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Elevation-dependent warming in mountain regions of the world

Observational Evidence for EDW

There have been numerous global and regional studies of EDW. Table S1 provides a summary, including the number of stations, time period and other useful metadata. A study of maximum and minimum temperatures at 126 mountain stations from different regions of the world by Diaz and Bradley (1997) found that trends in minimum temperatures (1951-1989) generally increased with elevation, but maximum temperatures were less consistent, with the strongest warming at 500-1000m, showing that different mechanisms may be of importance in each case. Another study by Pepin & Lundquist (2008) of trends in mean annual temperature for 1948-2002 at 1084 high elevation stations found no significant correlation between trend magnitude and elevation on a global scale, but there was a strong relationship between mean annual temperature and warming rate, with the strongest warming centered around the 0ºC isotherm. They argued that cryospheric feedbacks (melting snow and ice, and changing albedo) controlled the observed pattern of temperature change. They also demonstrated that topography and exposure to the free atmosphere also influenced the warming signal, with mountain summits showing more consistent warming rates (and more similar to the free atmosphere). Decoupled mountain valleys on the other hand showed highly variable warming rates. Ohmura (2012) found observational evidence of EDW in 13 out of 18 regions in spring or summer during the last 40 years. Wang et al (2014) examined trends in mean annual temperatures (1961-2010) at 2367 stations around the globe, extracting the elevational warming component from the overall warming rate at individual stations over each high-elevation region. A significant warming amplification with elevation was found for many regions including the Tibetan Plateau, the European Alps and the United States Rockies. Yan & Liu (2014) showed a clear elevational dependency of warming over the Tibetan plateau region over the last 50 years, and an increase in both the magnitude of warming and the elevational dependency in recent decades. There are also numerous other regional studies, where transects or small numbers of surface stations in a particular region have been examined (e.g. Liu and Chen, 2000, Vuille and Bradley 2000, Liu et al. 2009, You et al. 2010, Li et al. 2012).

Future Needs

In this section we outline in more detail the requirements needed to fully investigate the phenomenon of EDW. The three main approaches are surface observations, satellite data and modelling.

a) Surface in-situ observations

To fully document and understand EDW, air temperature measurements at ground stations are essential. Since the current network is skewed towards low elevations, this requires the establishment of a considerable number of high elevation stations, particularly in areas currently under-represented, such as the tropics. Station siting is critical and the influence of topography is of particular concern; isolated summits are much more representative of larger scale climate changes. Although the minimum data requirement would be daily maximum and minimum temperature at screen level (2m), at selected sites (close to locations where the driving mechanisms are expected to be focused, e.g. near the 0°C isotherm) energy balance stations should be established, with all sky cameras to monitor cloud cover and changes in surface conditions such as snow cover. Such sites also offer "ground truth" information to calibrate and verify satellite-derived data (see below). Detailed transects across tree-lines and snow-lines, in areas affected by the Asian Brown Cloud, and in areas such as tropical cloud forests where changes in water balance are likely to be equally important, are suggested for intensive case-studies into the mechanisms driving EDW.

As well as expanding the current observational network, which should involve a long-term commitment to maintain high quality measurements, an attempt should also be made to retrieve, collate and homogenize existing mountain station data, in order to create the most comprehensive, freely available dataset. This has been done for the European Alps (HISTALP - see Auer et al., 2007), but this example needs to be extended and combined with other regions (through initiatives such as GEO/GEOSS and its component GEO-GNOME, the Global Network for Observations and Information in Mountain Environments, see https://www.earthobservations.org/ts.php?id=224). Metadata information would add considerable value to the data, archiving information on operational procedures, including observational practices or data conversion algorithms that might have changed over time, as well as information on observed parameters, instrument maintenance routines, corrections applied to the data, and other information. Within certain regions such as the Tibetan Plateau, a systematic assessment of high-elevation meteorological data quality, as influenced by issues such as the replacement of manual by automatic stations, is urgently needed.

For a better understanding of the mechanisms behind EDW, supplementary station information such as land-cover characterization, local topography (as measured by terrain factors such as topographic exposure, aspect, slope gradient), surface roughness, distance to centers of population etc, is also extremely useful. This will allow analysis of EDW for subsets of stations for which known mechanisms are likely to be enhanced. Finally, further research is needed to address the multi-collinearity factors, acknowledging that large-scale position (latitude and longitude) and local scale factors (aspect, exposure, land-use, local hydrology) also influence warming through regional heterogeneity, which complicates the isolation of any EDW signal.

b) Satellite Data

Operating meteorological stations in mountain regions is expensive, and so remotely-sensed land surface temperature (LST) data may partly overcome some of the drawbacks of the in-situ network. LST data are generated with high frequency (roughly twice daily for instruments on polar orbiting satellites and at 3-hour intervals or shorter for instruments on geostationary satellites) for most points on the Earth's surface. These instruments generate snapshots or individual scenes over large areas covering up to thousands of square kilometers, within which all points are observed simultaneously. Thus by providing regular observations of poorly monitored high-elevation areas, remotely sensed data could complement existing in-situ station data. However, the advantages of frequency and spatial coverage of LST observations for supplementing in-situ data are subject to the caveats of differences between respective variables observed, i.e. LST and near surface air temperature, in terms of their physical nature and levels of uncertainty inherent in the measurement of each parameter. With regards to uncertainty, an observation campaign (Guillevic et al. 2012) to establish validation methodology for the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument – successor to the MODIS instrument – found, "*Using ground-based data without scaling, the accuracy and precision of MODIS LST products ... are −0.3 K and 3.0 K, respectively. ... However, the product accuracy and precision calculated using scaled-up ground data are around 0 K and 2 K, respectively.*" With regards to the physical differences between near surface air temperature and LST, the variables are linked via the sensible heat flux component of the surface energy balance. Beyond this physical mechanism, a study (Gallo et al., 2011), carried out using in-situ LST observations from radiometers installed at U.S. Climate Reference Network (USCRN) stations, tested prediction of LST using near surface air temperature (Tair) under both clear sky and cloudy conditions. Gallo et al. (2011) found not only that prediction of Tair from LST was feasible, but also that even under cloudy conditions each variable accounts for 90% or more of the variance in the other.

Imagery from successive generations of the Advanced Very High Resolution Radiometer (AVHRR) instrument flown on NOAA Polar-orbiting Environmental Satellites (POES) provides a promising option for producing time-series of remotely sensed land surface temperature (LST) over high-elevation regions. AVHRR-derived LST, with spatial resolutions of 1km to 4km, has been used to calculate temperature trends for periods of twenty years or more in studies of the Tibetan Plateau (Zhong et al, 2011) and Northern Siberia (Urban et al, 2013), although both of these limited their published findings to regional averages. Urban et al (2013) found negative correlations between trends in albedo and LST suggestive of shortwave radiative feedbacks due to changes in snow cover. Zhong et al (2011) also presented results showing increasing LST and decreasing surface albedo.

The use of AVHRR-derived LST datasets for trend assessment presents a number of obstacles. The first is the issue of data homogeneity. AVHRR homogeneity is primarily degraded by the problem of "orbital drift," as the local equatorial crossing time, and hence time of imagery acquisition at any given location, gradually moves later during the operational life-time of the satellite platform (Price 1991). A number of numerical approaches have been proposed to overcome this issue and create temporally-consistent time-series (Gutman 1999, Jin and Treadon 2003, Julien and Sobrino 2012). Another challenge is that the "split-window" algorithm used to calculate LST values (Li and Becker, 1993) is dependent on "clear-sky" conditions, i.e. it cannot be applied to pixels containing cloud cover, which presents particular problems for mountain regions. A number of cloud detection methods have been developed for AVHRR imagery including the CLAVR-I (Stowe et al., 1999), CASPR (Key 2000, Di Vittorio and Emery 2002) and ASMC (Simpson and Gobat, 1996) algorithms. An alternative to direct cloud filtering, the Maximum Value Composite (MVC, Holben, 1986) consists of selecting the highest geo-referenced pixel value for a 10-day temporal composite. The MVC approach selects the warmest conditions observed in the compositing period. For a temporal mixture of clear and cloudy conditions during repeated observations, the value retained for an individual pixel will represent clear sky conditions. This method assumes that the compositing period is long enough that at least one clear observation will be made for each pixel in the geographic zone of interest. For regions and terrain with very frequent cloud cover, this assumption may be questionable. Zhong et al (2011) used the MVC approach in their study, while Urban et al (2013) opted to apply the CASPR algorithm. Beyond the technical difficulties of cloud filtering, the “clear sky” dependency of remotely-sensed LST raises questions about the interpretation of overall trends (which use all days) compared to those calculated for LST using only cloud-free conditions. Context for this interpretation could be provided by cloud climatology and occurrence-frequency trend estimates from the aforementioned cloud algorithms. In summary, the multi-decadal record length and good spatial resolution of AVHRR combined with established algorithms for cloud-filtering and LST calculation, whose outputs can be tested (for the post-2000 time period) against comparable MODIS data products, offer an exciting potential to assess elevation dependency of surface temperature change over the past three decades. Given the affordability of data storage and processing capacity, this potential can be realized with relatively modest investments of research staff time and equipment.

One study has been conducted on Elevation Dependent Warming (EDW) using the Moderate-resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature (LST), demonstrating significant potential to use this sensor for EDW related questions. Qin et al. (2009) show that the warming rate on the Tibetan Plateau increased from 3,000 to 4,800m by approximately 0.04 K per year between 2000 and 2006. Above 4,800m the warming stabilized, with a small decrease toward the highest elevations (~6,600m). The MODIS sensor is on two space-borne platforms, Terra and Aqua. These platforms are in near-polar orbits, which display a swath overlap at latitudes greater than 30°. The overlap produces progressively more daily observations toward each pole and every other day observations at the equator. MODIS data are available from February 2000 (from Terra) and July 2002 (from Aqua). Two methods are used to produce LST products, the split window technique which produces LST at a 1 km grid cell or the day-night technique which produces LST at a 5km grid cell (Wan et al., 2002). MODIS LST products are determined from the thermal infrared portion of the electromagnetic spectrum and therefore require clear skies. Undetected cloud contamination is a persistent issue, even though MODIS uses 14 spectral band radiance values to evaluate atmospheric contamination and determine whether scenes are affected by cloud shadow (Ackerman et al. 2008). The MODIS Collection-5 unidentified cloud contamination is approximately 15% of grid cells (Ackerman et al., 2008; Williamson et al., 2013). Radiance-based validation of MODIS LST indicates that over land cover which is not arid, LST errors are within ±1 K (Wan et al., 2002), although validation has not been carried out for elevations greater than ~4000 m. Air temperature and infrared surface temperature are separate physical entities that respond to the same forcing over different time scales (Jin & Dickensen, 2010). Thus there is a strong linear correlation between MODIS infrared surface temperature and air temperature for many land cover types, with a typical range of differences between LST and air temperature of approximately 2-3 °C (Zaksek et al., 2009) irrespective of the methodology, spatial or temporal resolutions. Over permanent snow and ice, the discrepancy between air temperature and infrared temperature should be nearer to ±1 °C, regardless of the clear sky bias in infrared surface temperature acquisition (Comiso, 2003). However, temporal averaging of winter LST causes a cold bias of approximately 3 K because clear sky values of LST are colder than in-situ values measured under cloudy conditions (Westermann et al., 2012). The variable differences between LST and air temperature require much further investigation and certainly poor understanding of these differences is a current limitation to documenting EDW using satellite data.

c) Models

Our understanding of climate change in mountainous regions, and of EDW in particular, is quite limited, not only because of inadequacies in observations but also in climate model simulations (Rangwala and Miller 2012). Global climate models (GCMs) are the only viable tools for capturing the main physical aspects of the global climate system, the effects of large-scale circulation and teleconnection patterns, and the feedbacks and inter-relationships between different variables required for large-scale projections of future climate. However, due to the limited capability of GCMs to resolve climate phenomena at small scales, the climate variations predicted for a specific location, particularly at high altitudes where strong spatial and temporal gradients in climate elements are common, are usually affected by systematic errors and significant uncertainties.

An approach for obtaining higher resolution output starting from coarse scale models is based on the concept of climate downscaling and uses both dynamical and statistical techniques. Dynamical downscaling consists of nesting Regional Climate Models (RCMs) into the low-resolution GCMs, where the ratio of GCM/RCM resolutions is of the order of 100-200 km/10-50 km. In the framework of EDW, the recent projections of surface temperature change in mountainous regions under high-end emission scenarios, such as RCP4.5 or RCP8.5, produced within the Coupled Model Intercomparison Project phase 5 (CMIP5) and the Coordinated Regional Climate Downscaling Experiment (CORDEX) can be exploited. In particular, the use of global and regional model outputs from the CMIP5 and CORDEX experiments would allow investigation of the links between temperature and the other model variables representing the expected EDW mechanisms discussed in the main paper: snow cover and albedo, cloud radiative effects and thermodynamics, downward longwave forcing from water vapor, and aerosols. Moreover, the use of GCMs would allow EDW to be examined in relation to large scale atmospheric modes and teleconnection patterns (e.g. ENSO and NAO) in different parts of the world. On the other hand, extracting and assessing the output of the hydrostatic RCMs (e.g., from the CORDEX database) would allow a focus on the relevant sub-domains nested into continental scale dynamics. The implementation of non-hydrostatic equations for the atmosphere has allowed handling of finer scales (down to 1-3 km). While this approach has been widely used over meteorological timescales, it is still in its infancy for climatic applications, since the computational effort required is rather formidable (Kendon et al., 2014; Maussion et al., 2014). Climate change experiments with a very high-resolution model typically used for weather forecasting, (1.5 km grid spacing), have been performed by Kendon et al. (2014) for a small region of the United Kingdom, to simulate rainfall extremes and characteristics at very high spatial and temporal scales. Rasmussen et al. (2014) used a regional model at 4km horizontal grid spacing to both validate the hydrological processes in the Colorado Rocky Mountains and to study the changes in the hydrological/cryospheric response under climate change.

Statistical/stochastic downscaling methods represent a further approach to increase the resolution of global and regional models, to reduce their systematic errors, to generate probabilistic information at a small scale and to extend the set of predictions to other climate-derived quantities e.g. Kettle and Thompson (2004), Fowler et al. (2007), Hashmi et al. (2013), Forsythe et al. (2014). Stochastic downscaling models, in particular, can be used to produce ensembles of possible realizations of high-resolution fields from the GCM and RCM data. D’Onofrio et al. (2014), for example, discussed the results of a downscaling chain in which the ~50-yr long precipitation output of one RCM at 30 km resolution is stochastically downscaled down to 1 km resolution over the mountainous regions of northwestern Italy. The statistical properties of the downscaled precipitation were compared with rain gauge measurements over the same time period and region. Stochastic downscaling has the advantage that it can be applied to the outputs of an ensemble of climate models and therefore used to compare the large-scale uncertainty represented by the climate model ensemble with that modelled by the use of stochastic downscaling at small scales (e.g., von Hardenberg et al., 2007), thus allowing an assessment of the propagation of uncertainties through the modeling chain. Downscaling, in its various forms, has the potential of adding considerable value to global and regional projections, by increasing the spatial and temporal resolution of the climate picture they provide. Downscaling represents also a necessary step to develop climate and environmental change scenarios specifically designed for mountain regions, whose complex orography, extreme environmental conditions, steep spatial and temporal gradients in variables, and low density of in-situ observational data make reliable predictions difficult to obtain. Development of techniques that combine statistical/stochastic downscaling and regional process models with observations as a basis for providing quantitative information on EDW (that can then be propagated to impact/assessment models) is strongly recommended.

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Table S1

Table S1: Metadata describing studies (observations and models), which have investigated the evidence for EDW. References are listed in the reference list for the main paper.

Observations	**Study**	**Region**	**Time Period**	**Elevation Range (m)**	**No. of Stations**	**Comments**
Meteorological						
	Diaz and Bradley, 1997	Global	20th Century	1055-3310	126	
	Pepin and Lundquist, 2008	Global	1948-2002	500-4700	1084	
	Ohmura, 2012	Global	20th Century	0-4500	56	
	Wang et al., 2014	Global	1961-2010	200-4700	2367	
	Beniston and Rebetez, 1996	Swiss Alps	1979-1993	271-3572	88	
	Liu and Chen, 2000	Tibetan Plateau	1955-1996	200-4801	197	
	Liu et al., 2009	Tibetan Plateau	1961-2006	0-5000	116	
	Lu et al., 2010	Tibetan Plateau	1960-2005	1000-5000	140	
	Rangwala et al., 2009	Tibetan Plateau	1961-2000	1000-5000	43	
	You et al., 2010	Tibetan Plateau	1951-2004	2100-4700	71	
	Li et al., 2011	Hengduan Mtns, China	1960-2008	1245-4200	27	
	Bhutiyani et al., 2007	Indian Himalayas	1901-1989	1200-3800	10	
	Shrestha et al., 1999	Nepal Himalayas	1971-1994	72-3705	49	
	Vuille and Bradley, 2000	Tropical Andes	1939-1998	0-5000	268	
	Vuille et al., 2003	Tropical Andes	1950-1994	0-5000	277	
	Tang and Arnone, 2013	Great Basin, USA	1901-2010	500-3000	93	
	McGuire et al., 2012	Front Range, Rocky Mountain	1953-2008	1672-3749	5	
Gridded						
	Ceppi et al., 2010	Swiss Alps	1959-2008	203-3580	91	2km gridded data
	Diaz and Eischeid, 2007	Colorado Rockies	1987-2006	1250-4000	—	4km gridded data
Satellite						
	Qin et al., 2009	Tibetan Plateau	2000-2006	2000-5000	—	
	Tao et al., 2013	Tibetan Plateau	2003-2012	3000-6000	—	
Radiosonde						
	Seidel and Free, 2003	Global	1979-2000	2-3649	—	
Proxy Data						
	Gibert and Vincent, 2013	French Alps	1900-2004	4240-4300	—	Proxy estimation from Boreholes
Models						
GCMs						
	Bradley et al., 2006	American Cordillera	21st Century	1000-7000	—	CMIP3 SRES A2
	Rangwala et al., 2010	Tibetan Plateau	21st Century	0-5000	—	GISS AOM, SRES A1B
	Rangwala et al., 2013	Boreal Mid-latiude	21st Century	0-5500	—	27.5N-40N; CMIP5 RCPs 4.5,6.0,8.5
Downscaling						
	Giorgi et al., 1997	Swiss Alps	Doubled CO2 Experiment	400-3600	—	Regional Model, 50km grid
	Ceppi et al., 2010	Swiss Alps	1959-2008	0-3000	—	21 ENSEMBLES RCMs
	Zubler et al., 2014	Swiss Alps	21st Century	0-4250	—	Spatial Disaggregation to 2km from 20 ENSMEBLES regional models using a Bayesian Approach
	Chen et al., 2003	Tibetan Plateau	21st Century	500-5500	—	Regional Model, 60km grid
	Im and Ahn, 2011	Korea	21st Century	0-800	—	RCM, 20km
	Rangwala et al., 2012	Southern Rocky Mountains	Mid-21st century	1500-3350	—	NARCCAP Regional Climate Models, 50km grid
	Hu et al., 2013	Yellow River Headwaters	21st Century	3200-4600	13	Statistical Downscaling: SDSM - large scale predictor from GCMs to linearly condition local weather
Reanalysis						
	Hu et al., 2014	Central Asia	1979-2011	0-4300	—	CFSR, ERA-Interim, MERRA