Spatiotemporal variations of alpine climate, snow cover and phenology

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***Abstract*— Understanding the relationships between vegetation phenology and its seasonal drivers under varying site conditions is of high interest in mountain areas, since alpine ecosystems are assumed to be particularly sensitive to climate change. Through the joint analysis of NDVI, snow metrics, and climate data at 250 m and 2 km spatial resolution, respectively, we aim at identifying their temporal and spatial variability and statistical inter- and intra-annual relationships on an alpine-wide scale. Apart from clear patterns in the vegetation and snow metrics related to topography, a negative relationship of mean March NDVI to snow cover duration in the preceding month was detected, indicating a high sensitivity of green-up to snow accumulation and melt. In contrast, positive correlations between early winter SCDs and late summer NDVI indicate a lagged water storage effect. On the local scale of South Tyrol, climate variability interacted with topography could explain on average 30% of NDVI variations from late-October till late-May.**

Keywords—climate; phenology; NDVI; snow; time series; Alps

I. Introduction

As the timing and magnitude of phenological events rely strongly on seasonal and inter-annual climate variability [1], understanding the relationships between plant phenomena and their seasonal drivers under varying site conditions is of high interest. To derive spatially explicit information on plant development, satellite remote sensing data that trace seasonal changes in the spectral signature of vegetation have been used increasingly during the last decades, known as land surface phenology (LSP) [2, 3].

Mountain ecosystems are assumed particularly sensitive to climate change [4, 5], which is likely to have implications for the compositing and functioning of mountain ecosystems. However, the processes of mountain phenology have been insufficiently analyzed [e.g. 6, 7], with even fewer studies covering the entire European Alps [e.g. 8, 9]. The knowledge on LSP patterns and trends over the Alps is hence fragmentary. In addition, alpine phenology patterns are very spatially variable, as factors such as elevation, solar radiation, soil moisture, and especially snow cover affect vegetation on a small scale. Most studies stress the relevance of snow cover and snowmelt for mountain phenology as an inhibiting and enhancing factor for plant development [e.g. 6]. Nevertheless, the relationship between snow cover seasonality and vegetative phenology is rarely assessed over large scales on a per-pixel basis. In addition, the available studies rely on coarse remote sensing data of 1-8 km resolution. Considering that mountains are heterogeneous landscapes with strongly varying altitudinal gradients and microclimatic conditions, this is a limiting factor.

In this study, we aim at closing these gaps by using the highest possible spatial resolution of the MODIS land surface reflectance data (250 m) for the derivation of the Normalized Difference Vegetation Index (NDVI) and of snow metrics. Through the joint analysis of NDVI, snow metrics, and climate data, we aim at identifying the temporal and spatial variabilities of these parameters as well as their statistical inter- and intra-annual relationships in dependency of altitude and exposition on an alpine-wide scale. Since a comprehensive set of climate parameters was only available for the Italian province of South Tyrol, the influence of climate parameters was tested there.

II. Study Area And Data

A. *Study Area*

The study area includes the Alpine range (43.0° - 48.6° N / 4.2° - 15.1°E). The Alps as defined by the Alpine Convention stretch across 1200 km and eight states. The Autonomous Province of Bolzano (South Tyrol) is the northernmost province of Italy, bordered by Austria to the north and east, and by Switzerland to the west. The land cover and altitudinal range of South Tyrol is comparable of that of the Alpine range.

B. *Data Sets*

1) *Snow cover and derived metrics*

Daily snow cover maps in the Alps are derived using MODIS surface reflectance data, taking into account specific characteristics of mountain areas. The two main improvements of the algorithm compared to the standard product are the higher ground resolution (250 m) and a tailored topographic correction [10]. The algorithm uses bands in the red (0.62 – 0.67 µm) and near infrared (0.84 – 0.88 µm) spectrum for the recognition of snow, while clouds are classified using bands in the green (0.55 – 0.57 µm) and shortwave infrared (1.63 – 1.65 µm) at lower resolution. The approach was validated through 148 in situ measurements and shows an accuracy ranging from 82% - 94% [11]. The daily snow cover maps were generated for October 2002 to January 2017, and allow the calculation methodology of snow cover duration (SCD), first snow fall (FSF), and last snow day (LSD) to be kept as simple as possible: for SCD, the daily snow cover maps are accumulated. Gaps due to clouds or missing data are linearly interpolated. If a gap day is preceded and followed by "snow" or "no snow", the SCD for the gap is 1 or 0 day, respectively. If either of the two fringe days is "snow" and the other "no snow", the resulting SCD of the gap is 0.5 days. The same principle is applied if several consecutive days have data gaps. Monthly SCD maps were calculated by applying the algorithm to data of individual months. The FSF and LSD are defined as the first and last dates in the hydrological year (1 Oct - 30 Sept) that a pixel is snow covered. The proposed approach hence takes into account sporadic snowfall in early fall and possible multiple late season transient snowfall events, i.e. FSF and LSD don't necessarily refer to the start and end of a continuous winter snow covered period. Additionally, the snow cover area (SCA) in each map was computed.

2) NDVI and phenology

Also the NDVI was derived from the daily MOD09GQ product at 250 m resolution for all vegetated areas. It is used in conjunction with the daily MOD09GA product which includes geolocation statistics (solar / sensor angles and acquisition quality flags) at 1 km spatial resolution. 4-day maximum value composites omitting pixels of poor observation and geolocation quality were generated for 2002 to 2016. These are used in a next step to model LSP metrics, namely start of season (SOS) and length of season (LOS), using median filtering (Spike value = 0.5) for outlier removal, a double logistic fitting method (2 - 3 envelope iterations and adaptation strength 3 - 8, depending on the land cover), and a 0.5 amplitude threshold in the TIMESAT software [12]. Additionally, monthly and 16-days mean NDVI maps were calculated.

3) Elevation data

The resampled Shuttle Radar Topographic Mission (SRTM) digital elevation model (DEM) v4.1 [13] was used to derive information about altitude and exposition. Using aspect in quantitative analyses is hampered by its circular nature, so aspect, slope, and latitude were used to derive a heat load index (HLI) of potential direct incident radiation ranging from 0 to 1.

4) Land cover data

For discriminating differently vegetated land surfaces, the CORINE (COoRdination of INformation on the Environment) land cover classification for the reference year 2012 was used.

5) Climate data for South Tyrol

Hourly climate data (temperature, precipitation, radiation, relative humidity, wind, air pressure) were available on a 2 km grid for the period 2004 – 2013 in the South Tyrol area. The Weather Research and Forecasting (WRF) model reanalysis data were provided by the meteorological service company CISMA. Besides, day length was derived using latitude and date. All values were aggregated to 16-day means or sums.

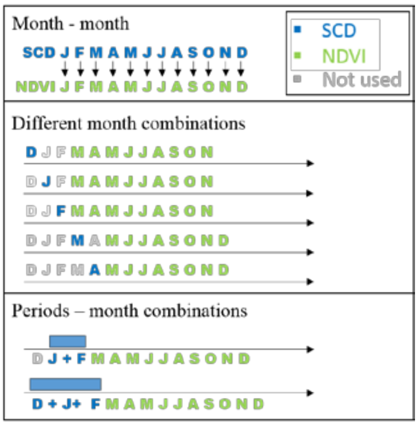

Fig. 1. Schematic representation of the different pixel-wise correlations.

III. Methodology

A. *Pixel-wise correlations NDVI-SCD*

In order to analyze the inter-annual influence of snow cover on vegetation, pixel-wise Pearson correlation coefficients between the 14-year time series of monthly mean NDVI and monthly SCD were calculated for each month separately. To identify possible time lags in the relationship, correlations between selected winter month (Dec - Apr) or longer winter periods and the remaining month of the vegetation period (Mar - Dec) have been calculated similar to [14, 15] (see Fig. 1).

B. *Seansonality and time-lags of climatic drivers*

To evaluate how the seasonality of NDVI is related intra-annually to its climatic drivers (SCD, mean temperature [t_{mean}], radiation [rad], day length, precipitation), cross-correlations were calculated in each 2 km grid cell for 2004-2013 over South Tyrol in dependency of altitude, and the time lag for the maximum correlation between the variables was identified.

C. *Combined effects of climate variability on NDVI*

In a last step, the NDVI anomalies were associated to snow and climate parameter variabilities in dependency of altitude and HLI. As the seasonal cycle induces high correlation between these phenomena, all variables were first deseasonalized for each grid cell using penalized cyclic splines:

$$y_{ij} = f(doy_j)+\varepsilon_{ij}, \qquad (1)$$

where y_{ij} is a variable (NDVI, SCD, …) at year i and 16-day group j, f is a cyclic function, and doy_j is the day-of-year. The ε_{ij} are the deseasonalized values, hereafter denoted with prefix *d*. Then for each 16-day group separately, 16-day mean *d*NDVI was regressed on climate variables, altitude and HLI using 50% of the data as training and the other 50% as test set:

$$dNDVI_{si} = \beta_0 + \beta_1 dSCD_{si} + \beta_2 dTmean_{si} + \beta_3 dRad_{si} + \beta_4 WinterSCD_{si} + \beta_5 Altidtude_s + \beta_6 HLI_s + \mathrm{Altitude}_s(\gamma_1 dSCD_{si} + \gamma_2 dTmean_{si} + \gamma_3 dRad_{si} + \gamma_4 WinterSCD_{si}) + \mathrm{HLI}_s(\delta_1 dSCD_{si} + \delta_2 dTmean_{si} + \delta_3 dRad_{si} + \delta_4 WinterSCD_{si}) + \varepsilon_{si} \quad (2)$$

where s is a pixel index, i is a year, β are the main effects, γ and δ are interactions with altitude and HLI, WinterSCD is the SCD of the previous winter (Dec-Feb; variable only included in Mar-Nov models), and $\varepsilon_{si} \sim N(0,\sigma^2)$ are errors. P-values for the coefficients were adjusted for multiple testing (23 models).

IV. Results And Discussion

A. Snow parameters & NDVI correlations

The inter-annual analyses show strong negative correlations ($r < -0.5$) for 72.6 – 91.2 % of the available data (i.e. vegetated areas) for the month-month analyses, with a maximum in the winter month (Jan – Mar). The high values of the correlations of the same months' NDVI and SCD maps stress the direct but also confounding influence snow cover can have on LSP. Snow exacerbates the seasonal dampening of the vegetation signal, making it difficult to separate the green-up due to the emergence of leaves from an NDVI increase due to the snow disappearance. However, also the correlations between different months achieve high percentages of strongly negative correlating pixels (23.9 – 87.6 %) with a seemingly higher influence of December SCD and generally decreasing correlation strength from in average 70 % in spring (Mar – May) to 45 % in summer (Jun – Sep). Pixels deviating from this pattern are mostly dominated by cultivated agricultural areas (see Fig. 2). The winter period – month correlations reached similarly high shares of negatively correlated pixels (24.7 – 86.2 %), and negligible differences between the two and three month accumulation periods. Interestingly, the percentage of positively correlated pixels exceeds the percentage of negatively correlated pixels in the Dec/Jan/Feb - Sept/Oct months and period combinations, indicating a long term lagged positive effect of SCD on NDVI.

B. Common seasonality of vegetation and climatic drivers

The seasonality of vegetation activity correlated best to different climate variables depending on altitude (Fig. 3). In the

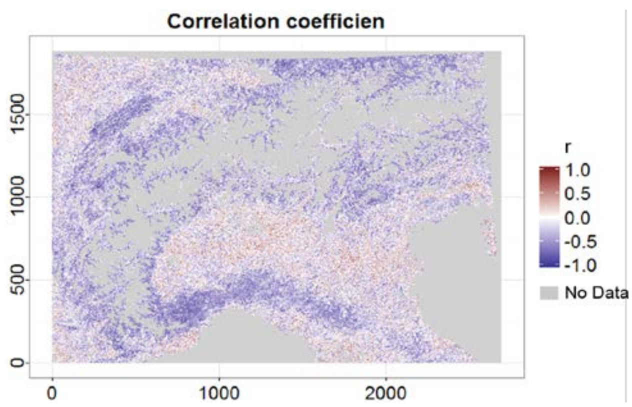

Fig. 2. Significantly (p<0.1) positively (red) and negatively (blue) correlated January SCD and April NDVI.

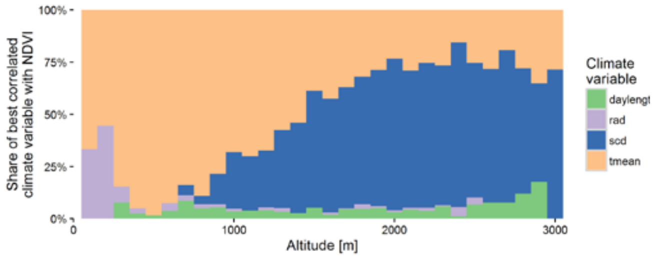

Fig. 3. Percentage of climate variables that have highest correlations with NDVI by altitude for South Tyrol. For abbreviations see text.

lowest altitudes up to 300 m, NDVI was correlated best with radiation and temperature, then until 700 m almost only to temperature. From 700 m to 2000 m the share of pixels where NDVI was correlated best to SCD increased continuously reaching 70 %, while at the same time the share of pixels correlating best to temperature decreased to 25 %. Across all altitudes from 300 m onwards, approximately 5 % of pixels had the best correlation of NDVI to day length.

C. Combined effects of climate variability on NDVI

By removing the seasonality from NDVI and climate variables, the combined influence of climate variables on NDVI was assessed. At average altitude and HLI, SCD had the highest effect on NDVI, followed by T_{mean}, rad, and WinterSCD, however, the influence of all variables varied throughout the year. Furthermore, the effects of climate variability on NDVI variability depended on altitude (Fig. 4). Subsequently, high and low altitudes correspond to 700 and 2300 m, and high and low HLI to 0.55 and 0.95, which are approximately the 5 and 95% quantiles in the study region. The

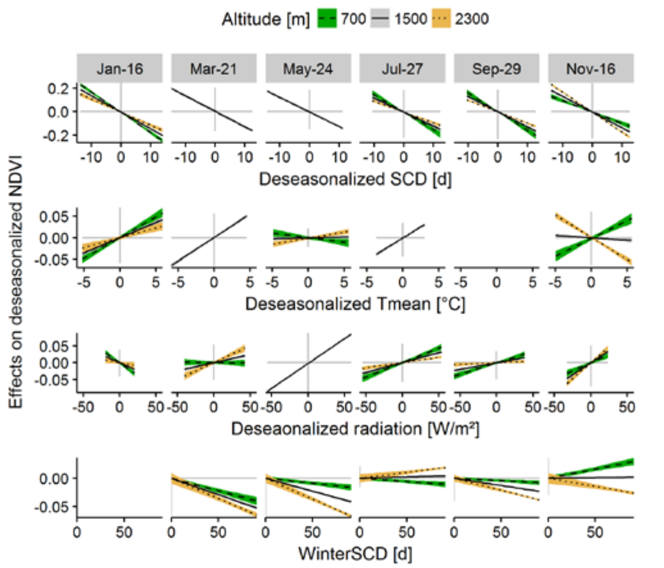

Fig. 4. Influence of climate variability on NDVI variability throughout the year and depending on altitude. Shown are effects of deseasonalized climate variables on deseasonalized NDVI at three altitudes for a heat load index of 0.75 and holding other variables constant. If lines for 700 m and 2300 m are missing, the interaction with altitude was not significant. In empty panels the coefficient of the climate variable was non-significant or the variable was not included in the model (e.g. WinterSCD in January).

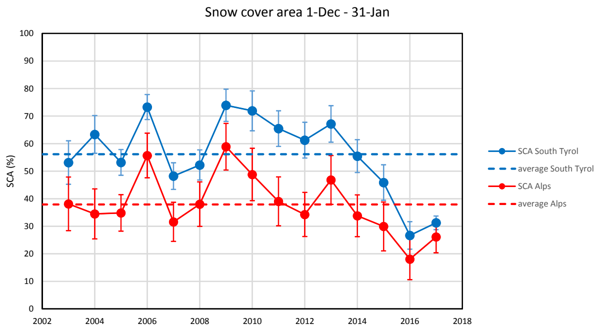

Fig. 5. Percentage snow coverage during the start of winter period (December – January) in South Tyrol and the Alps.

effect of SCD was stronger in lower than in higher altitudes (average difference 0.005/d), but the interaction non-significant in spring (March to May). Higher effects of mean temperature were observed in January and February for lower altitudes, while from mid-April to mid-July effects were higher for higher altitudes. The rest of the year, interactions were non-significant or inconclusive. Radiation effects were higher in lower altitudes throughout the year, except for a few dates, and few non-significant interactions. Effects of WinterSCD were more positive at low altitudes for June, October, and early November (~0.003/10d), more positive at higher altitudes for July and late August (~0.002/10d), and negative at higher altitudes late-Septemper till mid-November (~ 0.002/10d). Interactions with HLI resulted in higher effects of mean temperature for higher HLI for mid-February till late-April (average difference 0.005/°C), and in more negative effects of WinterSCD for low HLI in March. For the other climate variables and other dates, interactions with HLI were mostly non-significant.

D. *Spatial and temporal patterns of snow and phenology*

Both MODIS-derived products, snow cover and NDVI, as well as the phenological metrics derived from them show spatially distinct distribution patterns according to altitude. The SOS at different altitudes [100 – 3000 m] has a time lag of 45 – 75 days, while the inter-annual variability of mean SOS in different altitudes ranges from 17 to 32 days, with a higher variability in higher altitudes. Also SCA shows a high temporal variability in the Alps as well as in South Tyrol, with below-average SCA percentages during the last three seasons (Fig.5).

V. Conclusions

In this study we jointly analyzed the temporal and spatial variability of snow and plant phenology on an alpine-wide scale at 250 m resolution. Both parameters and derived metrics showed clear patterns related to topography. While no distinct trend in phenology could be detected, the alpine- and South Tyrol-wide SCA are below-average in recent years. Regarding the interrelationships of plant photosynthetic activity and its drivers, the mean NDVI of March shows the highest negative relationship to SCD in the preceding (Dec – Feb) as well as the same month, indicating the high sensitivity of green-up to snow accumulation and snow melt. Positive correlations between early winter SCDs and late summer mean NDVIs point to a lagged water storage effect. However, the strength of the correlations varies with altitude. Climate variability interacted with altitude and HLI could explain on average 30% of NDVI variation from late-October till late-May, and 9% on average for June till early-October. Explained variation was the highest in December and March with values around 40%.

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