Supplemental Materials

S1. Material and Methods in Detail

S1.1. Datasets

The primary data sets used in the study were NDVI (normalised difference vegetation index), LST (land surface temperature), and TRMM (Tropical Rainfall Measurement Mission). Time series NDVI were used to extract phenology and productivity metrics (PPMs), and the LST and rainfall data sets were used to derive climate variables (temperature and rainfall).

S1.1.1. NDVI Data

NDVI time-series were acquired for 2001 to 2011 from moderate resolution sensor (MODIS) images taken at 16-day intervals and 250 m spatial resolution provided in a standard product (MOD13Q1, Level 3 Product) by the Land Processes Distributed Active Archive Center (LP DAAC), at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre (lpdaac.usgs.gov). The study area comprises 2 tiles (swath scenes) of the product (h23v05 and h24v05). A total of 253 NDVI 16-day composite images were used in the analysis.

S1.1.2. Temperature and Rainfall Data

LST derived from MODIS can be considered as an independent climate variable and/or substitute for air temperature (e.g., [1,2]). Remotely sensed LST measurements have a high temporal density and provide spatially averaged rather than point values [3], which are particularly appropriate for analyses in which response variables are averaged over space. The accuracy of the MOD11C3 product has been assessed over a widely distributed set of locations and time periods via several ground truth and validation efforts [4]. Data for temperature estimates were acquired for 2001 to 2011 from the MODIS MOD11C3 product, which provides monthly estimates of LST with a spatial resolution of $0.05° \times 0.05°$ (~5.6 km at the equator) [1]. This is a monthly composite average derived from MOD11C1 (daily global product) and stored as clear-sky LST values over a month to avoid persistent errors [5].

TRMM rainfall measures are estimated from analysis of data from multiple satellites and gauges using a calibration-based sequential scheme [6]. Various studies suggest that TRMM rainfall measures can be used as a substitute for ground-based observations [7–9]. A high degree of accuracy was achieved in developing a predictive hydrological model for the upper Indus basin using TRMM rainfall estimates (3B43 product) calibrated with daily discharge data and stream flow [10]. Rainfall estimates were obtained from a TRMM monthly global product (3B43), spanning from 50° N to 50° S at a spatial resolution of $0.25° \times 0.25°$ (~ 28 km), giving a monthly average precipitation rate (mm/h) [1]. The monthly average was converted into monthly accumulated rainfall (mm) by multiplying the hourly rate with the total hours in the month [6,7,10].

S1.1.3. Other Datasets

In order to understand the land cover dynamics, a MODIS land cover type product (MCD12Q1, 500 m, Level 3 product) was acquired for both tiles. Other data sets used included a recent medium resolution

(30 m) detailed land cover map of the study area provided by the International Centre for Integrated Mountain Development (ICIMOD), and SRTM 90 m digital elevation data provided by CGIAR-CSI [11].

S1.2. Methods

S1.2.1. NDVI Data Cleaning

The NDVI data nearly always include disturbances caused by cloud contamination, atmospheric variability, and bidirectional effects [12]. These disturbances show up as undesirable noise and affect the monitoring of land cover and ecosystems [13]. The NDVI product is accompanied by a quality assessment (QA) layer with auxiliary information on the quality of the pixels which enables pixels to be excluded, or weighted, when reconstructing the time series. A "double logistic regression" approach was used to reconstruct a continuous NDVI time-series for phenological analysis of the vegetation [14–17]. This is a well-established method particularly suited to phenological monitoring of rangelands or grasslands from time series remote sensing data [16]. However, the asymmetry of the function which results from the assumed equal and opposite curvature may reduce its ability to fit the time-series [17], although it is helpful in avoiding the effect of random noise at the beginning and end of the season. The NDVI time series described by the double logistic function is explained by the following equation [17]:

$$\boldsymbol{NDVI_t = NDVI_{min} + NDVI_d} \left(\frac{1}{1+e^{\beta_\theta(t-\beta)}} + \frac{1}{1+e^{\alpha_\theta(t-\alpha)}} - 1\right) \quad \textbf{(1)}$$

where, $NDVI_t$ = NDVI of the pixel on Julian day t (JD); $NDVI_{min}$ = minimum NDVI of NDVI trajectory during the year (lower asymptote); $NDVI_d$ = difference of minimum and maximum (lower and upper asymptote) of NDVI trajectory during the year; β = position of left inflection point (change of concavity, JD) where the slope of the function has maximum change in spring (maximum rate of increase in NDVI), the nominal start of the season; α = position of right inflection point (change of concavity, JD), where the slope of the function has maximum change (maximum rate of decrease in NDVI) in autumn; β_θ = maximum slope of the curve at left inflection point; α_θ = maximum slope of the curve at right inflection point.

Parameters describing the shape of the fitted model were optimized through a multistep procedure involving upper envelope fitting and least square adjustment. Initially, parameters were obtained by solving the system of normal equations including the weights (w_1, w_2, …, w_n) from the pixel quality index. To reduce the noise, bad quality (cloudy) pixels were excluded from the analysis, and high and medium weightage were given to good and mixed quality pixels. Data values lower than the modelled NDVI values were considered less important and given weightage in the next loop of system solving that led to the upper envelope fitting of the modelled function. A non-linear least square adjustment was done by minimizing the difference between the modelled NDVI and input NDVI values using a separable Levenberg-Marquardt curve fitting method (MPFIT), where the box constraints on non-linear parameters are implemented by projecting on to the feasible parameter interval [16–18].

The general form of the above model function, which is a local fit to the data in the interval around the maxima and minima of the time series, can be expressed as

$$\gamma(t) = \gamma\,(t; C, x) = C_1 + C_2\,\vartheta(t; x) \quad (2)$$

The corresponding form of least square function is

$$\varphi^2 = \sum_{i}^{n} \left[\omega_i \left(\gamma(t; C, x)\right) - y_i\right]^2 \tag{3}$$

where, the function depends linearly on "C" and non-linearly on "x"; $C = C_1, C_2$ = linear parameters defining the base level and amplitude; x = non-linear parameters describing the shape of the basis function; y_i = input data values.

S1.2.2. Biome Stratification (Bioclimatic and Elevation Zones)

The high spatial variability that characterizes mountain areas suggests that regional studies should include a microclimatic component which can be defined by proxy variables such as altitude, slope, and aspect [19]. Altitude was taken as a proxy micro-ecological zone to further minimize the effect of spatial variance; the altitudinal gradient was stratified into 10 classes at 500 m intervals of elevation ranging from <500 to >4500 masl [20]. Altitudinal gradient, phenology, and productivity metrics were characterized spatially and further analysed for temporal variation in response to climatic factors in each zone of elevation, thus defining sub-bioclimatic zones. Table S3 summarizes the main features of the four bioclimatic regions identified in the study area, and the grassland classes (vegetation communities) associated with them.

Table S1. Classification scheme for bioclimatic zones and grasslands in the study area.

Bioclimatic Zone	Description	Elevation Range (masl)	Elevation Zone (masl)
Humid subtropical region (HSR)	Low forests of branchy, thorny, evergreen trees, and shrub, xerophytic woods/scrub	500–1000	Zone 1(<500) Zone 2 (500–1000)
Temperate region (TR)	Predominantly forest zone with forage areas for livestock grazing during summer growing season	1000–3000	Zone 3 (1000–1500) Zone 4 (1500–2000) Zone 5 (2000–2500) Zone 6 (2500–3000)
Subalpine region (SAR)	Predominantly grassland with some small trees and shrubs; excellent forage for livestock grazing during growing season	3000–4000	Zone 7 (3000–3500) Zone 8 (3500–4000)
Alpine region (AR)	Alpine grassland	> 4000	Zone 9 (4000–4500) Zone 10 (>4500)

S1.2.3. Extraction of Phenology and Productivity Metrics (PPMs)

NDVI time-series analysis has been widely used to determine timing and productivity metrics and thus track the dynamics of vegetation growth [21]. There are a variety of methods available to define timing and productivity metrics from NDVI time-series, although as yet no globally accepted definition. The methods can be grouped into four types: thresholds, derivatives, smoothing functions, and fitting methods [22]. This study used a combination of derivative [16] and threshold [22] methods. First, the NDVI values describing the maximum rates of increase and decrease within 11 years of mean annual values were calculated. These NDVI values were used as thresholds in determining the annual timing metrics of vegetation growth. Three timing and two productivity metrics were characterized to give vegetation patterns: SGS (start of growing season), EGS (end of growing season), LGS (length of growing season), SIN (seasonally integrated NDVI), and MSN (maximum seasonal NDVI (Table S1). LGS was calculated as the difference between SGS and EGS; SIN is the area under the function curve of SGS and EGST or the sum of all NDVI values from SGS to EGST, and MSN is the maximum NDVI value between SGS and EGS [23–27]. The selected metrics were chosen to reveal spatio-temporal response patterns of grasslands to climatic variables [19–20].

Table S2. Ecological relevance of PPMs derived from NDVI time-series.

PPM	Metric Type	Description	Ecological Meaning
Start of growing season (SGS)		Time when NDVI reaches a defined threshold value in spring	Approximates the start of the season when green forage becomes available; time of highest quality forage
End of growing season time (EGS)	Phenology	Time when NDVI decreases to a defined threshold value in autumn	Approximates the end of the season when seasonally active vegetation becomes senescent or has been covered in snow; green forage becomes scarce
Length of growing season (LGS)		Number of days between start and end of growing season	Number of days when forage is available
Seasonally integrated NDVI (SIN)	Productivity	Cumulative positive NDVI values of the season	Proxy for seasonal primary production of vegetation
Maximum seasonal NDVI (MSN)	Biomass	Maximum NDVI value of season	Proxy for maximum forage biomass of the season

S1.2.4. Climate Variables (Seasonal and Annual Rainfall and Temperature)

Annual and seasonal (four seasons) layers of variables were created for rainfall (cumulative) and temperature (average) (Table S2); December, January, and February (DJF) were taken as winter; March, April, May (MAM) as spring; June, July, and August (JJA) as summer; and September, October, and November (SON) as autumn [28–30]. DJF_T (mean seasonal temperature of winter), MAM_T (mean seasonal temperature of spring), JJA_T (mean seasonal temperature of summer), SON_T (mean seasonal temperature on autumn), ANN_T (Mean annual temperature), DJF_R (cumulative seasonal rainfall of winter), MAM_R (cumulative seasonal rainfall of spring), JJA_R (cumulative seasonal rainfall of summer), SON_R (cumulative seasonal rainfall of autumn) ANN_R (cumulative annual rainfall); Winter (December, January, February), spring (March, April, May), summer (June, July, August), autumn (September, October, November).

S1.2.5. Grasslands Mask

A preliminary analysis of the available land cover map using the NDVI seasonality indicated commission errors in the grassland classes. Ground truth information from field surveys in 2010 and 2011 showed that grasslands are usually mixed with croplands along valley bottoms and low altitude plains, with scrub forest at mid altitudes, and with sparse forest (mostly small broadleaved trees) at higher elevations and in the alpine regions. The lack of pure grassland patches meant that it was first necessary to prepare a grasslands mask with minimum commission errors so that grassland variation could be analysed [29]. A rule based exclusion approach based on a combination of mean PPMs, a digital elevation model (DEM), in situ information, the land cover map, and mean "NDVI climatology" (11 years of mean PPMs, MSN_m) was followed to identify grassland patches with no or a minimum admixture of other land cover regimes. Pixels with weak NDVI values ($MSN_m < 0.05$) were excluded. Pixels already classified in classes such as forest, snow and glaciers, cultivated land, water, bare land, and urban areas were removed. At higher elevation, evergreen scrub forest was eliminated using a decision rule of "prolonged seasonal length together with high productivity with lower maximum seasonal NDVI". At mid altitudes in forest zones, forested areas were identified and eliminated based on extended seasonal length and high NDVI throughout the year. The noisy pixels were further filtered using a histogram analysis of PPMs, such as very late start of growing season ($SGS_m > 230$) and end of season ($EGS_m > 360$); where SGS_m and EGS_m are the average of 11 years mean SGST and EGS, respectively.

S1.2.6. Spatial and Temporal Aggregation

The variability of phenological metrics within each elevation zone in terms of both space and time was taken as a measure for assessing the heterogeneity within each zone. The spatial variability of a metric within an elevation zone may result from a range of biotic and environmental gradients and associated responses in the grassland system; a high spatial variability represents a diversity of habitat conditions. Temporal variability (over 11 years) represents how the system is experiencing change over time; a high temporal variability indicates a high degree of change.

PPMs and climate variables (CVs) derived from time-series were aggregated to give a spatial average per grasslands zone [16,28]. Averaging the variables in elevation zones provided annual values for the representative class and reduced the effect of inter pixel spatial variations. Spatial and temporal statistics were also calculated. The temporal standard deviation, σ_t, refers to the dispersion of the phenology metric in time. The standard deviation for a time series of a phenology metric was calculated per pixel and averaged over all pixels within an elevation zone. The spatial standard deviation, σ_s, is the standard deviation of the (temporal) mean phenology pixel values that fall within a grassland zone and indicates the dispersion of the phenology metric in space. High values of σ_t indicate that the metric has high temporal variability and high values of σ_s indicate that the phenology metric is spatially heterogeneous within the grassland class [28].

S1.2.7. Modelling PPMs as a Function of Climate Variables

The year to year responses of the five PPMs to the climate variables (CVs) were evaluated. For each of the PPMs, a regression model was run for each class of grasslands over the 11 years from 2001–2011 [28]. A total of 500 separate models were computed. Inter annual variation of the PPMs was modelled as a function of yearly change in the seasonal and annual climate variables. Measures of explanatory power, R, sign of proportionality, slope, and significance of the relation were obtained for individual climate variables using the function—*PPM = f(CV).*

Table S3. Significant correlations between start of growing season and climate variables.

Elevation Zone	DJF_T	MAM_T	JJA_T	SON_T	ANN_T	DJF_R	MAM_R	JJA_R	SON_R	ANN_R
Zone 1	—	0.92	—	—	—	−0.77	−0.64	—	—	—
Zone 2	—	0.89	—	—	—	—	−0.74	—	—	—
Zone 3	—	—	—	—	—	—	—	—	—	—
Zone 4	0.66	—	—	—	—	—	—	—	—	—
Zone 5	0.69	—	—	—	—	—	—	—	—	—
Zone 6	0.63	—	—	—	—	—	—	—	—	—
Zone 7	—	−0.79	—	—	−0.69	0.62	—	—	—	—
Zone 8	—	−0.69	—	—	—	—	—	—	—	—
Zone 9	—	−0.62	—	—	—	—	—	—	—	—
Zone 10	—	−0.58	—	—	—	—	—	—	—	—

Table S4. Significant correlations between end of growing season and climate variables.

Elevation Zone	DJF_T	MAM_T	JJA_T	SON_T	ANN_T	DJF_R	MAM_R	JJA_R	SON_R	ANN_R
Zone 1	—	—	−0.77	—	—	—	—	—	—	—
Zone 2	—	—	—	—	—	—	—	—	—	—
Zone 3	—	—	—	—	—	—	—	—	—	—
Zone 4	—	—	—	—	—	—	—	—	—	—
Zone 5	—	—	—	—	—	—	—	—	—	—
Zone 6	—	—	—	—	—	—	—	—	—	—
Zone 7	—	—	—	—	—	—	—	0.73	—	—
Zone 8	—	—	—	—	—	—	—	0.69	—	—
Zone 9	—	—	—	—	—	—	—	—	—	—
Zone 10	—	—	—	—	—	—	—	—	—	—

Table S5. Significant correlations between length of growing season and climate variables.

Elevation Zone	DJF_T	MAM_T	JJA_T	SON_T	ANN_T	DJF_R	MAM_R	JJA_R	SON_R	ANN_R
Zone 1	—	—	−0.66	—	0.64	—	—	—	—	—
Zone 2	—	—	−0.71	—	0.67	—	—	—	—	—
Zone 3	—	—	—	—	—	—	—	—	—	—
Zone 4	−0.73	—	—	—	−0.62	—	—	—	—	—
Zone 5	−0.92	—	—	—	−0.66	—	—	—	—	—
Zone 6	−0.85	—	—	—	—	—	—	—	—	—
Zone 7	—	0.62	—	—	0.73	—	—	0.74	—	—
Zone 8	—	0.64	—	—	0.84	—	—	0.60	—	—
Zone 9	—	0.59	—	—	0.85	−0.60	—	—	—	—
Zone 10	—	0.61	—	—	0.83	−0.59	—	—	—	—

Table S6. Significant correlations between maximum seasonal NDVI and climate variables.

Elevation Zone	DJF_T	MAM_T	JJA_T	SON_T	ANN_T	DJF_R	MAM_R	JJA_R	SON_R	ANN_R
Zone 1	—	—	—	—	−0.63	—	—	0.69	—	0.92
Zone 2	—	—	—	—	−0.69	—	0.64	—	—	0.93
Zone 3	—	−0.61	—	—	−0.82	0.69	—	—	—	0.80
Zone 4	—	−0.74	−0.61	—	−0.81	0.65	0.63	—	—	0.68
Zone 5	—	−0.84	−0.77	—	−0.81	—	0.69	—	—	0.66
Zone 6	—	−0.74	−0.80	—	−0.64	—	0.66	—	—	—
Zone 7	—	—	—	—	—	—	—	—	—	—
Zone 8	—	—	—	—	—	—	—	—	—	—
Zone 9	—	—	—	—	—	—	—	—	—	—
Zone 10	—	—	—	—	—	—	—	—	—	—

Table S7. Significant correlations between seasonally integrated NDVI and climate variables.

Elevation Zone	DJF_T	MAM_T	JJA_T	SON_T	ANN_T	DJF_R	MAM_R	JJA_R	SON_R	ANN_R
Zone 1	—	—	—	—	—	—	—	0.78	—	0.81
Zone 2	—	—	—	—	—	—	—	0.66	—	0.80
Zone 3	−0.71	−0.64	—	—	−0.67	0.76	—	—	—	0.67
Zone 4	−0.66	−0.70	−0.65	—	−0.74	0.66	0.64	—	—	0.66
Zone 5	−0.64	−0.84	−0.76	—	−0.79	—	0.79	—	—	0.71
Zone 6	—	−0.62	−0.81	—	−0.60	—	0.63	—	—	0.69
Zone 7	—	0.62	—	—	0.69	—	—	0.72	—	—
Zone 8	—	0.65	—	—	0.81	—	—	0.60	—	—
Zone 9	—	0.66	—	—	0.82	—	—	—	—	—
Zone 10	—	0.62	0.64	—	0.84	—	—	—	—	—

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