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Variability in projected elevation dependent warming in boreal midlatitude winter in CMIP5 climate models and its potential drivers

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Abstract The future rate of climate change in mountains has many potential human impacts, including those related to water resources, ecosystem services, and recreation. Analysis of the ensemble mean response of CMIP5 global climate models (GCMs) shows amplified warming in high elevation regions during the cold season in boreal midlatitudes. We examine how the twenty-first century elevation-dependent response in the daily minimum surface air temperature [d(ΔTmin)/dz] varies among 27 different GCMs during winter for the RCP 8.5 emissions scenario. The focus is on regions within the northern hemisphere mid-latitude band between 27.5°N and 40°N, which includes both the Rocky Mountains and the Tibetan Plateau/Himalayas. We find significant variability in d(ΔTmin)/dz among the individual models ranging from 0.16 °C/km (10th percentile) to 0.97 °C/km (90th percentile), although nearly all of the GCMs (24 out of 27) show a significant positive value for d(ΔTmin)/dz. To identify some of the important drivers associated with the variability in d(ΔTmin)/dz during winter, we evaluate the co-variance between d(ΔTmin)/dz and the differential response of elevation-based anomalies in different climate variables as well as the GCMs' spatial resolution, their global climate sensitivity, and their elevation-dependent free air temperature response. We find that d(ΔTmin)/dz has the strongest correlation with elevation-dependent increases in surface water vapor, followed by elevation-dependent decreases in surface albedo, and a weak positive correlation with the GCMs' free air temperature response.

Keywords Elevation dependent warming · Mountains · Rocky Mountains · Tibetan Plateau · Water vapor · Snow albedo · Feedbacks · Temperature · EDW · Winter · CMIP5 · GCM

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1 Introduction

A critical climate research question that has emerged during the last two decades is whether high elevation regions are more sensitive than other regions to global climate change (Beniston et al. 1997; Messerli and Ives 1997; Rangwala and Miller 2012; Ohmura 2012). This is critical because of its implications for future rates of change in mountain cryospheric systems and their associated hydrological regimes (e.g., Bradley et al. 2006), as well as changes in the ecosystem response and the impacts on biodiversity (e.g., Trujillo et al. 2012; Rull and Vegas-Vilarrubia 2006). Our understanding of both historical and projected climate change in mountainous regions is limited by a sparsity of observations at high elevations and by a relatively coarse-representation of mountain topography in climate models (e.g., Rangwala and Miller 2012). Global climate models (GCMs) smooth the topography within a mountainous region and underrepresent the range of elevations, particularly if the mountain range is narrow. However, by examining the elevation dependent temperature response at continental to

hemispheric scales, issues related to resolution are significantly reduced because the focus is on differences between the mountain regions and the surrounding lower elevations rather than within the mountainous region itself. Such studies help us to acquire important insights into physical processes that inform the wider scientific research in mountain regions (e.g., Liu and Chen 2000; Rebetez and Reinhard 2008; Stewart 2009; Forsythe et al. 2014).

Historically, many studies have used GCMs to examine elevation dependent warming (EDW) (e.g., Fyfe and Flato 1999; Bradley et al. 2006; Liu et al. 2009; Rangwala et al. 2013). Fyfe and Flato (1999) analyzed a single GCM simulation for the U.S. Rocky Mountains and found enhanced warming at higher elevations during winter and spring because of increases in the anthropogenic radiative forcing during the twenty-first century. Similarly, Liu et al. (2009) and Rangwala et al. (2010) used a single GCM simulation to examine temperature response over the Tibetan Plateau under climate change, and found enhanced warming at higher elevations during the cold season. Bradley et al. (2006) analyzed eight GCM simulations and found greater increases in free air temperature at higher elevations along the entire extent of the American Cordillera, from Alaska to southern Chile, by the end of the twenty-first century. They suggested that this response in free air temperature could amplify the surface warming rates at higher elevations in these mountain regions, and that it could account for EDW in the tropical Andes.

Rangwala et al. (2013) used an ensemble of GCM simulations (n = 86) available from the Coupled Model Intercomparison Project-Phase 5 (CMIP5) to examine the twenty-first century mean ensemble response in the daily minimum and maximum surface air temperatures (Tmin and Tmax) as a function of elevation in the mid-latitude band between 27.5°N and 40°N, which includes both the Rocky Mountains and the Tibetan Plateau/Himalayas. They found a robust signal for EDW during winter, particularly an amplified increase in Tmin at higher elevations. They also found that this amplification in warming with elevation is greater for a higher emission scenario. For example, the value of d(ΔTmin)/dz for RCP 8.5 was found be more than twice that for RCP 4.5, where z is elevation and ΔTmin is the change in minimum temperature between the end and beginning of the twenty-first century.

The primary motivation for this study is to address some important follow-up questions raised by Rangwala et al. (2013). The objectives are to (a) examine how d(ΔTmin)/dz varies among the individual GCMs during winter, and (b) determine the degree to which the relevant climatic drivers, such as water vapor, clouds and snow cover, modulate the variability in d(ΔTmin)/dz. This study will be particularly useful to scientists who use climate models to investigate high-elevation climate change because it provides insights into how specific models respond to EDW relative to other models.

2 Methods

Based on the availability of the important climate variables, including the daily minimum temperature, specific humidity, surface elevation, and downward shortwave and longwave radiation at the land surface, we selected 27 individual GCM simulations (the first member model from each parent GCM) forced with the RCP 8.5 emissions scenario (see Table 1). The choice of this high-end emissions scenario from CMIP5 (see Vuuren et al. 2011) was made to facilitate a stronger signal-to-noise ratio under climate change. All of the analyses are based on the original grid of the individual GCM and are carried out only for winter (December, January and February). To reduce the influence of latitude, we consider land-only grid-cells (exclude water bodies) within the northern hemisphere mid-latitude band between 27.5°N and 40°N (region within the dashed lines in Fig. 1a), similar to Rangwala et al. (2013). Furthermore, our study domain includes only the North American (80°W–115°W) and Central/East Asian (55°E–115°E) regions within this band unless specified differently for a particular analysis. To explicitly reduce some of the maritime influence on the results, we do not include grid cells with elevations below 200 m, thus removing low-lying coastal regions and reducing the variability they introduce. We find that this exclusion does not significantly alter our findings. All data are accessed from the Koninklijk Nederlands Meteorologisch Instituut's (KNMI) Climate Explorer (http://climexp.knmi.nl) and the Earth System Grid (ESG) (http://www.earthsystemgrid.org) data portals for CMIP5 output.

The twenty-first century changes (denoted by Δ) in all the climate variables examined in this study are calculated based on the mean change in the variable between the 2081–2100 and 1981–2000 periods. Next, we calculate these changes as a function of the grid-cell elevation for each variable, i.e. d(Δvariable)/dz, which is the slope of the linear regression between the change in the variable (Δvariable) and elevation. Figure 1b shows an example

Table 1 CMIP5 GCMs considered in this study based on the data accessibility of required climate variables

ACCESS1_0	CSIRO_Mk3_6_0	INMCM4
ACCESS1_3	FGOALS_g2	IPSL_CM5A_LR
BCC_CSM1_1	GFDL_CM3	IPSL_CM5A_MR
BNU_ESM	GFDL_ESM2G	IPSL_CM5B_LR
CanESM2	GFDL_ESM2M	MIROC_ESM_CHEM
CCSM4	GISS_E2_H_p1	MIROC_ESM
CESM1_BGC	GISS_E2_R_p1	MIROC5
CESM1_CAM5	HadGEM2_CC	MRI_CGCM3
CNRM_CM5	HadGEM2_ES	NorESM1_M

Output from only the first member run (r1i1p1) from each GCM for the RCP 8.5 scenario were analyzed in this study

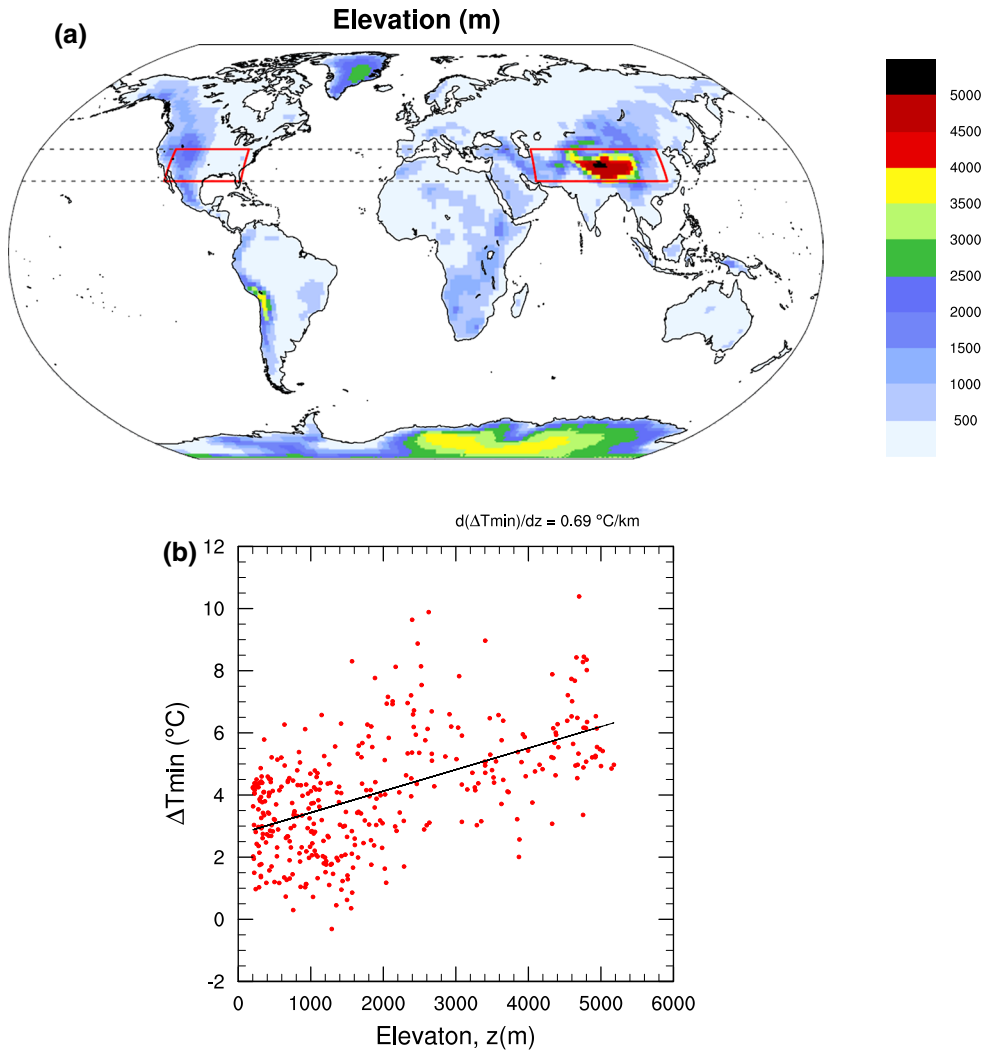

Fig. 1 **a** Land surface elevation field (m) in the INMCM4 climate model. The two regions demarcated by the *red borderlines* show the study domain between 27.5°N and 40°N (*grey dashed lines*) in the Northern Hemisphere Mid-latitude. Only grid cells with elevation above 200m are considered for the analysis. **b** Scatter plot showing d(ΔTmin)/dz for the study domain during winter from INMCM4 (r1i1p1; RCP 8.5)

using Tmin from one specific GCM. Finally, because the motivation for this study is to examine the variability in d(ΔTmin)/dz across the different GCMs and to understand the importance of the different drivers in contributing to that variability, we perform linear regressions between d(ΔTmin)/dz and metrics representing elevation-based changes in water vapor, clouds (daytime effects only that are inferred from solar radiation data), and snow cover. Owing to limited availability of GCM cloud cover output and the lack of monthly cloud data that archives night versus daytime output separately, we do not include a direct analysis of clouds, but we do assess them through their potential influence on the shortwave fluxes. We use a linear correlation *t* test to assess the statistical significance of the relationship between these variables.

In addition to examining the effects of the various climate variables on d(ΔTmin)/dz, we also evaluate the impact of the GCMs' spatial resolution, global climate sensitivity, and elevation-dependent free air temperature response. We further assess the statistical significance of our results by excluding the models with extreme d(ΔTmin)/dz values, although the availability of extreme cases is very useful for detecting signals and associations when other factors can create large variability in the signal and weaken it.

3 Results

Figure 2 shows that there is significant variability in d(ΔTmin)/dz across the different GCMs: 0.16 and 0.97 °C/km for the 10th and 90th percentiles respectively. A central range of values depicted by the 25th and 75th percentiles (gray box in the figure) lies between 0.33 and 0.72 °C/km. For our study domain, 24 of the 27 GCMs show a significant EDW trend during winter [i.e., d(ΔTmin)/dz > 0.25 °C/km].

Next, we examine the co-variance between d(ΔTmin)/dz and the selected climate variables to infer which drivers have significant influence in modulating d(ΔTmin)/

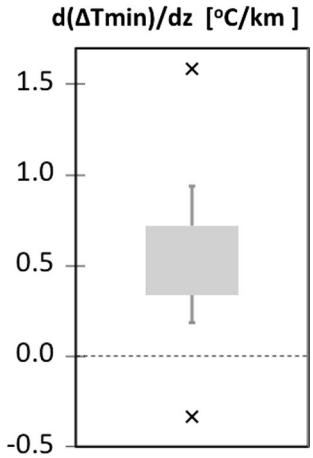

Fig. 2 Variability in d(ΔTmin)/dz (°C/km) among the 27 CMIP5 GCMs. The *box* shows the range of values between the 25th and 75th percentiles, whiskers show 10th and 90th percentiles, and the *crosses* show the minimum and maximum value

dz across the different GCMs. Figure 3 shows the linear regression between d(ΔTmin)/dz and elevation based anomalies in selected variables. We find that the highest co-variance of d(ΔTmin)/dz occurs with normalized increases in specific humidity (q) with elevation ($R^2 = 0.64$; $p < 0.001$; Fig. 3a). It is not the absolute change in q, but the normalized change ($\Delta q/q_o$), to which d(ΔTmin)/dz is most sensitive (q_o is the mean value of q for the historical time period). We discuss this issue further in the next section.

Figure 3b describes a linear regression between d(ΔTmin)/dz and elevation-based anomalies in surface albedo, which we use as a proxy for changes in snow cover. Here, we calculate surface albedo as the ratio (in %) of reflected to incident shortwave radiation (ISR). We find that there is a significant co-variance ($R^2 = 0.44$; $p < 0.001$) between d(ΔTmin)/dz and decreases in albedo with elevation, although this correlation is not as strong as that between d(ΔTmin)/dz and $d(\Delta q/q_o)/dz$.

Figure 3c shows the relationship between d(ΔTmin)/dz and elevation-based anomalies in ISR at the surface. Although differences in model treatments of atmospheric aerosol loading could account for some of the ISR variability among the different models, we expect that most of the variability in ISR is influenced by changes in cloud cover. Figure 3c shows that there is a small negative, but not a statistically significant, relationship between the two variables.

One important question that arises in high elevation regions where EDW occurs is whether it can be explained by the local increase in free air temperature. To investigate this, we evaluate the influence of the free air temperature response to anthropogenic greenhouse forcing on d(ΔTmin)/dz. The CMIP5 GCMs project a differential warming of the atmospheric column however this response has a strong latitudinal dependence (e.g., Collins et al. 2013): (a) In the tropics, between 30°N and 30°S, increases in free air temperature are greater at higher elevations with largest increases between 400 and 200 mb levels because of Clausius–Clapeyron effects, negative lapse rate feedbacks and positive upper-tropospheric water vapor feedbacks (e.g., Bony et al. 2006); (b) in mid-latitudes, there tends to be a smaller signal of EDW in free-air temperatures in the atmospheric column; (c) in polar regions, the largest free air temperature response occurs near the surface, a pattern opposite to that in the tropics. In Fig. 4a, we correlate d(ΔTmin)/dz with amplification in the zonal mean free air temperature response with elevation between 1000 and 500 mb (this level is equivalent to the highest land surface elevation in our study domain) within the selected latitudinal band. Although the correlation is statistically significant ($R^2 = 0.30$), the amplification of the surface air temperature with elevation is much greater than the free air temperature response. This implies that there are other factors, including local land–atmosphere interactions (e.g. Pepin and Lundquist 2008), that are important drivers of EDW in this mid-latitude region.

One important difference among the various CMIP5 GCMs is their spatial resolution. The spatial resolution of CMIP5 GCMs varies between 1° and 3°. With finer resolution, there are more grid cells and relatively higher elevation fields within a mountain region such as the Rocky Mountains. However, we do not find any relationship between d(ΔTmin)/dz and the spatial resolution of the GCMs. In fact, some of the highest and lowest values for d(ΔTmin)/dz are found for the models with coarser resolution. Another important difference among the GCMs is their global climate sensitivity. We use the change in the global mean temperature during the Northern Hemisphere winter (DJF) between 1981–2000 and 2081–2100 as a measure of an individual GCM's climate sensitivity, and then examine its relationship with the GCM's d(ΔTmin)/dz response in our study region. We find a weak positive but statistically significant relationship ($R^2 = 0.21$; $p < 0.05$) between a GCM's global climate sensitivity and its projected value of d(ΔTmin)/dz (Fig. 4b). However, when we exclude some of the models with extreme values of d(ΔTmin)/dz, the relationship is no longer significant.

4 Discussion: processes influencing d(ΔTmin)/dz

Rangwala et al. (2013) found a strong signal for amplified increases in Tmin at higher elevations during winter in Northern Hemisphere midlatitudes during the twenty-first century based on the ensemble mean response of CMIP5

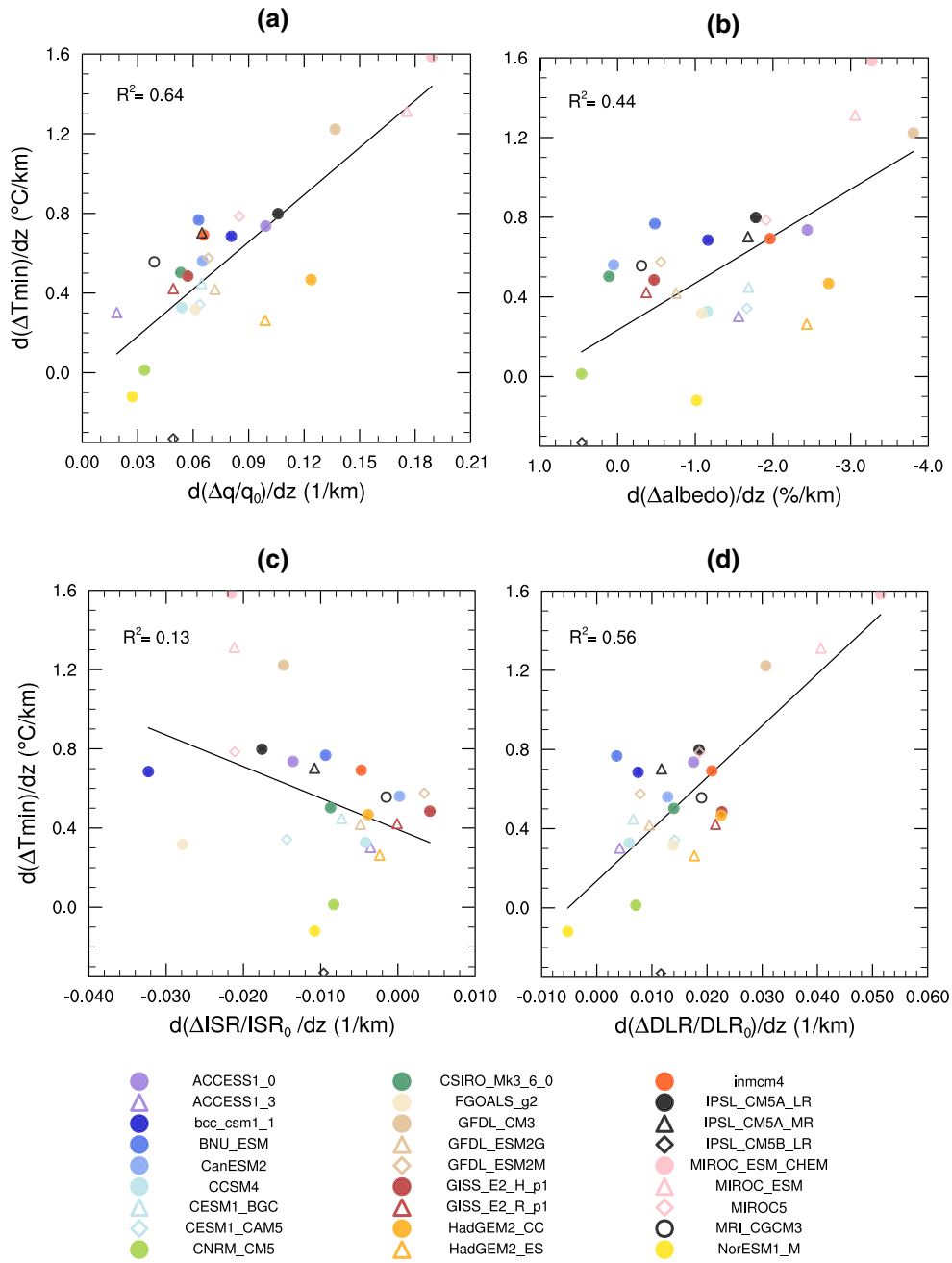

Fig. 3 Linear regression of d(ΔTmin)/dz with elevation based changes in **a** specific humidity, **b** surface albedo, **c** incoming solar radiation (ISR) and **d** downward longwave radiation (DLR)

GCMs [d(ΔTmin)/dz = 0.50 °C/km]. This follow-up study finds that there is significant variability in d(ΔTmin)/dz among the individual models ranging from 0.16 °C/km (10th percentile) to 0.97 °C/km (90th percentile). Nearly all of the GCMs (24 out of 27 models) simulate a significant positive value for d(ΔTmin)/dz. We examine the variability in d(ΔTmin)/dz based on how and to what extent the different climate variables are changing as a function of elevation in the different GCMs. Furthermore, by understanding the co-variance of the differential response of elevation-based anomalies in various relevant climate variables with respect to d(ΔTmin)/dz among different GCMs, some of the important drivers for d(ΔTmin)/dz could be identified.

We find that the largest variability in d(ΔTmin)/dz is explained by normalized changes in surface water vapor. This is consistent with previous studies that have suggested the importance of atmospheric moistening in facilitating an amplified warming response during winter in high elevation regions (Ruckstuhl et al. 2007; Rangwala et al. 2009, 2010; Rangwala 2013). For water vapor, it is the normalized change (change relative to historical climatology) and not the absolute change that is a better predictor of d(ΔTmin)/dz in the GCM simulations. This is

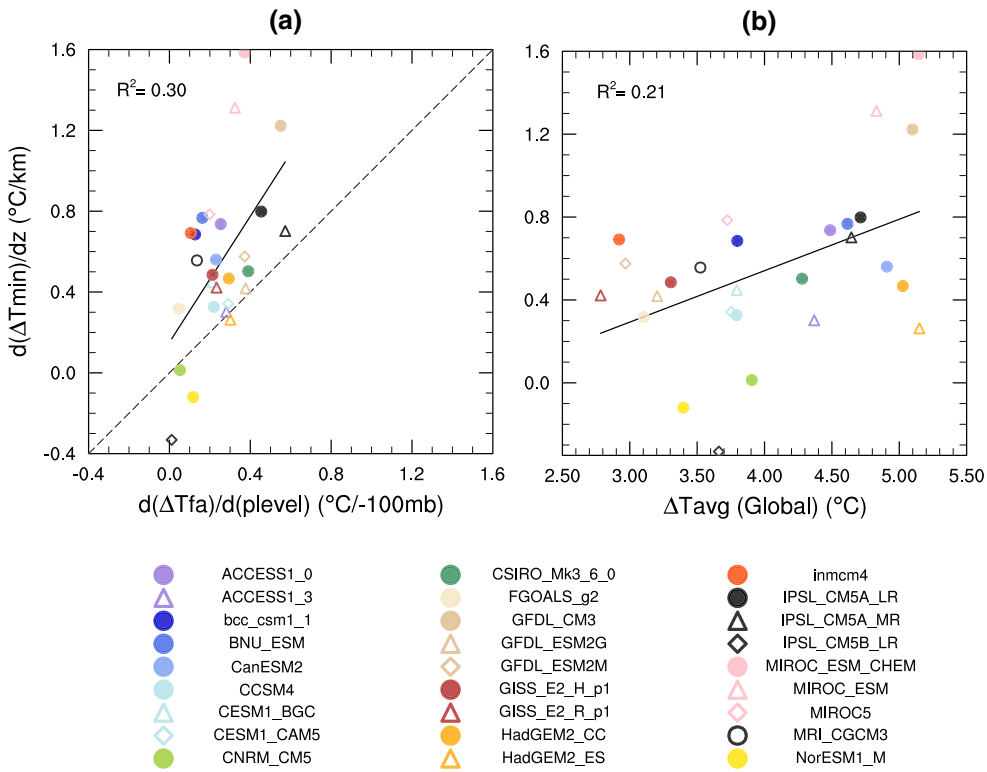

Fig. 4 Relationship between d(ΔTmin)/dz and **a** the amplification of free air temperature increases (ΔTfa) with decreasing atmospheric pressure levels (plevel) between 1000 and 500 mb within the 27.5°N–40°N latitudinal band (100 mb ≈ 1 km), **b** a GCM's climate sensitivity as represented by its transient global mean surface temperature increase (DJF only) between 1981–2000 and 2081–2100

relevant considering the sensitivity of surface downward longwave radition (DLR) to changes in water vapor, which is dependent on the degree of optical undersaturation in longwave absorption in the lower atmosphere. This undersaturation, which is primarily a function of air temperature, increases with elevation and seasonally from summer to winter (Rangwala 2013; Naud et al. 2013). Based on this mechanism, Rangwala (2013) found that for identical increases in the amount of water vapor at a high and low elevation site in the Tibetan Plateau during winter, there were substantially greater (e.g. 8 times in their study) increases in DLR at the high elevation site. Furthermore, the signal in the thermal amplification from this mechanism will be greater for the daily minimum temperature relative to the daily maximum temperature (Rangwala and Miller 2012). Figure 3d shows the relationship between d(ΔTmin)/dz and elevation-based normalized anomalies in DLR, which is very similar to the relationship found for specific humidity in Fig. 3a. There is also a very high correlation ($R^2 = 0.84$) between $d(\Delta q/q_o)/dz$ and $d(\Delta DLR/DLR_o)/dz$.

Our findings here are consistent with previous studies of the DLR-q relationship, and illustrate that atmospheric moistening, as well as the nature of moistening along the elevation gradient, is important in facilitating an amplified warming response with elevation in CMIP5 models. A critical open question is how water vapor will increase in the future, and in particular, how it will increase with elevation. Furthermore, both cloud cover and cloud optical thickness can influence d(ΔTmin)/dz through their effect on surface downward longwave radiation (DLR) (e.g., Naud et al. 2014). However, Naud et al. (2013) showed that the DLR-q relationship is not appreciably affected by the absence or presence of clouds.

Another variable that affects the radiation budget at high elevations is snow, through its effect on surface albedo. We find a statistically significant relationship between elevation changes of surface albedo and d(ΔTmin)/dz, although this correlation is not as strong as that between d(ΔTmin)/dz and $d(\Delta q/q_o)/dz$. Perhaps this is not surprising since our focus is on winter, and the snow albedo effect at higher elevations is more pronounced in the transition seasons (e.g., Ghatak et al. 2014). In our case study, surface albedo is primarily a proxy for snow cover, so we discuss the temperature response in that context. The elevational dependence of snow cover depends on the atmospheric freezing level unless other factors exist that influence snowmelt processes, such as dust or black carbon deposition on snow. As the climate warms, the freezing level and snowline will continue to move upward toward higher elevation (e.g., Ghatak et al. 2014). Where there is a loss of snow within a specific elevation zone, there will be a thermal response owing to substantial increases in the absorption of ISR at the surface. Fyfe and Flato (1999) found this to be the main reason for winter/spring EDW in the western US based on their analysis of a GCM simulation.

Cloud cover also modulates ISR at the surface, however surface albedo is more important for the temperature response. In winter, owing to high surface albedo at high elevations (because of snow on the ground) nearly all ISR is reflected independent of how the cloud cover is changing. Therefore, small changes in snow cover at the surface can cause a large temperature response because of changes in ISR absorbed at the surface (Betts et al. 2014). Another related question is whether the thermal response from the snow/albedo mechanism will be apparent in the daily maximum (Tmax) or minimum (Tmin) temperature? We hypothesize that it will depend on the dynamics of surface energy fluxes that balance the increases in absorbed solar radiation. Therefore, if the latter is primarily balanced by increases in sensible heat fluxes (latent heat fluxes), the response will be more prominent in Tmax (Tmin). Based on regional climate models, Rangwala et al. (2012) found an amplified response in Tmin relative to Tmax in lower elevation regions (1500–2500 m) of the Colorado Rocky Mountains during winter. They showed that this was caused, in part, by increases in the absorbed solar radiation at the surface, which is primarily balanced by increases in the latent heat fluxes because of the increases in surface soil moisture from snowmelt. Therefore, a specific temperature response (Tmin vs. Tmax) will depend strongly on soil moisture (e.g., Betts et al. 2013).

In their analysis of the ensemble mean response in Tmin and Tmax within the same latitudinal band for CMIP5 models, Rangwala et al. (2013) found that increases in Tmin and Tmax were quite similar for most cases—both seasonally and regionally—with increases in Tmax slightly higher than Tmin, except for high elevation regions in the cold season when the opposite is true. This suggests that the responses in Tmin and Tmax are largely coupled, although in cases where there are significant soil moisture losses during summer or large snow cover decreases in spring, the Tmax response is substantially greater.

A portion of the EDW in the region can be attributed to corresponding elevation-dependent increases in free air temperature, a phenomenon that GCMs generally find to be strongest in the tropics because of the impacts of changes in the tropical atmospheric-column water vapor through the Clausius–Clapeyron effect. Our results indicate that this phenomenon accounts for less than half the EDW response simulated at the land surface for our study region. Previous studies have shown that although changes in free atmosphere temperatures can influence climate response in high elevation regions, local land-surface processes that influence the surface energy budget may be equally important, and in some instances, can dominate the surface temperature response (e.g., Pepin and Losleben 2002; Pepin and Lundquist 2008). Nonetheless, this effect could be more important in driving surface temperature response in the tropics.

We are aware that within our study domain a typical GCM does not realistically represent the elevation fields, except for the Tibetan Plateau. Most mountain systems are represented in models by elevations that are lower than observed (e.g. the Colorado Rocky Mountains have topography above 4000 m, but below 2500 m in most GCMs). This issue affects the relative importance of different processes and feedbacks. Although Rangwala et al. (2013) found a significant influence of snow-albedo feedbacks in the Rocky Mountains in winter in CMIP5 GCMs, that result is likely affected by the representation of elevation fields in GCMs. Furthermore, we expect that increases in water vapor will be important for winter warming at higher elevations in the Rocky Mountains (>3000 m) that are not well represented in GCMs. Naud et al. (2013) found high sensitivities of DLR to changes in q, particularly during winter, using high elevation observations (>3500 m) in the Rocky Mountains.

We did not have ready access to CMIP5 cloud diagnostics, but we inferred their impacts indirectly by examining changes in ISR. Changes in ISR, and the corresponding implied changes in clouds, have little effect on our results, although we do not examine cloud effects at night when they could influence Tmin. This is consistent with Betts et al. (2014) who found that the temperature response in winter in snow dominated regions on the Canadian Prairies is more sensitive to snow cover changes than to changes in cloud cover. There is also much uncertainty associated with representing cloud processes in GCMs, and even more so in mountains. In future climate projections, there is limited understanding of how cloud cover and other cloud properties will change as a function of elevation.

5 Conclusions

We find that there is significant variability among the CMIP5 GCMs in simulating an EDW response during winter in a selected Northern Hemisphere mid-latitude band. However, in spite of that variability, nearly all of the CMIP5 GCMs (24 out of 27 models) produce significant amplification of the warming rate as a function of elevation. Among the variables we analyzed, this EDW response has the strongest association with elevation-dependent increases in surface specific humidity. We also found that snow albedo feedbacks are important. Corresponding elevation-dependent increases in free air temperatures are correlated with EDW but account for less than half the EDW response for Tmin. In addition to the issues related to EDW, our results raise questions about (1) the causes for these differential responses among the GCMs in projecting changes in variables such as water vapor and snow cover as a function of elevation and (2) how to better constrain the range

of these responses in order to improve our understanding of the sensitivities of the thermal response to changes in these variables in high elevation regions.

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