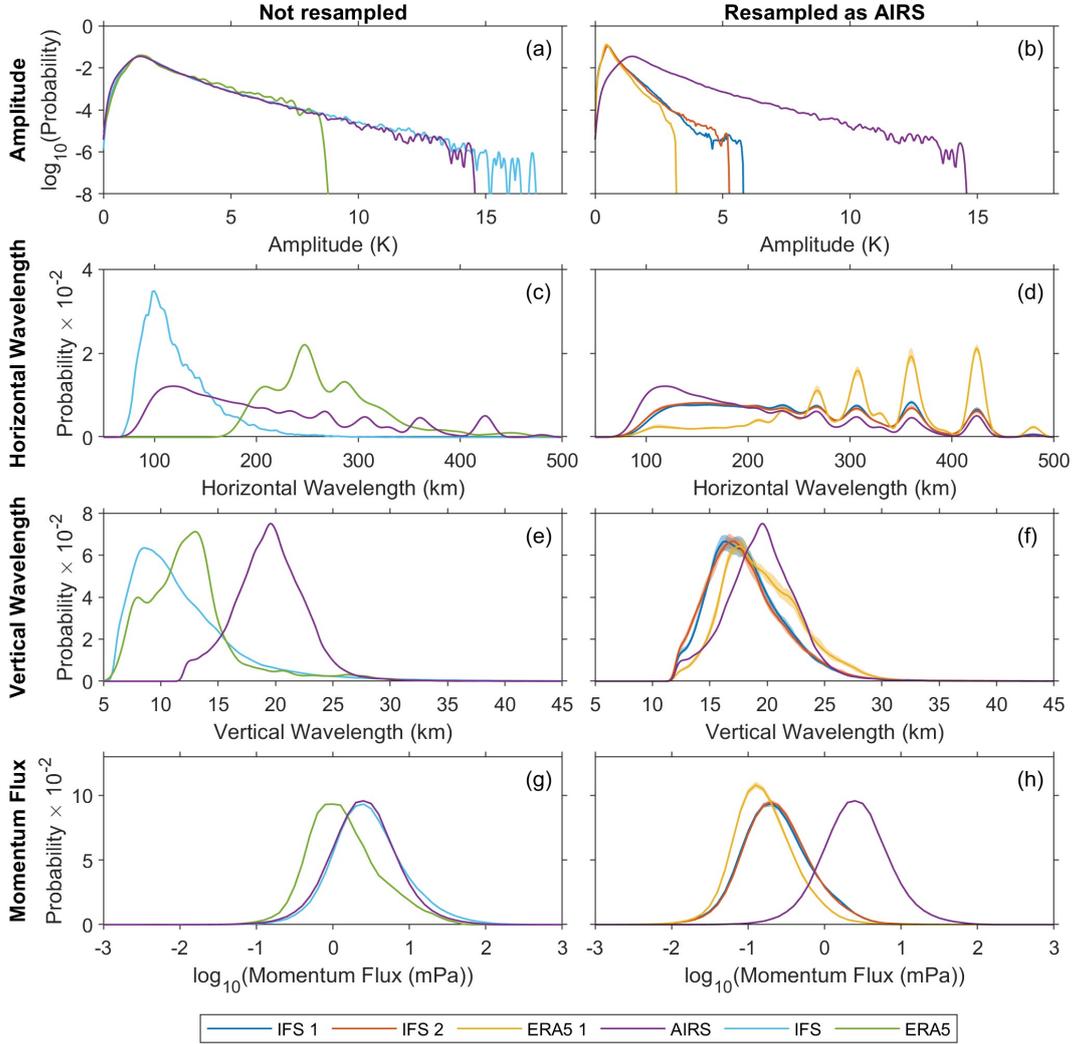
**Figure 6.** As in Figure 4 at 39 km altitude, but for wave properties for the granules shown in Figure 5. The zonal and meridional momentum flux (MF) are shown on a log color scale.



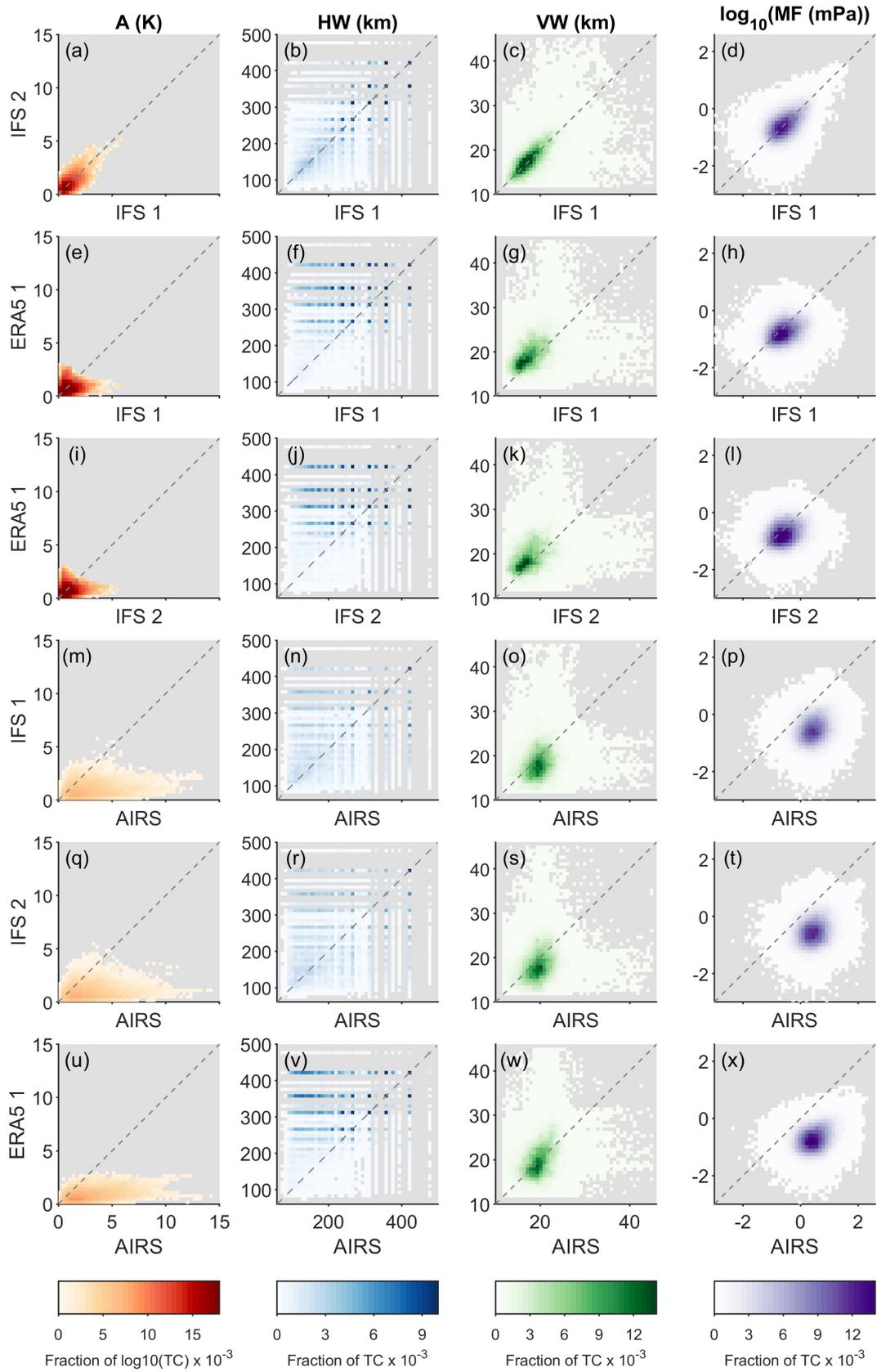
**Figure 7.** Mean amplitude (a–d) and mean zonal (e–h) and meridional (i–l) momentum flux at 39 km altitude in the region shown in Figure 1 for nighttime data in the first 10 days of November 2018. These are plotted on a regular distance grid with a point spacing of 50 km by 50 km. AIRS amplitudes in (a) are divided by 2. The zonal and meridional momentum flux are shown on a log color scale.



**Figure 8.** Mean amplitude (a) and the mean of the logarithm to base 10 of the momentum fluxes (b) for each night in the first 10 days of November 2018. The day on the x-axis shows the day of the start of each night in November 2018. Crosses show the mean for AIRS and the resampled models without added scaled AIRS noise. The circles show the median of the means for an ensemble with 100 members where scaled AIRS noise is added to the resampled models and the shading behind the solid lines with circles shows the range from the minimum to the maximum mean value for each day of the 100 ensemble members. Lines are shown between the data points to make it clearer where all the data points are for each dataset.



**Figure 9.** Kernel distribution functions (KDFs) for the wave properties in nighttime data at 39 km altitude for AIRS and the models before resampling (the 1 km IFS run (IFS) and ERA5) (panels a, c, e and g) and for the median distribution from a 100 member added noise ensemble for the resampled 1 km IFS run (IFS 1 and 2) and the median for the added noise ensemble for ERA5 resampled as AIRS (ERA5 1) shown with the KDFs for AIRS in panels (b, d, f and h). The KDFs for the amplitude have been logged to base 10. Noise is reduced by using a 70<sup>th</sup> percentile amplitude cutoff for the resampled models and AIRS, and AIRS’s amplitude cutoff is also used for ERA5 and the 1 km IFS run before resampling. The shading behind the lines showing the median distribution for the resampled model ensembles shows the range from the minimum to the maximum probability in the ensemble.



**Figure 10.** Bivariate histograms of wave properties (amplitude (A), horizontal wavelength (HW), vertical wavelength (VW) and momentum flux (MF)) plotted using nighttime data from the first 10 days of November 2018 in the region shown in Figure 1 at 39 km altitude. The color scales show the fraction of the total bin counts (TC) for each subplot.