Comparison of the sensitivity of surface downward longwave radiation to changes in water vapor at two high elevation sites

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Abstract
Among the potential reasons for enhanced warming rates in many high elevation regions is the nonlinear relationship between surface downward longwave radiation (DLR) and specific humidity ($q$). In this study we use ground-based observations at two neighboring high elevation sites in Southwestern Colorado that have different local topography and are 1.3 km apart horizontally and 348 m vertically. We examine the spatial consistency of the sensitivities (partial derivatives) of DLR with respect to changes in $q$, and the sensitivities are obtained from the Jacobian matrix of a neural network analysis. Although the relationship between DLR and $q$ is the same at both sites, the sensitivities are higher when $q$ is smaller, which occurs more frequently at the higher elevation site. There is a distinct hourly distribution in the sensitivities at both sites especially for high sensitivity cases, although the range is greater at the lower elevation site. The hourly distribution of the sensitivities relates to that of $q$. Under clear skies during daytime, $q$ is similar between the two sites, however under cloudy skies or at night, it is not. This means that the DLR–$q$ sensitivities are similar at the two sites during daytime but not at night, and care must be exercised when using data from one site to infer the impact of water vapor feedbacks at another site, particularly at night. Our analysis suggests that care should be exercised when using the lapse rate adjustment to infill high frequency data in a complex topographical region, particularly when one of the stations is subject to cold air pooling as found here.

Keywords: sensitivity, elevation dependent warming, mountain climate, cold air drainage, water vapor feedback, downward longwave radiation, climate change

1. Introduction
There are multiple factors that can lead to enhanced warming at high elevations, including changes in snow cover/surface albedo, clouds, atmospheric water vapor, and changes in atmospheric circulation (Rangwala and Miller 2012 and references therein). The water vapor feedback operates primarily through its effect on downward longwave radiation (DLR) at the surface. Increases in specific humidity ($q$), tend to increase DLR which in turn causes the surface temperature to increase. The sensitivity of DLR to changes in $q$ (i.e., partial derivatives of DLR with respect to $q$) depends on the extent to which the lower atmosphere is optically undersaturated in longwave absorption. This relationship is
nonlinear with the sensitivities increasing as $q$ becomes small. As a consequence, the magnitude of the water vapor feedback is enhanced at higher elevations where the air tends to be drier (e.g. Ruckstuhl et al 2007, Rangwala et al 2009, Naud et al 2012, 2013).

The recent study of Naud et al (2013) used a combination of ground-based measurements and coincident satellite retrievals to investigate the DLR–$q$ relationship at a high-elevation site in Southwestern Colorado. They found that the DLR–$q$ sensitivity depends primarily on $q$, and the sensitivity is greater in winter than in summer, primarily because $q$ is much smaller in winter. Although they found that the sensitivities are smaller when clouds are present, this was primarily because $q$ tends to be larger when clouds are present than when the sky is clear. Their study only examined the sensitivities of DLR to $q$ and other cloud properties during daytime and at one location.

In this study, we investigate the DLR–$q$ relationship at two nearby high-elevation sites. Owing to the relatively sparse data in mountainous regions, we focus on whether the sensitivity of DLR to changes in $q$ exhibits a similar behavior at nearby sites within a mountain range. Pepin and Lundquist (2008) examined the change of temperature over high elevation stations across the globe and found that the warming rates depend on where the sites are, i.e. summits versus incised valleys. Furthermore, we also investigate whether the DLR–$q$ sensitivity depends on local thermodynamics in surface air temperature ($T$), $q$ and cloudiness at the sites. Finally, we discuss the impact of using the lapse rate adjustment to infill hourly data using two neighboring sites.

To tackle these questions, we compare the sensitivities of DLR to changes in $q$ at two neighboring high-elevation sites in Southwestern Colorado. We use almost seven years (January 2005–September 2011) of ground-based observations obtained from the Center for Snow and Avalanche Studies (CSAS, www.snowstudies.org) at two sites in Southwestern Colorado: the Senator Beck (SB) site at 3719 m and 37.9°N–107.725°W and the Swamp Angel (SA) site at 3371 m and 37.9°N–107.711°W. The local environments of these two nearby sites are different. The SB site sits above tree line in the alpine tundra, and is more exposed to strong winds. The SA site is below the tree line and surrounded by sub-alpine forest in an enclosed and protected valley-like location. Thus air temperature and humidity at SA can be influenced by the surrounding terrain, and cold air draining from the upper basin often ‘pools’ at the site overnight (Landry et al 2014). In fact, since SA and SB are within the same catchment basin, we expect air masses measured at SB to be flowing downward and pooling at SA at night.

2. Data and methodology

We provide a brief description of the sites and instrumentation; additional details can be found in Landry et al (2014) and on the CSAS website. We use the CSAS automated observations of hourly surface temperature ($T$), relative humidity (RH), surface downward longwave (DLR) and downward shortwave radiation (DSR). Surface pressure is available only at the SA site, and a linear relationship of pressure with elevation is used to estimate it for the SB site (Naud et al 2013) verified that a linear relationship is a good approximation over such a small difference in altitude). The specific humidity is calculated using surface pressure, RH and surface temperature, as in Naud et al (2013) based on equation (10) in Bolton (1980). The cloud mask used to determine clear (0% cloudiness) and cloudy (100% cloudiness) points is based on DSR: if the daily DSR is more than one standard deviation above the monthly mean, it is flagged as clear sky and anything below one standard deviation is cloudy (see Naud et al 2013). All other points are deemed ambiguous and thus removed from our study. Using satellite retrieved cloud cover, Naud et al (2013) found that this cloud mask is more reliable during daytime than at night with an error of 3% during the day and 22% at night. When the cloud mask reaches a solution, about 14% and 15% of the available observations are clear at SB and SA respectively (18% and 16% cloudy).

A known problem at SA is the deposition of snow on the detectors of the radiometers when a storm occurs (Landry

![Figure 1. Scatter plot of surface downward longwave radiation (DLR) versus specific humidity ($q$) at the Swamp Angel site. (a) Is the original data. (b) Is the filtered data, i.e. after discarding all data points with DLR differences larger than 25 W m$^{-2}$ between the two sites. The solid horizontal line represents the value of DLR when the temperature is 273.15 K according to the Stephan–Boltzman law.](image)
et al 2014). The detector is not heated, so the snow will accumulate until a technician can reach the site and remove it. Consequently, the DLR observations at SA can be erroneous in the winter. In the most extreme case of the detector being completely covered, fresh snow being at about 273 K, the Stephan–Boltzmann law predicts that DLR should be close to 315 W m$^{-2}$. Figure 1(a) shows the relationship between DLR and $q$ at the SA site for all hourly observations between 2005 and 2011. We note that there is indeed a cluster of data points at low values of $q$ that is capped at about 315 W m$^{-2}$ (solid line in figure 1(a)). This implies that when the sensor is snow covered, its temperature is rarely above freezing; however the air temperature above may be below freezing and produce lower values of DLR if the snow cover is not fully opaque. Since the detector at the SB site does not suffer from the snow issue because of its more exposed location, we use the observations at the SB site to remove the potentially erroneous measurements at SA.

Assuming that the simultaneous DLR measurements are similar at SA and SB, we removed the DLR measurements at SA when the difference in DLR between the two sites was larger than one standard deviation ($\sim$25 W m$^{-2}$). Figure 1(b) shows that the erroneous data points are successfully removed by this simple filtering. Of the initial 58365 hourly data points, 50719 remained after the filtering. Most of the removed data points occur during the cold months, often at night and morning when $q$ and $T$ are low. There are also more cloudy sky points than clear sky ones in the removed data, consistent with the association of the problem with snow storms. For consistency we also removed coincident measurements at SB when comparing the two sites.

In this study, we incorporate ground-based observations into a neural network (NN) algorithm to examine the sensitivities of DLR to changes in $q$ at the two sites. A detailed description of the method is given in Chen et al (2006) and Naud et al (2013). The NN model relates one or several input variables to an output variable in a nonlinear way. It provides a Jacobian matrix which contains the partial derivatives of a given output variable with respect to a given input variable. This, by definition, is the sensitivity of the output variable to all input variables as inferred by the NN model. The NN Jacobians provide not only an estimate of the mean sensitivity between two variables, but also an estimate of the distribution of the sensitivity. The advantage of this NN Jacobian is that it gives a direct statistical evaluation of the multivariate and nonlinear sensitivities that depends on each configuration of input and output variables (Aires and Rossow 2003). Stephens (2005) recommends extending the classical feedback diagnostics to investigate instantaneous sensitivities instead of equilibrium estimates. These sensitivities constitute a step toward a more realistic representation and evaluation of feedback processes, particularly in their time evolution and their roles in governing cloud–radiation interactions. Stephens suggests that the Aires and Rossow (2003) method of using a NN approach to examine the Jacobian matrix is one way to obtain the instantaneous sensitivities. Consequently, we examine not only the NN outputs, but also the Jacobian matrix within the NN, following the method of Aires and Rossow (2003). Here, the input variable is $q$ and the output variable is DLR. The sensitivities of DLR to $q$ analyzed in this study are provided by the Jacobian matrix.

3. Temperature and humidity hourly distribution

The influence of surrounding terrain on temperature and humidity is different at the two sites, so we first examine the temperature and moisture characteristics at the SA and SB sites. Figure 2 shows the mean of $T$ and $q$ as a function of time for all hourly observations available at the two sites (after the filtering procedure is applied at SA, with the coincident data also removed at SB for consistency). The cloud mask is used to separate clear and cloudy points. These hourly distributions differ from a typical diurnal cycle in that each hourly observation is averaged independently based on values from the clear or cloudy sky cases during the entire seven-year record.

In both clear and cloudy sky cases, the hourly variations in $T$ and $q$ are much greater at the SA site. During the daytime hours, temperatures are higher at SA relative to SB (figures 2(a) and (c)) as expected because of the lower elevation of SA. However, the nighttime temperatures are lower at SA than at SB in clear sky conditions (figure 2(a)), probably indicating the cooling effect at SA caused by cold air pooling (Landry et al 2014). Although the temperatures at SA in cloudy conditions are still larger than the temperatures at SB at night, the difference between the two is much smaller than during the day. One of the methods for filling in missing data at high elevation sites where observations are often sparse is to use data from a nearby site with a lapse rate adjustment. However, where cold air pooling occurs, this adjustment is less accurate, although it appears to work better during daytime (Landry et al 2014). By using the lapse rate of a standard atmosphere, we fill in SA temperatures using the measured SB temperatures, and find the mean differences between the hourly filled SA temperatures and the measured temperatures of about 2 °C. However, when using daily averages, this difference is halved. Furthermore, the lapse rate adjustment (figures 2(a) and (c) dotted line) shows a potential problem in filling the high frequency temperature data at the SA site because it cannot capture the temperature response from cold air pooling at night, especially during clear sky conditions.

Figure 2(d) shows that $q$ is larger and exhibits a more pronounced hourly variation that is in phase with the temperatures in cloudy sky conditions at both sites, relative to clear sky conditions. The figure also indicates that it is drier at SB than at SA at almost all times. This is also true at night in clear sky conditions, but during the early part of the day, SB is slightly more humid. At SA, the humidity reaches a peak near sunset for clear sky conditions (figure 2(b)) and in the middle of the day for a cloudy sky (figure 2(d)). The $q$ increase at night at SA may be tied to a temperature inversion at sunset when local moisture cannot advect away, and downslope advection from cold air pooling brings in more...
moisture that accumulates during the lifetime of the inversion. The timing of the maximum and minimum \( q \) at SB is similar to that at SA in cloudy sky conditions. For clear sky conditions, however, the maximum occurs in the early morning, with a secondary maximum in late afternoon and the minimum occurs at sunrise. The more pronounced peak at SA than SB around sunset could be caused by a greater accumulation of moisture through the day because (1) there is more vegetation around the SA site, which would favor greater evapotranspiration, and (2) more importantly the SB site is more exposed and so moisture may be more efficiently advected away from the site.

We also checked the seasonal variations of the hourly distribution of \( T \) and \( q \) (not shown). The specificities of the \( T \) and \( q \) variations at SA are more pronounced in summer than winter: the cold air pooling effect is more prominent and the clear-sky moisture peak near sunset at SA is more pronounced while the shift in the peak in \( q \) from mid-day to sunset at SA is clearer.

4. **Comparison of DLR–q sensitivities at swamp angel and SB**

In this section, we examine and compare the sensitivity of DLR to changes in \( q \) separately for clear and cloudy skies at SA and SB sites. These sensitivities are obtained from the Jacobian matrix, which is a product of the NN analysis. Both
day and night observations are included in the analysis, which complements the previous work by Naud et al. (2013).

The DLR–$q$ sensitivities in clear sky conditions are sorted into four separate bins with equal width to examine the mean properties of the DLR–$q$ relationship. The number of bins is arbitrary, but the results are unchanged when increasing this number. Table 1 gives the number of data points in each bin, the mean sensitivities for each bin, and the mean DLR, $q$ and $T$ for clear sky conditions at the two sites using all day data. Overall, the mean sensitivities for each bin at SB are similar to those at SA for clear sky conditions, although more of the data points fall into the highest and lowest sensitivity bins. The distribution of sensitivities in cloudy-sky conditions is dominated by the lower sensitivity bin at both sites, although slightly greater at SB (table 2). In general, SB has higher mean sensitivities for each bin compared to SA under cloudy sky with relatively lower values of DLR, $q$ and $T$. For both clear and cloudy skies at both sites, the sensitivities of DLR to changes in $q$ increase as the mean values of DLR, $q$ and $T$ decrease.

There is a bi-modal distribution at both sites with the lowest and highest sensitivity bins being most represented except for cloudy sky conditions at SA. The monthly distribution of the Jacobians indicates that these two bins (1 and 4) include data points for mostly summer and winter months, respectively (not shown). So for clear and cloudy sky conditions at SB, and clear sky at SA, the data points fall into bins for the most extreme sensitivities, which is slightly different from the daytime only results of Naud et al. (2013) that found fewer points in the lowest sensitivity bin. One possible reason for this is that sensitivities at night tend to be larger than during daytime, and therefore the sensitivity bins used here which include both day and nighttime data are in fact populated by data points with higher mean sensitivities than in Naud et al. (2013) which considered daytime only data. Nonetheless, at both sites, the sensitivity of DLR to changes in $q$ is significantly larger when $q$ is low for both clear and cloudy cases. In the next section we examine the hourly variations of the DLR–$q$ sensitivities to investigate potential differences in the sensitivities between day and night.

In addition, we investigate how the relationship of the DLR–$q$ sensitivity changes with $q$ as a function of location, season and cloud presence. Figure 3 shows a scatter plot of the mean DLR–$q$ sensitivity against mean $q$ per season for clear (+, o) and cloudy (*, △) conditions at SA and SB sites based on results using both day and night data points. Each point is the averaged sensitivity over three months, e.g. December, January, February for DJF; June, July, August for JJA. The mean sensitivity is highest in winter under clear sky (two points at upper left of the plot), and lowest in summer under cloudy sky (two points at lower right of the plot). Overall, the sensitivities are fairly similar at the two sites in clear sky, with slightly larger values at SB for a given $q$ in cloudy sky. A simple model fitting of this relationship (i.e. $d$DLR/$dq$ against 1/$q$) indicates that for a given $q$, the sensitivity is greater when clouds are absent, and as $q$ increases, the difference between clear and cloudy sky fits increases too. The fit that includes all data points (solid line in figure 3) is significant at 95% level, which suggests the mean sensitivities at the two sites are consistent.

### 5. Hourly distribution of sensitivities

Within each sensitivity range discussed above, we can further examine different distributions according to different criteria, and we next examine the hourly changes in the sensitivities. We focus on the hourly distribution of the sensitivities in the lowest and highest sensitivity bins (1 and 4) of section 4. Their frequencies of occurrence dominate in summer and winter months respectively. As discussed in section 2, the

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**Table 2.** Same as table 1 but for cloudy sky.

| NN bins: | SA cloudy sky: average per bin | SB cloudy sky: average per bin |
|----------|--------------------------------|--------------------------------|
| dDLR/$dq$ | (W m$^{-2}$ (g kg$^{-1}$)$^{-1}$) | (W m$^{-2}$ (g kg$^{-1}$)$^{-1}$) |
| $N$ | DLR (W m$^{-2}$) | $q$ (g kg$^{-1}$) | $T$ (°C) | DLR (W m$^{-2}$) | $q$ (g kg$^{-1}$) | $T$ (°C) |
|-------|----------------|----------------|--------|----------------|----------------|--------|
| 1     | 4247           | 6 (3)          | 297    | 5.7            | 3.1            | 6557   | 10 (2) | 287 | 5.5 | 1.9 |
| 2     | 2202           | 15 (3)         | 294    | 5.4            | 0.6            | 1292   | 19 (2) | 258 | 2.9 | −7.0 |
| 3     | 877            | 26 (3)         | 266    | 2.5            | −8.4           | 1185   | 28 (3) | 248 | 2.4 | −9.4 |
| 4     | 795            | 36 (3)         | 240    | 1.7            | −11.4          | 1559   | 37 (3) | 220 | 1.6 | −12.1 |
Figure 4. Hourly distribution of the lowest sensitivity bin 1 (a), (c) and highest sensitivity bin 4 (b), (d) for clear sky at (a), (b) Swamp Angel (SA) and (c), (d) Senator Beck (SB) sites.

Figure 5. Same as figure 4 but for cloudy sky.
cloud masking technique degrades at night, and so we place less confidence in the night time results than day time results. However, as we compare two sites to which the same cloud masking procedure is applied, this uncertainty in the presence of clouds at night is expected to be similar at the two sites and so should not affect the conclusions of this section.

Figures 4 and 5 show the hourly distribution of the DLR–q sensitivities for SA and SB separately for clear and cloudy cases. For clear sky, the hourly variation is less pronounced at SB than at SA for both low and high sensitivity bins (figure 4). The high sensitivity cases (bin 4) at both SA and SB have hourly distributions with a similar minimum in frequency occurring in the late afternoon around 1700–1800 LT, but with a maximum at noon for SA and in the early morning for SB. For the low sensitivity (bin 1) clear sky cases, the hourly variation is roughly out of phase with the high sensitivity cases. This is consistent with what we would expect for clear skies with generally colder and drier conditions in the early morning leading to higher sensitivities, and warmer and more humid conditions later in the day leading to lower sensitivities (see figure 2). The timing for maximum and minimum frequencies is consistent with the mean hourly distribution of q, with the highest (lowest) sensitivities occurring most frequently when q is minimum (maximum) (figure 2(b)).

Figure 5 shows that at both sites under cloudy skies, the hourly distributions of the sensitivities of maximum and minimum frequency for the low sensitivity bin 1 and the high sensitivity bin 4 occur roughly out of phase at both sites. However, the hourly variation is more pronounced for bin 4 than bin 1 at both sites. The maximum frequency for the high sensitivity bin 4 occurs during the middle of the night with the minimum between noon and early afternoon, which are consistent with the hourly variations of T and q (figures 2(c) and (d)).

6. Summary and conclusions

We have used ground-based observations to examine and compare the sensitivity of DLR to changes in q at two nearby high-elevation sites in Southwestern Colorado; the sites are locally different but subjected to similar large-scale influences. SA is a sub-alpine sheltered environment, while SB is above the tree line, close to a summit, and very exposed. On average, the higher elevation site at SB experiences cooler and drier conditions than the SA site. A key question that arises is whether a nearby site can be used to remove or reduce observational errors at another site. Our principal results and their implications for elevation dependent warming are summarized in this section, but we note that our study uses only two sites in one region, and they are not likely to be generally applicable everywhere. The results, however, do provide useful information for other investigators to consider when investigating elevation dependent warming, and processes that might be causing it, particularly in data sparse regions. In particular, our results show that the cold-air drainage and pooling, which occur in many mountain valleys and will impact local climate change (Daly et al 2010), also influence the DLR–q sensitivities, and hence the water vapor feedback.

The relationship between DLR and q is nearly the same at both sites. However, the magnitude of the DLR–q sensitivity depends on the value of q, with higher sensitivities for lower values of q and vice versa. Winter months being colder and drier than summer months tend to have the largest observed sensitivities while summer the lowest. There are distinct hourly variations for the high sensitivity cases in their frequency of occurrence at both sites. The hourly distributions of these sensitivities are nearly out of phase for the low and high sensitivity cases, and appear to be modulated by q, i.e. high sensitivities occurring preferentially when q is minimum. Since q tends to be lower at the higher elevation site, the sensitivities there are generally higher, although for clear sky conditions during daytime, the differences in q are much smaller at the two sites.

Our study confirms the nonlinear relationship between DLR and q in this high elevation region, with substantially higher sensitivities found at low levels of specific humidity, especially below 2.5 g kg$^{-1}$. These results provide important information for investigating the role of the water vapor feedback in enhanced warming at high elevations where data are often sparse. One follow-up study would be to use a multivariate NN analysis to quantify the relative influence of humidity and temperature on the DLR response, presumably for different seasons. We have shown that DLR observations at SB can be used to remove erroneous observations at the lower elevation and more sheltered SA site when snow covers the radiometer there. In cases where the DLR–q relationship is an important factor in elevation dependent warming, it would be most obvious in regions that are very dry, with limited pooling effect, and in periods when large scale moisture advection is limited (i.e., for low values of q). To determine the DLR–q sensitivity at a site where data are missing, the primary variable needed is q. One method sometimes used to fill in missing temperatures is to use temperatures from nearby stations but with a lapse rate adjustment to account for different elevations. The feature of the temperature differences at the two sites casts doubt on the practice of filling missing temperatures from nearby stations with a standard lapse rate adjustment in mountains, especially when using hourly observations and one of the sites is affected by cold air pooling. When using daily averages the adjustment appears to work better.

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