1	Characteristics of gravity waves from convection and implications
2	for their parameterization in global circulation models
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### ABSTRACT

Characteristic properties of gravity waves from convection over the Continental United States 7 are derived from idealized high-resolution numerical simulations. In a unique modeling ap-8 proach, waves are forced by a realistic thermodynamic source based on observed precipitation 9 data. The square of the precipitation rate and the gravity wave momentum fluxes both show 10 log-normal occurrence distributions, with long tails of extreme events. Convectively gener-11 ated waves can give forces in the lower stratosphere that at times rival orographic wave 12 forcing. Throughout the stratosphere, zonal forces due to convective wave drag are much 13 stronger than accounted for by current gravity wave drag parameterizations, so their con-14 tribution to the summer branch of the stratospheric Brewer-Dobson circulation is in fact 15 much larger than models predict. A comparison of these forces to previous estimates of 16 the total drag implies that convectively generated gravity waves are a primary source of 17 summer hemisphere stratospheric wave drag. Furthermore, intermittency and strength of 18 the zonal forces due to convective gravity wave drag in the lower stratosphere resembles 19 analysis increments, suggesting that a more realistic representation of these waves may help 20 alleviate model biases on synoptic scales. The properties of radar precipitation and gravity 21 waves seen in this study lead to a proposed change for future parameterization methods that 22 would give more realistic drag forces in the stratosphere without compromising mesospheric 23 gravity wave drag. 24

# <sup>25</sup> 1. Introduction

The meridional equator-to-pole Lagrangian-mean circulation in the stratosphere, the Brewer-Dobson circulation (BDC, Brewer (1949); Dobson (1956)), controls various dynamic and thermodynamic properties of the stratosphere. For instance, it plays a role in determining the temperature of the tropical tropopause, the amount of water vapor entering the stratosphere, the transport of aerosols, ozone and other trace gases, as well as the period of the tropical quasi-biennial oscillation.

The time scales of the BDC vary from several years in the upper stratosphere and meso-32 sphere to just weeks right above the stratosphere. The slow overturning into the mid and 33 upper stratosphere, often referred to as the "deep branch" of the BDC, is mainly present in 34 the winter hemisphere (e.g. Birner and Boenisch (2011)), mostly driven by planetary waves 35 (Plumb 2002) but partly by gravity waves (GWs). Okamoto et al. (2011) highlight the im-36 portance of orographic and non-orographic GWs in influencing the formation of the summer 37 hemispheric upward branch of the winter circulation. The summer hemisphere branch and 38 the seasonal variation in strength of the circulation is affected by small-scale GWs (Alexan-39 der and Rosenlof 1996). Alexander and Rosenlof (2003) show that smaller scale GWs also 40 dominate the wave forcing in the spring-to-summer transition season in each hemisphere. In 41 the lower stratosphere, the "lower branch" of the BDC is more symmetric between the hemi-42 spheres, mainly driven by synoptic- and planetary-scale waves and partly by GWs (Plumb 43 2002). 44

An intermodel comparison of the annual-mean upward mass flux at 70 hPa in comprehensive chemistry-climate models shows statistically significant agreement on the total strength of the circulation (Eyring et al. 2010). However, there is large variability in terms of the relative contributions of parameterized GWs versus resolved Rossby waves, ranging from close to zero to about half for GWs. The uncertainty is particularly large for non-orographic GWs. Furthermore, a 2.0-3.2% per decade acceleration of the BDC is seen across models but there again exists no consensus on the contributions from different waves types in driving this trend (Butchart et al. 2006, 2010; Cohen et al. 2014; Abalos et al. 2015). The differences in resolved versus gravity wave contributions reflect our poor ability to simulate gravity waves. Deficiencies, especially in parameterizations used for non-orographic GWs, remain a great motivation for improving our knowledge and understanding of atmospheric GWs, both through observations and numerical modeling (Alexander et al. 2010).

In this study an idealized version of the Weather Research and Forecasting (WRF) model 57 is used to determine characteristic properties of GWs from Continental U.S. convection, in 58 particular those quantities relevant to their parameterization in global models, for instance 59 the amplitude spectrum and frequency of occurrence. The modeling approach is unique 60 in that all simulations are carried out at a high horizontal resolution of 4 km and waves 61 are forced by a realistic thermodynamic source based on observed precipitation data. At 62 the same time the model is efficient enough to allow for long simulations on deep domains 63 covering most of the Continental U.S. The numerical model and use of precipitation data are 64 described in Section 2. In Section 3 the topic of wave intermittency is addressed, one of the 65 most challenging aspects of non-orographic GW drag parameterizations. We will first show 66 that the distribution of wave amplitudes over the summer U.S. agrees well with the universal 67 shape of amplitude spectra observed and modeled in other regions of the globe. Secondly, we 68 will compare the zonal wind tendencies from our model results to those in the Modern-ERa 69 Retrospective Analysis for Research and Applications (MERRA) reanalysis and highlight 70 deficiencies in their GW drag parameterizations. In Section 4 we compute the contribution 71 of our simulated GWs to the forcing of the BDC and compare to the parameterized wave 72 forcing in MERRA and the Community Atmosphere Model (CAM). Potential avenues for 73 improving GW drag parameterizations in global models are discussed in Section 5, which 74 also serves as a conclusion. 75

### <sup>76</sup> 2. Experimental setup

### <sup>77</sup> a. A numerical model with a realistic gravity wave source

This study uses the modeling approach described in Stephan and Alexander (2015), where a nonlinear idealized dry version of the WRF model is forced with high-resolution latent heating/cooling derived from precipitation observations over the Continental U.S. For several case studies, it was shown that this model produces an excellent quantitative comparison to waves observed by satellite.

Here, we simulate the entire month of June 2014 and an area covering most of the 83 Continental U.S. at a high horizontal resolution of 4 km. Fig. 1 shows the arrangement 84 of 10 sub-domains, each spanning 1000 km×1000 km. To exclude numerical artifacts close 85 to the domain boundaries the idealized WRF model is run on slightly larger domains with 86 a horizontal area of 1400 km $\times$ 1400 km. Fig. 1 shows the centers of these domains, but 87 there exist overlapping zones on each side of a domain that measure 200 km. This has the 88 additional benefit of accounting for wave horizontal propagation: GWs that are triggered by 89 convection close to a boundary and propagate out of their 1000 km  $\times$  1000 km domain will be 90 captured by the adjacent domain. Every 24 h independent model simulations are launched 91 for each sub-domain. 92

Each sub-domain is initialized every day at 00:00 UTC with a one-dimensional daily-93 mean MERRA horizontal wind and potential temperature profile computed at the MERRA 94 grid point closest to the center of the sub-domain. The 1000 km horizontal extent of the ten 95 sub-domains corresponds to the lower limit of what are considered synoptic length scales. 96 Therefore, large-scale background wind patterns, which are key for modeling wave-mean flow 97 interactions, are adequately captured by our experimental setup. In terms of the vertical 98 grid, there are 104 vertical levels with a spacing increasing linearly from 100 m at the surface 99 to 600 m at 2400 m, and a constant separation of 600 m above 2400 m. The model top is 100 at 65 km (0.1 hPa), with the upper 10 km consisting of a damping layer. For a detailed 101

description of the model, see Stephan and Alexander (2015).

The heating algorithm for converting rain rates to latent heating/cooling is developed, 103 tested and described in detail in Stephan and Alexander (2015). The algorithm is derived 104 from the precipitation and latent heating field of a full-physics WRF simulation which in-105 cludes the developing, mature and decaying stages of typical continental convection. It 106 relates 10-min surface precipitation rates averaged over an area of  $4 \text{ km} \times 4 \text{ km}$  that ex-107 ceed a convective threshold of 1 mm/10 min to the average profile of latent heating and 108 cooling. The amplitudes and depths of the heating/cooling profiles are linear functions of 109 precipitation rate. In Stephan and Alexander (2015) the idealized model was run with the 110 original heating and cooling field and with the algorithm-derived heating/cooling to show 111 that employing a convective threshold and using average profiles instead of original profiles 112 does not have a large impact on the generated GW momentum flux spectrum. The idealized 113 modeling approach reproduced the shape of full-physics GW momentum flux well and the 114 total integrated flux was within  $\pm 20\%$ . 115

The heating algorithm is suitable for precipitation data with a horizontal resolution of 116  $4 \text{ km} \times 4 \text{ km}$  and a temporal resolution of 10 min. Model runs over extended periods of time 117 and large areas require a gridded precipitation data set. In this study we use the National 118 Centers for Environmental Prediction/Environmental Modeling Center's (NCEP/EMC) 4 119 km gridded Stage IV precipitation data to derive the time-varying heating/cooling field. 120 The Stage IV analysis is based on the multi-sensor hourly Stage III analysis produced by the 121 12 River Forecast Centers in the Continental U.S. After a manual quality control performed 122 at the River Forecast Centers it is made into a national product. The horizontal resolution 123 of the idealized WRF model is chosen to match the Stage IV horizontal grid. The total 124 precipitation for June 2014 is shown in Fig. 1 as colors. 125

While the horizontal resolution of the Stage IV analysis is appropriate for modeling GW generating convective cells, the temporal resolution of 1 h is not high enough to capture the intermittency of localized intense cells that have been observed as intense GW sources. Therefore, we have developed a statistical method to construct 10 min precipitation data
from the hourly data.

#### <sup>131</sup> b. From hourly to 10 min precipitation values

132 1) DERIVATION OF THE PRECIPITATION ALGORITHM

Our goal is to compute the probability P(P10|P60), i.e. the probability of 10 min values of precipitation P10 given a 60 min value P60. The six 10 min values are not independent as their sum needs to equal P60.

Statistics that describe how hourly accumulation values break down into 10 min accu-136 mulation values can be inferred from analyzing precipitation data with an original temporal 137 resolution of 10 min. To this end, we obtain the Storm Total Rainfall Accumulation Product 138 (STP) for individual Next-Generation Radar (NEXRAD) stations. The STP product pro-139 vides radar-estimated rainfall accumulations within 230 km of the radar in polar coordinates 140 with a resolution of 2 km  $\times 1^{\circ}$ . Data from several stations are interpolated in space and 141 time to obtain a 10 min 4 km×4 km mosaic. In this process we average overlapping arrays 142 from different stations to obtain smooth maps. This procedure is carried out for areas of 143  $2000 \text{ km} \times 2000 \text{ km}$ , time periods of 24 h and for 5 different storms: A mesoscale convective 144 complex (20 June 2007), a squall line (5 June 2005), a mesoscale convective system (13 June 145 2013), and two events of intense convection with a smaller degree of organization, one in the 146 Southeast (8 June 2014), and one in the Midwest (19 June 2014). 147

The purple histograms, labeled original data, in Fig. 2 are the distributions of  $4 \text{ km} \times 4$ km 10 min rain rates greater than zero for the 5 storm cases. The 99th and 95th percentiles are shown in each panel. Solid lines are lognormal distributions with the same mean and standard deviation as the data.

The original 10 min accumulations, denoted P10, are next integrated to obtain hourly accumulations, P60. Then, for each 10 min interval that was used in computing P60, we calculate the factor m = P10/P60, where  $0 \le P10 \le P60$  and  $0 \le m \le 1$ . A value of m = 1 corresponds to all precipitation falling within 10 min. The goal is to compute the probability distribution P(m|P60) of the factors m given a value for P60: The higher the value of P60, the higher is the probability that it rained for a longer period of time and the probability distribution becomes more strongly peaked around m = 1/6. For small P60 the probability that all rain fell within only 10 min increases and larger values of m occur more frequently.

For use in the algorithm, we combine the data from all storms and separate it into five 161 categories based on the values of the hourly accumulation: 0 mm/h < P60 < 10 mm/h, 162  $10 \text{ mm/h} \le P60 < 20 \text{ mm/h}, 20 \le P60 < 30 \text{ mm/h}, 30 \text{ mm/h} \le P60 < 40 \text{ mm/h}$  and 40 163 mm/h  $\leq P60$ . For each category let  $\nu$  denote the probability that no rain fell within a 10 164 min interval (m = 0). The values of  $\nu$  are given in Table 1. As expected, the likelihood that 165 no rain falls within some fraction of the hour decreases with increasing hourly accumula-166 tions. The probability distributions P(m|P60) for m > 0 can be approximated by lognormal 167 distributions with mean values  $\mu$  and standard deviations  $\sigma$ , also given in Table 1: 168

$$P(m|P60) = \frac{1}{m\sigma\sqrt{2\pi}}e^{\frac{-(\ln(m)-\mu)^2}{2\sigma^2}}$$
(1)

Indeed, as argued earlier,  $\mu$  decreases with larger P60, which means that small values of mbecome more likely. This translates to P60 being more equally distributed over the hour.

The algorithm for deriving 10 min values from an hourly value P60 works as follows. 171 First, the precipitation strength category is determined. If  $P60 \ge 40 \text{ mm/h}$  we assign 172 P10 = P60/6 for all six 10 min intervals that make up this hour. Otherwise we use the 173 appropriate values for  $\nu$ ,  $\mu$  and  $\sigma$  from Table 1 and loop through five of the six 10 min 174 intervals. These five intervals do not correspond to the first 50 minutes of the hour but are 175 chosen randomly to ensure that precipitation statistics are identical for all 10 min intervals 176 within the hour. For each of the 5 randomly chosen 10 min intervals  $1 \le j \le 5$  we determine 177 whether rain fell or not in a binomial trial, where the probability that rain fell is  $p = (1 - \nu)$ . 178 If rain fell, the lognormal distribution given by  $\mu$  and  $\sigma$  is randomly sampled to obtain  $m_i$ 179

and we assign  $P10_j = m_j \times P60$  to time interval j. Should for some time j > 1,  $\sum_{i=1}^{j} m_i > 1$ , the random sampling of the lognormal distribution is repeated. For the last interval, j = 6, we assign  $m = 1 - \sum_{j=1}^{5} m_j$  to ensure that P60 is matched exactly.

The green histograms in Fig. 2 show the distributions of 10 min precipitation values reconstructed from the hourly data. A two-sided Kolmogorov-Smirnov test is performed to quantify the similarity of the two histograms shown in each panel and the significance is shown at the bottom. Overall there is excellent agreement. The worst match is found for the squall-line case (5 June 2005). We suspect this can be attributed to the fast propagation speed of this storm and/or to this storm having particularly high precipitation rates.

The precipitation algorithm accurately reproduces the statistical distributions of 10 min 189 precipitation values. A good match of overall precipitation amount and of intense rain events 190 found in the tails of the distributions is essential for triggering a realistic GW spectrum in 191 the idealized model. However, there are additional factors that can affect the shape of the 192 GW spectrum above the storm, for example the horizontal distribution and organization of 193 precipitation cells and the frequency distribution of the heating in time. When applying the 194 precipitation algorithm outlined above, these variables are partially constrained because the 195 precipitation algorithm is designed to exactly reproduce the hourly accumulation value at 196 each grid point. The sub-hourly distribution of precipitation on the other hand is left to 197 chance. Therefore, additional validation of the GWs generated by the precipitation algorithm 198 is required. 199

### 200 2) VALIDATION OF WAVES GENERATED BY THE PRECIPITATION ALGORITHM

To validate GWs generated by the precipitation algorithm we perform a total of four simulations using the configuration described in Section 2 but domain sizes of 2000 km×2000 km. Two simulations are carried out for the mesoscale convective complex (20 June 2007) and two for the squall line (5 June 2005) case. For each case one simulation is based on the original 10 min precipitation data set and the other on the reconstructed 10 min data. We selected these two storms because in terms of the distributions shown in Fig. 2 they represent the best and worst match of reconstructed and original 10 min data.

Fig. 3 shows the absolute GW momentum flux spectra at 15 km as a function of phase 208 speed and propagation direction for the 4 runs. The spectra are computed from 24 h of 209 horizontal and vertical wind velocities saved every 10 min, using the method described 210 in Stephan and Alexander (2014). The white line in each panel corresponds to the 700 hPa 211 wind and the black dashed lines to the winds at levels between 700 hPa and 15 km. In 212 agreement with theory, the black dashed lines coincide well with regions of dissipation, as 213 critical level filtering occurs when a wave approaches a level where the phase speed equals 214 the wind speed. Overall, the similarity between the runs based on the original and the 215 reconstructed data is remarkable. For the squall line case there is some flux missing in the 216 direction of the 700 hPa wind. The 700 hPa wind is commonly used for estimating the 217 propagation direction and speed of the convective cells. The fact that the difference between 218 the simulations is largest in this direction supports the assertion that it is the higher-than-219 average propagation speed of this storm which causes the relatively poor match found in the 220 analysis of Fig. 2. 221

The spectra in Fig. 3 represent daily averages over a very large area and do not contain information about instantaneous and local magnitudes of momentum flux. The amplitude of GWs above convection is strongly tied to the strength of the underlying heating cells, which remain subgrid-scale in most climate models and represent one of the most difficult parameters to constrain in GW drag parameterizations (Richter et al. 2010). Knowledge of the local, instantaneous wave amplitudes is crucial because they determine the breaking levels of GWs.

The benefit of the modeling approach introduced in Stephan and Alexander (2015) is that the heating magnitude is directly related to observed precipitation. To verify that the realism of local wave amplitudes is not suffering from constructing 10 min precipitation data from hourly data, Fig. 4 shows the probability distributions of 100 km×100 km instantaneous

flux magnitude at 15 km (left) and 35 km (right) height, for the squall line case (top) 233 and the mesoscale convective complex (bottom). The flux magnitudes are derived by first 234 computing  $\hat{u}(x, y, k, l)$ ,  $\hat{v}(x, y, k, l)$  and  $\hat{w}(x, y, k, l)$  every 10 min using a two-dimensional 235 S-transform (Stockwell et al. 1996). Here,  $\hat{u}$ ,  $\hat{v}$  and  $\hat{w}$  are the zonal, meridional and vertical 236 wind component amplitudes, x and y denote the horizontal grid coordinates, k and l the 237 zonal and meridional wave numbers. Fig. 4 shows values of momentum flux up to the 90th 238 percentile, obtained by integrating  $\sqrt{(\hat{u}\hat{w}^* + \hat{v}\hat{w}^*)}$  over all k and l and areas of 100 km×100 239 km and multiplication by the air density  $\rho$ . Here,  $\hat{w}^*$  denotes complex conjugation. The 240 range of fluxes is shorter at the higher altitude because the largest amplitude waves have 241 dissipated below. The similarity of the purple (original resolution of 10 min) and green 242 histograms (reconstructed data) is assessed with a two-sided Kolmogorov-Smirnov test. The 243 largest discrepancy occurs at 35 km for the squall line case as should be expected from the 244 previous discussion. In general the differences between the distributions are small and the 245 agreement very good. 246

## <sup>247</sup> 3. Intermittency in simulated gravity wave spectra

Previous modeling efforts as well as observational studies with stratospheric balloons and 248 satellites emphasize the high intermittency of the GW field (e.g., Hertzog et al. (2012);Hert-249 zog et al. (2013)). This has implications for GW parameterizations in global models. A 250 given average flux produced by a large number of small-amplitude wave events will produce 251 drag at much higher altitudes than the same average flux carried by a small number of 252 high-amplitude wave packets. As argued in the previous section, the idealized model uses a 253 precipitation field with a highly realistic variability as input. In this section we quantify the 254 intermittency of the GW momentum flux spectrum over the Continental U.S. for the month 255 of June 2014. 256

#### <sup>257</sup> a. Momentum flux amplitude

The top panel of Fig. 5 shows probability density functions of simulated absolute zonal 258 momentum flux amplitudes averaged over 100 km  $\times$  100 km and 3 h for different altitudes. 259 The average is computed from an accumulated value of u'w', which is updated every 15 260 seconds. Cloud-resolving models predict that convectively generated GWs typically have 261 time periods ranging from 10 min to several hours (e.g. Piani et al. (2000)). The 3 h interval 262 for averaging is chosen to include contributions of waves with a large range of frequencies 263 while minimizing the effect of wave cancellation that can occur when waves propagating in 264 opposite directions overlap: The speed at which average storms travel is small enough to 265 produce an approximately concentric wave field of waves propagating out and away from the 266 source. 267

The mean value, 90th and 99th percentiles as well as the percentages of flux associated 268 with values larger than the percentiles are also indicated. The black dashed line is a log-269 normal distribution with the same mean and standard deviation as the spectrum at 15 km. 270 Lognormal distributions have been found to describe well the spectra of GW momentum 271 flux in other regions of the world. Hertzog et al. (2012) examined Vorcore balloon and High 272 Resolution Dynamics Limb Sounder (HIRDLS) satellite observations of absolute zonal mo-273 mentum flux between  $50^{\circ}$ S and  $65^{\circ}$ S at 20 km over the Southern Ocean and found that both 274 data sets are well approximated by lognormal distributions. In their study of deep tropical 275 convection, Jewtoukoff et al. (2013) also obtained lognormal distributions of absolute mo-276 mentum flux from balloon observations during the PreConcordiasi campaign. In particular, 277 they found a typical mean momentum flux value of 5 mPa in the tropics at 20 km during 278 the months of February to May, which is close to our mean value of 6 hPa at 20 km. 279

Another feature that our results share with previous findings is self-similarity. The 90th and 99th percentiles of momentum flux distributions explain about the same proportions of the total flux at different altitudes, 50% for the 90th percentile and 10% for the 99th percentile. Hertzog et al. (2012) reported self-similarity with identical fractions in their WRF simulations over Antarctica, examining different heights. These findings are in agreement with work by de la Camara et al. (2014), who encountered these same proportions in their analysis of a multiwave stochastic parameterization of non-orographic GWs tuned and tested against Concordiasi observations. Specifically, their analysis suggests that this self-similarity holds independent of season, latitude and height.

Furthermore, de la Camara et al. (2014) suggest that the lognormality of the GW momen-289 tum flux source spectra may be related to a lognormal behavior of the squared precipitation 290 probability density function. This quantity is shown as histograms in the bottom panel of 291 Fig. 5 for the Stage IV data, labeled observations (green), and the reconstructed precipitation 292 data (black), which we use in the heating algorithm for forcing the idealized WRF model. 293 The resolution has been degraded to  $100 \text{ km} \times 100 \text{ km}$  and 3 h to match that of the momen-294 tum flux amplitudes. The dashed lines are lognormal distributions with the same mean and 295 standard deviation. Indeed, the lognormal curves represent the precipitation strength dis-296 tributions very accurately up to the 99th percentiles. They tend to slightly overestimate the 297 occurrence frequencies of large precipitation rates, but this is also true for the momentum 298 flux amplitudes in the upper panel. 299

Also shown are the precipitation strength distributions for MERRA reanalysis data during June 2014 and the CAM5 model. The CAM5 precipitation data used in this plot are composed of different years of CAM5 runs, as will be explained in detail in section 4.*a*. We notice that both MERRA and CAM5 underestimate stronger precipitation rates and do not follow lognormal distributions, as can be seen by comparing the histograms to the corresponding dashed lines. This has implications for the potential of improving the parameterizations of non-orographic GWs in these models.

### 307 b. Zonal wind tendencies in the stratosphere

Next, we will examine the GW drag in the idealized WRF model and compare to MERRA reanalysis. Orographic waves are stationary and break at lower levels, whereas the non-

orographic spectra include a range of phase speeds. Orographic GW drag in MERRA is 310 parameterized using the scheme by McFarlane (1987) and non-orographic wave effects are 311 based on Garcia and Boville (1994). In MERRA history files, orographic and non-orographic 312 GW drag are combined and saved in one field. To compare to the non-orographic component 313 of the forcing, we select regions 2, 7 and 8 (see Fig. 1), because the contribution of orographic 314 waves is negligible there. The top panel of Fig. 6 shows the WRF daily mean zonal forcing, 315 which is given by  $F_z = -\frac{1}{\rho} \frac{\delta}{\delta z} \left[ \overline{\rho u' w'} \right]$ , where  $\overline{\rho u' w'}$  is the momentum flux as computed in 316 Section 2.b.2. To facilitate the comparison to MERRA, values have been interpolated to 317 MERRA pressure levels. The blue line below the top panel shows the time evolution of 10 318 min Stage IV precipitation averaged over sub-domains 2, 7 and 8. Daily mean MERRA 319 precipitation averaged over these 3 sub-domains is almost identical to Stage IV. The panel 320 in the center shows the MERRA GW drag and the bottom panel the MERRA GW drag 321 plus analysis zonal wind increments. During a 6h-update cycle, the analysis corrections 322 (observation-minus-background departures) are applied to the forecast model through an 323 additional tendency term in the model equations (Rienecker et al. 2011). The panels on the 324 right show the monthly mean forcing (solid purple line) plus/minus one standard deviation 325 (dotted green lines). 326

Comparing the WRF and MERRA GW drag, it is apparent that the forcing in WRF 327 is at least one order of magnitude stronger. This can be attributed to waves with large 328 amplitudes that are triggered by intense convection and break in the stratosphere. The 329 GW source spectrum in MERRA is not tied to the underlying convection, misses these 330 high-amplitude waves completely, and therefore exhibits a very homogeneous behavior in 331 time in the stratosphere. Analysis wind increments in the middle atmosphere are thought 332 of as partially correcting for missing GW drag in coarse models (e.g., McLandress et al. 333 (2012)), and when considering MERRA GW drag plus analysis increments the temporal 334 intermittency in the lowermost stratosphere below 50 hPa compares much better to WRF. 335 This suggests that a more realistic representation of convectively generated GWs may help 336

alleviate model biases near the tropopause on synoptic scales and represents a problem worth
 further investigation in the future.

# <sup>339</sup> 4. The contribution to the Brewer-Dobson circulation

In this section we quantify the role of GWs from Continental U.S. convection in driving the Brewer-Dobson circulation by comparing to the forcings in MERRA and CAM5.

### 342 a. CAM5 data

For a detailed description of the CAM5 model used in this section see Richter et al. (in review) and the references therein. The model has 46 vertical levels with a model top at 0.3 hPa and a horizontal resolution of 100 km. The parameterization of non-orographic GWs follows Richter et al. (2010) and includes a frontal GW drag scheme as well as a convective GW drag scheme.

The convective GW drag scheme is a so-called source parameterization based on Beres 348 (2004). Source parameterizations link characteristics of GWs to the underlying wave source, 349 namely the convective heating field in the model. One key parameter in the Beres scheme 350 is the convective heating rate, which determines the amplitude of the waves. However, this 351 quantity is only known as an average over a model grid box. To estimate a heating rate 352 representative of individual convective cells, it is assumed that convection takes up 5% of 353 the area of a grid box. Wave amplitude, specified as momentum flux, is proportional to the 354 square of this local heating rate. As a consequence, the amplitude of the waves is the least 355 certain aspect of this parameterization. 356

In addition to wave amplitude, wave horizontal phase velocities and propagation directions need to be estimated. These are primarily affected by the depth of the heating and by the mean tropospheric winds. Once amplitude and propagation characteristics are determined, the parameterization launches waves at the top of the convective heating. Wave drag is created at levels where the upward propagating waves dissipate above the wave breaking level according to the Lindzen-McFarlane parameterization method (see Garcia et al.
(2007)).

Given this sensitivity to the heating and the background wind profile, for a comparison 364 between the GW drag in WRF versus CAM5 it would be ideal if both models had identical 365 mean background wind profiles and similar precipitation characteristics. Since this is gener-366 ically not the case, we find a corresponding June from the 10 year CAM5 simulation that 367 most closely matches the zonal wind and precipitation strength in the WRF simulations, 368 separately for each domain. Fig. 7 shows the corresponding June monthly mean zonal wind 369 and precipitation strength distributions for WRF (solid lines) and CAM5 (dashed lines). For 370 all domains the monthly mean value of 100 km  $\times 100$  km average precipitation rate, shown 371 in the panel, is smaller for CAM5. In addition, as noted beforehand in the discussion of 372 Fig. 5, CAM5 as well as MERRA underestimate stronger precipitation rates. 373

#### 374 b. Missing convective GWD

The left panel of Fig. 8 displays the zonal wind tendencies averaged over June 2014 and the area covered by the 10 model domains for the WRF simulations (purple), all CAM5 GW drag schemes combined (orange) and MERRA GW drag plus analysis corrections (green). The middle panel shows how the CAM5 tendencies break down into forcing from convective, frontal and orographic GWs, and the panel on the right distinguishes between MERRA GW drag and analysis increments. Recall that the values for the CAM5 model are composed of different years of simulations as described in the previous paragraph.

Alexander and Rosenlof (1996) computed the contribution of small-scale waves (wavelengths  $\leq 1000$  km) to the forcing of the BDC as the residual difference between total and resolved forcing estimates for data sets from the National Meteorological Center and the UK Meteorological Office, and the Upper Atmosphere Research Satellite (UARS). For June they obtained typical values of -1 m/s/day at 10 hPa and +4 m/s/day at 1 hPa (their Figure

1). Table 2 lists the contribution of the modeled area to the zonal mean forcing for all 387 available components of GW drag and in three different altitude layers representing lower 388 (100-10 hPa) and upper (10-1h Pa) stratosphere and stratopause (1-0.4 hPa), i.e. the forcing 389 averaged over the simulated area multiplied by 0.16, because our simulations cover 16% of 390 the total area in the latitude band  $25.7-48.5^{\circ}$ N. Assuming that the remaining 84% of the 391 latitude band provide a similar wave driving, the WRF GW drag tendencies averaged over 392 10-1 hPa and 1-0.4 hPa constitute a fairly good match of the values reported by Alexander 393 and Rosenlof (1996). There is evidence that this assumption may be valid because the pre-394 cipitation averaged over the area of our study is similar to precipitation averaged over the 395 full latitude band. This comparison of the WRF GWD to Alexander and Rosenlof (1996) 396 provides further evidence that our model of convectively generated waves is realistic, and 397 that these waves can provide all of the unresolved stratospheric forcing needed to drive the 398 Brewer-Dobson circulation at these latitudes. 399

It is particularly noteworthy that the GW drag in our simulations, which is purely convec-400 tive, is larger than the CAM5 orographic GW drag averaged over 100-10 hPa. The changes 401 of GW drag with altitude seen in Fig. 8 and Table 2 highlight a common misconception that 402 it is primarily only orographic GW drag that is relevant in the lower stratosphere owing to 403 its large-amplitude waves that break at lower levels, while non-orographic GW drag, as it is 404 currently parameterized, primarily only affects high altitudes. The middle panel of Fig. 8 405 as well as the numbers in lines 2 and 3 of Table 2, showing separately the convective and 406 orographic GW drag contributions in CAM5 at different levels, illustrate this condition in 407 CAM5. In reality convectively generated GWs can have large amplitudes and therefore also 408 break in the lower stratosphere. Even the more advanced source parameterization in CAM5 409 underestimates high-amplitude waves, which results in missing GW drag in the stratosphere. 410 We also note that the MERRA GW drag and analysis increments combined (last line of Ta-411 ble 2) are of similar magnitude compared to the WRF tendencies in the lower stratosphere 412 (100-10 hPa), even though their structure with height (Fig. 8) is quite different. 413

# <sup>414</sup> 5. Discussion and conclusion

We analyzed observed precipitation data and GWs in high-resolution simulations of June 415 2014 over the Continental U.S. In an idealized version of the WRF model, waves were forced 416 by a realistic thermodynamic source based on observed precipitation data. At horizontal 417 scales of  $100 \text{ km} \times 100 \text{ km}$  we found that the probability distribution of momentum flux 418 amplitudes above the storms and the square of precipitation rate both follow lognormal 419 distributions, a characteristic that has been reported for simulations, as well as observations, 420 in multiple other regions of the globe. An important feature of lognormal distributions is the 421 long tail consisting of rare and extreme values. Not capturing this high degree of variability 422 in wave amplitudes has important implications for GW drag parameterizations, as the wave 423 amplitudes determine the height at which waves break and deposit their momentum. 424

Comparing the daily mean wave forcing in our simulations to GW drag in MERRA reanalysis data, we found the parameterization in MERRA is underestimating both the variability and the magnitude of the GW drag throughout the stratosphere. This result was somewhat expected because the GW source spectrum in MERRA is homogenous in space and time and therefore does not include high-amplitude wave events. The intermittency and magnitude of zonal wind tendencies stemming from MERRA analysis increments in the lowermost stratosphere are more similar to the simulations.

Lastly, we examined monthly mean zonal wind tendencies in the simulations to evaluate 432 their contribution to the Brewer-Dobson circulation, and compare these to MERRA, and 433 the CAM5 model. The CAM5 model includes an orographic and frontal GW drag scheme, 434 as well as a convective GW source parameterization. However, neither the GW drag scheme 435 in MERRA nor the more advanced source parameterization in CAM5 are including enough 436 high-amplitude waves. This results in missing GW drag, particularly in the stratosphere. 437 Previous studies found similar deficiencies in the tropics. For example, Schirber et al. (2014) 438 showed that aspects of the quasi-biennial oscillation can be improved by using a GW source 439 parameterization instead of assuming constant spectra in the WACCM model. Lott and Guez 440

(2013) also found a more intermittent spectrum caused wave breaking at lower altitudes, and
this helped to decouple the quasi-biennial oscillation from the annual cycle. Bushell et al.
(2015) tested a version of the Met Office global models spectral nonorographic scheme with
enhanced source intermittency at the launch level and report an improved representation of
the quasi-biennial oscillation.

An important aspect of our modeling approach is that we use a statistical method to 446 derive 10 min precipitation values from an hourly data set. Given that precipitation char-447 acteristics exhibit a universal behavior it seems conceivable that a similar method could be 448 applied to grid point precipitation values in global models, possibly providing a way to esti-449 mate a spatial sub-gridscale variability in addition to the temporal statistical refinement. As 450 a result one could obtain a realistic distribution of cloud-scale precipitation rates. Further, 451 by using a heating algorithm similar to Stephan and Alexander (2015), these precipita-452 tion rates could be converted to local heating amplitudes, the most uncertain parameter in 453 current parameterizations. Combining the Beres (2004) parameterization with a stochastic 454 approach by randomly choosing from this heating amplitude distribution has several ben-455 efits: A constant convective fraction of 5% would no longer need to assumed. A realistic 456 intermittency in wave amplitudes could be obtained with some waves breaking in the lower 457 stratosphere. Most waves will still have fairly small amplitudes such that it is unlikely to 458 cause aggravating effects on the mesospheric wave forcing as a result of these suggested pa-459 rameterization changes. This more physically based approach could potentially come at no 460 extra computational cost and adapt naturally to changes in climate. 461

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# 565 List of Tables

<sup>566</sup> 1 Values for the three parameters needed to derive 10 min precipitation rates <sup>567</sup> from hourly precipitation rates for the 4 precipitation categories. Values of <sup>568</sup> P60 are given in units of mm/h. Please refer to Section 2.*b*.1 for a description <sup>569</sup> of the parameters.

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Contribution of the area covered by WRF domains to the zonal mean wind tendency for different components of GW drag. Because the simulation area covers 16% of the latitude band 25.7-48.5°N, the numbers below are obtained by multiplying the simulated wave driving by 0.16. Numbers are given in units of m/s/day and are averages of the acceleration in m/s/day at individual pressure levels over the pressure ranges indicated in the top row.

TABLE 1. Values for the three parameters needed to derive 10 min precipitation rates from hourly precipitation rates for the 4 precipitation categories. Values of P60 are given in units of mm/h. Please refer to Section 2.*b*.1 for a description of the parameters.

category:	0 < P60 < 10	$10 \le P60 < 20$	$20 \le P60 < 30$	$30 \le P60 < 40$
ν	0.58	0.33	0.23	0.15
$\mu$	-1.29	-1.76	-1.86	-1.90
σ	0.97	0.98	0.96	0.88

TABLE 2. Contribution of the area covered by WRF domains to the zonal mean wind tendency for different components of GW drag. Because the simulation area covers 16% of the latitude band 25.7-48.5°N, the numbers below are obtained by multiplying the simulated wave driving by 0.16. Numbers are given in units of m/s/day and are averages of the acceleration in m/s/day at individual pressure levels over the pressure ranges indicated in the top row.

pressure range:	100 - 10  hPa	10 - 1 hPa	1 - 0.4 hPa
WRF gwd	-0.072	-0.156	0.639
CAM conv. gwd	-0.003	-0.014	0.044
CAM oro. gwd	-0.009	< 0.001	0.001
CAM fro. gwd	-0.008	-0.035	-0.030
CAM tot. gwd	-0.019	-0.048	0.015
MER gwd	-0.009	-0.029	0.025
MER gwd+ana	-0.052	-0.037	-0.183

### 576 List of Figures

1 Map of the locations of the ten  $1000 \text{ km} \times 1000 \text{ km}$  WRF domains that are 577 evaluated in this study. Colors indicate the NCEP 4 km Stage IV total pre-578 cipitation for June 2014. Latitude and longitude are shown on the axes. 579 Histograms of  $(10\text{-min precipitation rate})^2$  based on 24 h of data in an area of 2580  $2000 \text{ km} \times 2000 \text{ km}$ , showing occurrence frequencies at a horizontal resolution 581 of 4 km. The 5 panels correspond to 5 different storms. Violet colors denote 582 data with an original temporal resolution of 10 min and green colors are values 583 obtained after degrading the data to an hourly resolution and reconstructing 584 it using the algorithm described in the text. The 99th and 95th percentiles of 585 the distributions are indicated, as well as the probability that both histograms 586 are statistically identical. The solid lines are lognormal distributions with the 587 same mean and standard deviation as the data. 588

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<sup>589</sup> 3 Total momentum flux spectra for the squall line case (left) and mesoscale <sup>590</sup> convective complex (right) at 15 km altitude as a function of propagation <sup>591</sup> direction and ground-relative phase speed obtained from 24 h simulations on <sup>592</sup> 2000 km×2000 km large domains with a horizontal resolution of 4 km. Labels <sup>593</sup> indicate whether the model is based on the original 10 min data set or the <sup>594</sup> reconstructed data. White lines are the 700 hPa steering level winds and black <sup>595</sup> dashed lines the winds at levels between 700 hPa and 15 km.

<sup>596</sup> 4 Probability distributions of simulated 100 km×100 km instantaneous total
<sup>597</sup> flux amplitude at 15 km (left) and 35 km (right), for the squall line case
<sup>598</sup> (top) and the mesoscale convective complex (bottom), comparing simulations
<sup>599</sup> based on the original 10 min data (purple) and the reconstructed data (green).
<sup>600</sup> Values of momentum flux up to the 90th percentile are displayed.

5Combining data from all simulations, the top panel shows probability density 601 functions of absolute zonal momentum flux amplitudes averaged over 100 602  $km \times 100$  km and 3 h for different altitudes. The mean value, 90th and 99th 603 percentiles as well as the percentages of flux associated with values larger 604 than the percentiles are also indicated. The black dashed line is a lognormal 605 distribution with the same mean and standard deviation as the distribution at 606 15 km. The bottom panel displays probability density functions of 3 h squared 607 precipitation for the Stage IV data (green), the data used to force the WRF 608 model (black), MERRA (blue) and CAM (red). The respective horizontal 609 resolutions are indicated. Dashed lines are again lognormal distributions with 610 the same mean and standard deviation as the data. 33 611 6 Daily mean zonal wind tendencies for simulated GW drag (top), MERRA GW 612 drag (middle) and MERRA GW drag plus analysis increments. The blue line 613 below the top panel shows the time evolution of precipitation and the panels 614 on the right show the monthly mean forcing (solid purple line) plus/minus 615 one standard deviation (dotted green lines). 34 616 7 For each domain June monthly-mean zonal wind and monthly mean 100 km 617  $\times$  100 km average precipitation strength distributions are shown. WRF data 618 are solid lines and the corresponding values from the best matching CAM5 619 35year are dashed lines. 620 Left panel: Zonal wind tendencies averaged over June 2014 and the area 8 621 covered by the ten model domains for the WRF simulations (purple), all 622 CAM5 GW drag schemes combined (orange) and MERRA GW drag plus 623 analysis corrections (green). Middle panel: convective, frontal and orographic 624 CAM5 tendencies. Right panel: MERRA GW drag and analysis increments. 625 The values for the CAM5 model are composed of different years of simulations 626 as described in the text. 36 627



FIG. 1. Map of the locations of the ten 1000 km  $\times$  1000 km WRF domains that are evaluated in this study. Colors indicate the NCEP 4 km Stage IV total precipitation for June 2014. Latitude and longitude are shown on the axes.



FIG. 2. Histograms of  $(10\text{-min precipitation rate})^2$  based on 24 h of data in an area of 2000 km×2000 km, showing occurrence frequencies at a horizontal resolution of 4 km. The 5 panels correspond to 5 different storms. Violet colors denote data with an original temporal resolution of 10 min and green colors are values obtained after degrading the data to an hourly resolution and reconstructing it using the algorithm described in the text. The 99th and 95th percentiles of the distributions are indicated, as well as the probability that both histograms are statistically identical. The solid lines are lognormal distributions with the same mean and standard deviation as the data.



FIG. 3. Total momentum flux spectra for the squall line case (left) and mesoscale convective complex (right) at 15 km altitude as a function of propagation direction and ground-relative phase speed obtained from 24 h simulations on 2000 km×2000 km large domains with a horizontal resolution of 4 km. Labels indicate whether the model is based on the original 10 min data set or the reconstructed data. White lines are the 700 hPa steering level winds and black dashed lines the winds at levels between 700 hPa and 15 km.



FIG. 4. Probability distributions of simulated 100 km  $\times$  100 km instantaneous total flux amplitude at 15 km (left) and 35 km (right), for the squall line case (top) and the mesoscale convective complex (bottom), comparing simulations based on the original 10 min data (purple) and the reconstructed data (green). Values of momentum flux up to the 90th percentile are displayed.



FIG. 5. Combining data from all simulations, the top panel shows probability density functions of absolute zonal momentum flux amplitudes averaged over  $100 \text{ km} \times 100 \text{ km}$  and 3 h for different altitudes. The mean value, 90th and 99th percentiles as well as the percentages of flux associated with values larger than the percentiles are also indicated. The black dashed line is a lognormal distribution with the same mean and standard deviation as the distribution at 15 km. The bottom panel displays probability density functions of 3 h squared precipitation for the Stage IV data (green), the data used to force the WRF model (black), MERRA (blue) and CAM (red). The respective horizontal resolutions are indicated. Dashed lines are again lognormal distributions with the same mean and standard deviation as the data.



FIG. 6. Daily mean zonal wind tendencies for simulated GW drag (top), MERRA GW drag (middle) and MERRA GW drag plus analysis increments. The blue line below the top panel shows the time evolution of precipitation and the panels on the right show the monthly mean forcing (solid purple line) plus/minus one standard deviation (dotted green lines).



FIG. 7. For each domain June monthly-mean zonal wind and monthly mean 100 km  $\times$  100 km average precipitation strength distributions are shown. WRF data are solid lines and the corresponding values from the best matching CAM5 year are dashed lines.



FIG. 8. Left panel: Zonal wind tendencies averaged over June 2014 and the area covered by the ten model domains for the WRF simulations (purple), all CAM5 GW drag schemes combined (orange) and MERRA GW drag plus analysis corrections (green). Middle panel: convective, frontal and orographic CAM5 tendencies. Right panel: MERRA GW drag and analysis increments. The values for the CAM5 model are composed of different years of simulations as described in the text.