Journal of Arid Environments 103 (2014) 17–30

Contents lists available at ScienceDirect

Journal of Arid Environments

journal homepage: www.elsevier.com/locate/jaridenv

Net primary productivity in Kazakhstan, its spatio-temporal patterns and relation to meteorological variables☆

Christina Eisfelder*, Igor Klein, Markus Niklaus, Claudia Kuenzer

German Remote Sensing Data Center (DFD), German Aerospace Center (DLR), Oberpfaffenhofen, 82234 Wessling, Germany

ARTICLE INFO

Article history:
Received 28 September 2012
Received in revised form
2 December 2013
Accepted 24 December 2013
Available online

Keywords:
Net primary productivity
Vegetation dynamics
Arid regions
Semiarid regions
Kazakhstan
Time-series analyses

ABSTRACT

Arid and semiarid environments are susceptible to environmental degradation and desertification. Modelling net primary productivity (NPP) and analysis of spatio-temporal patterns help to understand ecological functioning especially in these areas. In this study, we apply the Biosphere Energy Transfer Hydrology Model (BETHY/DLR) to derive NPP for Kazakhstan for 2003–2011. Results are analyzed regarding spatial, monthly, and inter-annual variations. Mean annual NPP for Kazakhstan is 143 g C m^{-2} and maximum productivity is reached in June. Most monthly NPP anomalies occur in semiarid North of Kazakhstan. These regions seem to be most strongly affected by changes in meteorology and are likely to be vulnerable to changing climate. Arid ecosystems show lower inter-annual NPP variability than semiarid lands. Correlations between NPP and meteorological parameters reveal variable influence of temperature, PAR, and precipitation on vegetation productivity during the year. Reaction of vegetation growth to precipitation is delayed 1–2 months. Temperature is most critical in spring and precipitation in summer affects NPP in August–October. The results presented in this study help to identify regions that are vulnerable to global change. They allow predictions on possible effects of expected future climate change on vegetation productivity in arid and semiarid Kazakhstan and support sustainable land management.

1. Introduction

Arid and semiarid environments cover almost one third of the terrestrial world (FAO, 1989). These lands are especially susceptible to environmental degradation and desertification (e.g. Eswaran et al., 2001; UN, 1994; Verstraete, 1986). Environmental degradation has been identified as one of the major threats by the High Level Panel on Threats, Challenges and Change of the United Nations (UN, 2004). The vegetation cover in semiarid and arid regions is of high importance for protection against wind and aeolian erosion (Calvão and Palmeirim, 2004). The reduction in plant biomass lowers the soil quality and fertility, which in turn reduces the capacity for agriculture and keeping livestock. Reduction in biomass therefore has a negative effect on human well-being (e.g. Köchy et al., 2008; UNEP, 1999).

Quantification of biomass and monitoring of net primary productivity (NPP) are essential to identify and monitor those areas under high risk of degradation and desertification (e.g. Moleele et al., 2001; Niklaus et al., 2012). NPP is the dry matter production by green vegetation per unit area and unit time. It is a key variable for ecological monitoring activities and a sensitive indicator of climate and environmental change (Niemeijer, 2002; Schimel, 1995). NPP has therefore been identified by the Commission on Geosciences, Environment and Resources as a primary variable for observing ecological functioning and on-going degradation processes (CGER, 2000).

Large areas in Central Asia, including almost entire Kazakhstan, are characterized as arid or semiarid (Eisfelder et al., 2012; Lioubimtseva and Adams, 2004). Kazakhstan is an especially important area to study because land degradation and desertification already pose large ecological challenges (ADB, 2010). The country has experienced varying human influences and political decisions with dramatic ecological and environmental consequences such as the decline of the Aral Sea (ADB, 2010). Large areas in Kazakhstan were undergoing land cover change, especially

* Corresponding author. Tel.: +49 8153 28 2378; fax: +49 8153 281458.
E-mail addresses: Christina.Eisfelder@dlr.de, christina.eisfelder@gmx.de (C. Eisfelder), Igor.Klein@dlr.de (I. Klein), Markus.Niklaus@dlr.de (M. Niklaus), Claudia.Kuenzer@dlr.de (C. Kuenzer).

0140-1963/$ – see front matter © 2014 The Authors. Published by Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.jaridenv.2013.12.005

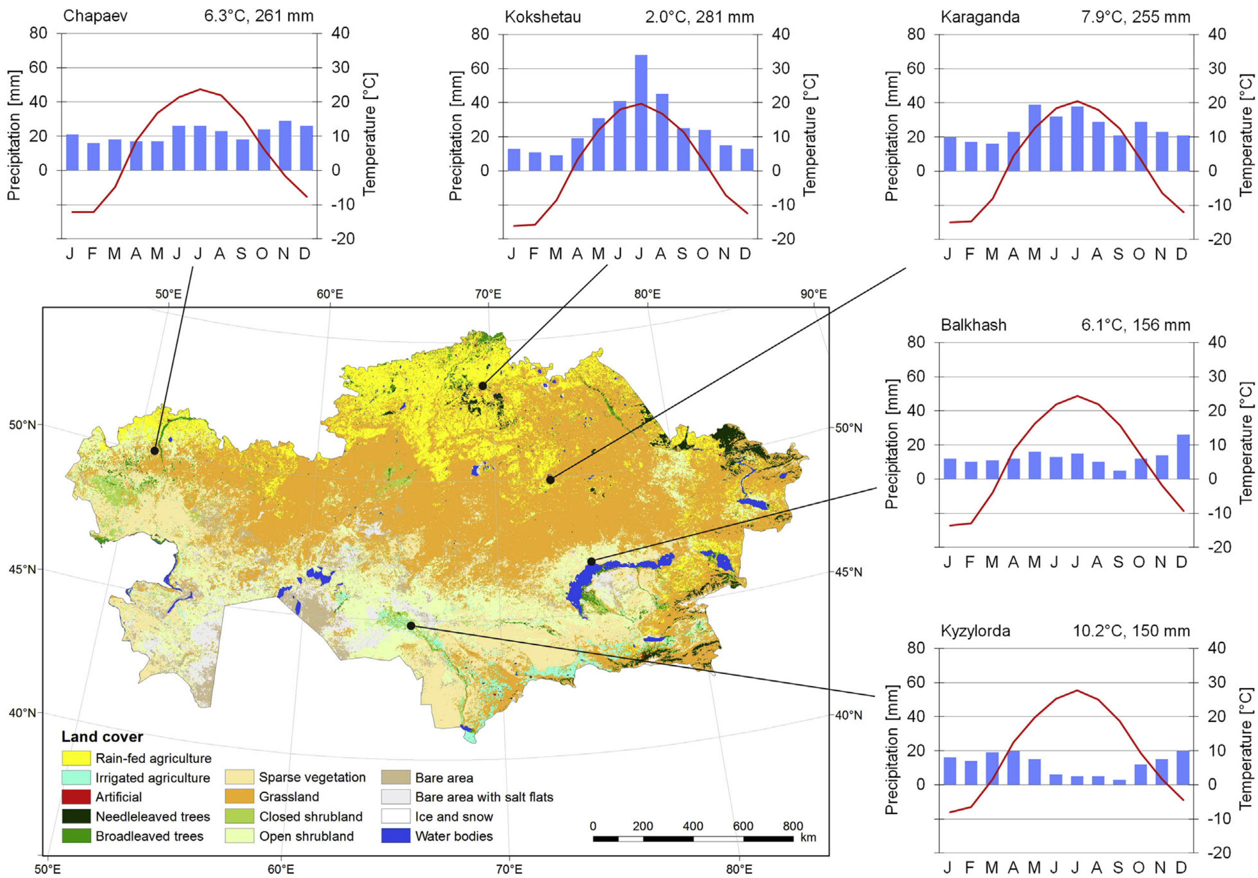


Fig. 1. Land cover and land use map of Kazakhstan (Klein et al., 2012) and representative precipitation (average monthly precipitation) and temperature (average daily mean temperature) diagrams.
Extracted from Hijmans et al., 2005.

during the second half of the 20th century when the ‘Virgin Lands Programme’ was initiated to transform traditional pasture lands of the Kazakh Steppe into crop agriculture (de Beurs and Henebry, 2004). The extensive land use led to dramatic steppe deterioration. After the breakdown of the Soviet Union, vast areas of ploughed land were abandoned. In recent years, the grazing impact on vegetation has decreased and undergrazing rather than overgrazing was reported. This was due to a reduction in the livestock population (de Beurs and Henebry, 2004; Lioubimtseva et al., 2005). In addition to human impacts on the environment, there are also the effects of changing climate. Increased annual and winter temperatures have been recorded since the beginning of the 20th century (Lioubimtseva et al., 2005). Temperatures in Central Asia are expected to further increase 1–2 °C by 2030–2050 (Lioubimtseva et al., 2005). Aridity is expected to intensify, especially in western Kazakhstan (Lioubimtseva et al., 2005). Trends in precipitation are highly variable, but indicate a small overall decrease (Lioubimtseva and Henebry, 2009).

In the context of these diverse influences on the arid and semiarid lands in Kazakhstan, it is of great interest to observe large-scale vegetation dynamics. In this study, we applied the Biosphere Energy Transfer Hydrology (BETHY/DLR) model, which has been adapted at the German Aerospace Center (DLR) to be driven by remote sensing data (Wißkirchen et al., 2013), to calculate NPP for Kazakhstan. The objectives were to (i) present the results of mean annual and monthly NPP for the period 2003–2011, (ii) locate areas with frequent NPP anomalies within the time period of interest, as well as areas of low and high NPP variability, and (iii) analyze temporal correlation between NPP and meteorological parameters.

Such detailed analyses of NPP time-series for Kazakhstan have not been published before. The methods and analyses presented here would be applicable to other arid environments in the world as well. The derived information helps to obtain knowledge about spatial distribution and temporal variation of vegetation productivity. Derivation of anomalies and relation between NPP and climate form valuable base information for understanding which areas might be most strongly affected by changing climate. This information may help to identify regions that are more vulnerable to global change, and thus, support sustainable land management.

2. Materials and methods

2.1. Study area

Kazakhstan is the world’s ninth largest country with an area of 2.72 million km^2. It is mainly characterized by arid and semiarid conditions (Eisfelder et al., 2012; Lioubimtseva and Adams, 2004). It spreads between 40° and 56°N and 46°–88°E and reaches from the Caspian Sea and Volga plains in the West to the Altay Mountains in the East. In the South and Southeast, the country is bordered by the Tian Shan Mountains and in the North, the geologically diverse steppe reaches the Western Siberian lowland (ADB, 2010).

Table 1
Overview of input parameters for BETHY/DLR used within this study.

Input parameter	Units	Spatial resolution	Temporal resolution	Source	Reference
LAI	$m^2\ m^{-2}$	~1 km	8-Daily	MODIS	Knyazikhin et al., 1999
Land cover map	(Classes)	~1 km	Once	DLR	Klein et al., 2012
Soil map	(Classes)	~1 km	Once	FAO	FAO et al., 2009
Digital elevation model	m	~1 km	Once	GTOPO30	USGS 1996
Surface geopotential	$m^2\ s^{-2}$	0.25°	Once	ECMWF	Berrisford et al., 2011
Large-scale and convective precipitation	m of Water	0.25°	>Daily	ECMWF	Berrisford et al., 2011
10 m Eastward and northward wind component	$m\ s^{-1}$	0.25°	>Daily	ECMWF	Berrisford et al., 2011
2 m Temperature	K	0.25°	>DAILY	ECMWF	Berrisford et al., 2011
Low, medium, and high cloud cover	(0–1)	0.25°	>DAILY	ECMWF	Berrisford et al., 2011

The climate is continental with a strong north–south gradient with hot summers and cold winters. Precipitation shows an irregular distribution in the different regions of the country. Annual precipitation typically ranges between 100 and 400 mm per year (Berg, 1959). Ecologically, primary ecosystems in Kazakhstan are 'temperate grassland, savannas, and shrublands' as well as 'deserts and xeric shrublands' (Olson et al., 2001). The Kazakh Steppe with large areas of grasslands and sparse shrubs vegetation occupies one third of the country and is typical for the semiarid conditions with annual precipitation between 200 mm and 400 mm (Fig. 1, Klein et al., 2012).

2.2. The model BETHY/DLR

BETHY/DLR is a soil–vegetation–atmosphere-transfer (SVAT) model (Wißkirchen et al., 2013). It simulates the CO_2 uptake by vegetation. Incoming and absorbed photosynthetically active radiation (PAR) are computed to describe light limitation. Heat limitation is considered by energy and water balance at the vegetated surface, and water limitation is calculated with a soil water model. The parameterization of photosynthesis is based on a combined enzyme kinetic approach after Farquhar et al. (1980) and Collatz et al. (1992) for C_3 and C_4 plants, respectively. The photosynthesis rate A is calculated as the minimum of two functions, which describe the carboxylation rate J_C and the electron transport rate J_E, minus dark respiration R_d.

$$A = \min(J_C; J_E) - R_d \tag{1}$$

For calculation of photosynthesis, plant specific parameters are needed. BETHY/DLR distinguishes 33 vegetation types. For each vegetation type, the following biochemical parameters are defined: maximum carboxylation rate, maximum electron transport rate, maximum rooting depth, and maximum height (Wißkirchen, 2005). For each land cover pixel, two vegetation types can be defined. A weighting factor gives the relative spatial fraction of the primary and the secondary vegetation type. This approach allows to model carbon fluxes for coverage of less than 100%. BETHY/DLR is thus especially suitable for modelling in arid regions as partial vegetation coverage is typical for these regions.

Finally, NPP is derived as the difference of total carbon assimilation and autotrophic respiration. Total carbon assimilation corresponds to gross primary productivity (GPP), while autotrophic respiration (R_a) is the carbon that is released by foliage respiration (Knorr, 1997). The NPP output represents total plant NPP, i.e. the sum of above-ground and below-ground NPP. The approach to model GPP and NPP has previously been described by Knorr and Heimann (2001).

$$\text{NPP} = \text{GPP} - R_a \tag{2}$$

BETHY/DLR is designed for regional modelling based on remote sensing data. Spatial resolution of the output products depends on the resolution of leaf area index (LAI) and land cover input data. Satellite derived LAI data is used to describe vegetation phenology. For this study, the spatial resolution of model outputs is 1 km. Continuous time-series of climatic and phenological information allow for a high temporal resolution. The temporal resolution of modelled parameters is one day. BETHY/DLR has previously been applied within a model comparison for a test site in Central Kazakhstan. The study showed that BETHY/DLR calculates reliable NPP for this semiarid to arid environment (Eisfelder et al., 2013).

2.3. Input data

BETHY/DLR is driven by remote sensing and meteorological data. Table 1 gives an overview on the required input parameters for BETHY/DLR. Operational data on air temperature, precipitation, wind speed, and cloud coverage are available from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim reanalysis (Berrisford et al., 2011; Dee et al., 2011).

Remote sensing based LAI is a main driving parameter and is needed with a high spatial resolution. MODIS LAI data from Aqua (MYD15A2) were used for this study (Knyazikhin et al., 1999), which are available as 8-day composites with a spatial resolution of about 926.6 m. The MODIS tiles were mosaicked and gaps and outliers in the time-series were identified and corrected applying a harmonic analysis.

Furthermore, the model requires information about land cover and land use to describe the spatial variability of vegetation types. This information was derived from a regional land cover and land

Table 2
Description of land cover classes for Central Asia from the land cover and land use map (Klein et al., 2012).

Class name	Description
Rain-fed agriculture	Rain-fed agriculture
Irrigated agriculture	Water supply mainly by irrigation
Artificial	Built up and sealed areas
Needleleaved trees	Needleleaved evergreen trees, main layer: trees > 65%
Broadleaved trees	Broadleaved deciduous trees, main layer: trees > 65%
Sparse vegetation	Sparse shrubs (5–15% 30 cm–3 m) and sparse herbaceous (5–15% 30 cm–3 m)
Grassland	Herbaceous closed to open vegetation: main layer: herbaceous: 15–100% (3 cm–3 m)
Closed shrubland	Closed medium to high shrubland, main layer: shrubs: >65% (50 cm–3 m)
Open shrubland	Open medium to high shrubland: main layer: shrubs: 15–65% (50 cm–3 m)
Bare area	Unconsolidated material(s), less than 4% vegetative cover
Bare area with salt flats	Unconsolidated material(s) with salt flats, less than 4% vegetative cover
Ice and snow	Artificial and natural
Water bodies	Artificial and natural

use classification for Central Asia (Huth et al., 2012; Klein et al., 2012, Fig. 1). The classification is based on a one-year time-series of MODIS NDVI and reflectances of the red and near-infrared bands as described by Klein et al. (2012) and delivers detailed spatial information about land cover and land use. The land cover map contains the land cover classes listed in Table 2. Further input data for BETHY/DLR comprise soil types from the FAO soil map (FAO et al., 2009) and topography from the latest version of the NOAA/NGDC GTOPO30 product (USGS, 1996).

2.4. Field data

For validation of the modelled NPP results, field data were collected at two field campaigns in Central Kazakhstan in December 2010 and June 2011. Seven test sites were selected along a North–South transect (49.3°N, 73.3°E to 46.8°N, 74.8°E) that spans a wide range of typical biomass amounts for arid and semi-arid Kazakhstan. The test sites were located in regions with relatively homogeneous vegetation cover.

The approach for biomass field data collection followed a stratified random sampling design (Hiernaux et al., 2009). The sampling approach combines destructive measurements of 1 m^2 sample plots with non-destructive stratification along transects. The sample plots were stratified in low, medium, and high biomass loads. In total, 84 destructive sample plots were collected in the seven test sites at both field campaigns. For each test site, the frequency of strata was recorded along a 1 km transect. The biomass of the test site ($\overline{M}$) was then calculated from the frequency of the vegetation strata k (p_k) and the arithmetic mean of sample items in strata k ($\overline{m}_k$).

$$\overline{M} = \sum_{1}^{k}\left(\frac{p_k\overline{m}_k}{\sum p_k}\right) \tag{3}$$

Field data collection for both campaigns was standardized. The same transects were visited and destructive measurements taken close to those of the other field campaign. Dry weight was obtained after oven drying for 48 h at 60 °C with the same equipment according to a standardized procedure for both field campaigns.

The difference between the two biomass amounts provides information about the vegetation growth. This information can be used for validation of the NPP model results. It can be compared to the integrated NPP between the two dates of field data collection. For comparison of field data and model results, the carbon content of the above-ground biomass field data was calculated using conversion factors published by the IPCC (2006) (herbaceous biomass: 0.47 t C $(\text{t DM})^{-1}$, woody biomass: 0.50 t C $(\text{t DM})^{-1}$).

2.5. Calculation of sums, means, deviations, anomalies, and variability

Based on the daily output parameters from BETHY/DLR, monthly, and annual NPP for the period 2003–2011 was calculated. NPP results as well as meteorological data were used to calculate derivative datasets on monthly or annual basis, as common for analyses of time-series (e.g. Dietz et al., 2013; Gessner et al., 2013; Kuenzer et al., 2008, 2009).

Mean monthly NPP as well as average monthly meteorological parameters (mean temperature, mean PAR, precipitation sum), were calculated from monthly data based on the 2003–2011 time-series. Mean annual NPP was calculated from the annual sums of NPP. Average mean annual NPP of individual land cover classes and mean annual NPP variability were also calculated.

The deviation of NPP for an individual month from the long-term mean monthly NPP for that month is the basis for calculation of monthly anomalies. Relative monthly NPP deviation was derived, which describes the deviation as a percentage from the mean monthly NPP. Monthly deviations of the climatic parameters were calculated, respectively.

The case of an anomaly is defined when the monthly NPP deviation is at least twice the mean standard deviation for that month above or below the 9-year mean. The mean plus or minus two standard deviations corresponds to a 95% confidence interval. This is common for definition of significant anomalies (Schweiger et al., 2008; Shackleton, 1986; Vellinga and Wood, 2002).

For the validation, the modelled NPP results from BETHY/DLR were made comparable to the field data. First, cumulative grass NPP was calculated from beginning of 2011 until the period of field data collection in June 2011 (DOY 1–160). Previous measurements of below-ground NPP (23% of total NPP, Propastin et al., 2012) were then applied to obtain above-ground grass NPP. This step was necessary because field data were above-ground biomass.

3. Results and discussion

3.1. Validation of modelled NPP

Field data from two field campaigns in Central Kazakhstan were available for validation of modelled NPP (see Section 2.4). As BETHY/DLR calculates NPP of the grass and shrub fraction within each grid cell separately, grass and shrub NPP can be validated independently. Grass cover was present in all ground test sites and the field data could be used for validation of modelled NPP.

The results of the modelled NPP and corresponding field-based NPP for the test sites in Central Kazakhstan are shown in Fig. 2. Ground-based above-ground grass NPP for the validation test sites ranges from 9 to 55 g C m^{-2}. Results from BETHY/DLR for above-ground grass NPP are between 8 and 45 g C m^{-2}. The slope of the regression line is 0.75 and the correlation is high with $R = 0.95$. The

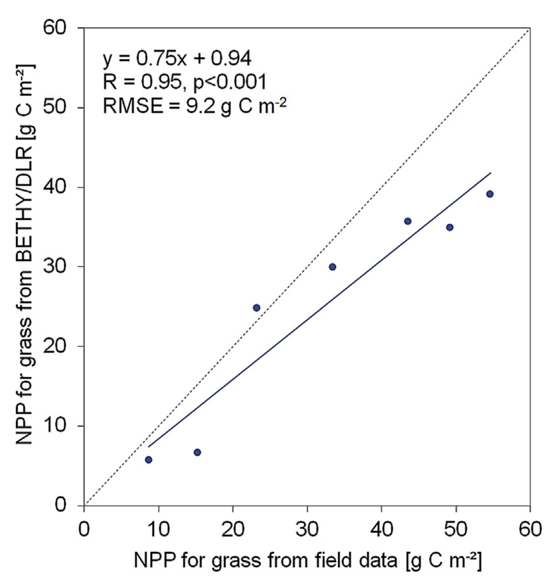


Fig. 2. Correlation between the NPP of above-ground grass/herb vegetation derived from field data and the results of above-ground grass NPP calculated with BETHY/DLR for seven test sites in Central Kazakhstan in 2011 (NPP sum for DOY 1–160).

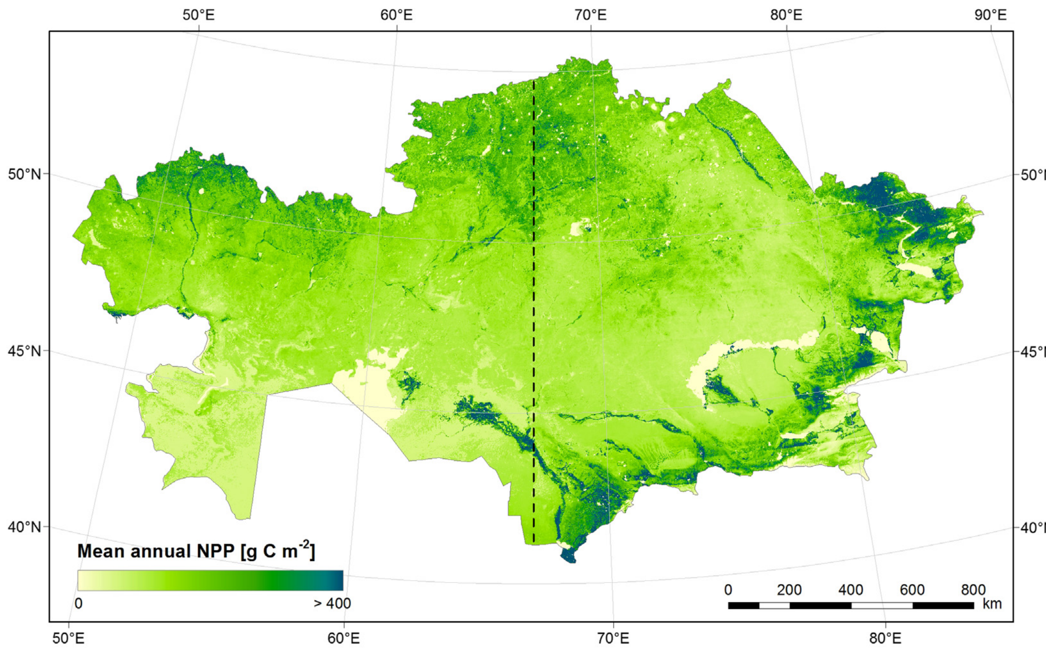


Fig. 3. Mean annual NPP for Kazakhstan for 2003–2011. The dashed line shows the transect line along the 67°E longitude.

RMSE is 9.2 g C m^{-2}. At six of the seven test sites available for validation NPP is underestimated by BETHY/DLR (cf. Fig. 2). Reliable validation of the shrub NPP was not feasible because the available field data for shrubs were not sufficient.

3.2. Mean annual NPP – spatial NPP patterns

The mean annual NPP for Kazakhstan for 2003–2011 is illustrated in Fig. 3. Table 3 gives the average mean annual NPP values for individual land cover classes. The overall mean annual NPP for Kazakhstan was 143 g C m^{-2}. Highest mean annual NPP can be observed for irrigated agriculture (338 g C m^{-2}) located in southern Kazakhstan, for example along the Syr Darya River and near the border to Kyrgyzstan. This is followed by forests (264 g C m^{-2}), which are mainly located in mountainous areas in the very East and Southeast of Kazakhstan or along rivers. The rain-fed agricultural areas in the northern parts of Kazakhstan also show high mean annual NPP (225 g C m^{-2}). The natural and semi-natural vegetation classes of closed shrubland, grassland, sparse vegetation, and open shrubland show lower average NPP values of 205 g C m^{-2}, 140 g C m^{-2}, 120 g C m^{-2}, and 112 g C m^{-2}, respectively. Lowest NPP can be observed in the deserts in southern Kazakhstan. These areas are mainly classified as bare area and have a very low vegetation cover (Table 2). Annual NPP over Kazakhstan sums up to a total of 543 Mt per year at average for 2003–2011.

The most important natural land cover classes in Kazakhstan are grassland, sparse vegetation, and open shrubland. These three classes together cover 69.3% of the country. The NPP values calculated with BETHY/DLR for these classes correspond well to productivities published in other studies. Propastin et al. (2012), for example, estimated annual NPP in Central Kazakhstan with a light use efficiency model for 2004. The mean annual NPP retrieved for the steppe grassland area was 168 g C m^{-2}. Field measured NPP was 131 g C m^{-2} for short grassland and 145 g C m^{-2} for dry steppe (Propastin et al., 2012). This is very close to our result of 140 g C m^{-2}. Further studies from Central Asia (Fartuschina, 1986; Makarowa, 1971; Perschina and Yakovlewa, 1960; Robinson et al., 2002; Tyurmenco, 1975), as summarized by Propastin et al. (2012), reported annual NPP values in the range 126–326 g C m^{-2} for dry steppe and 90–310 g C m^{-2} for semi-desert. In comparison, the results from this study are within the lower part of these ranges.

Further studies from similar environments also report comparable amounts. Yu et al. (2009), for example, estimated mean annual NPP values of 144.1 g C m^{-2} for open shrubland, 228.1 g C m^{-2} for grassland, and 26.2 g C m^{-2} for sparse vegetation within East Asia including eastern Kazakhstan. The result for open shrubland is very close to our result of 112 g C m^{-2}. For sparse vegetation, their results are lower. This can be explained by the different land cover map used in their study, which did not separate bare areas. NPP values obtained by Yu et al. (2009) for needleleaved forest (298–330 g C m^{-2}) and closed shrubland (266 g C m^{-2}) are also close to our results. For broadleaved forest (568 g C m^{-2}) and cropland (524.7 g C m^{-2}), they obtained higher values, which may be caused by different species and agricultural systems in East Asia. Feng et al. (2007) derived NPP over China and retrieved annual NPP values of 252.8 g C m^{-2} for deciduous shrubland, 122.6 g C m^{-2} for grassland and 14.3 g C m^{-2} for barren areas. These values are also consistent with the results obtained in this study (Table 3).

As the vegetation in Kazakhstan is characterized by a typical north–south gradient (see Fig. 1), a transect line along the 67°E longitude (shown in Fig. 3) was chosen to illustrate typical NPP for selected latitudinal zones. The mean annual NPP along the transect line is displayed in Fig. 4. Additional information on dominant land cover classes for the latitudinal zones is provided in Table 4.

The northern part of the transect line is characterized by a mixture of rain-fed agriculture and grassland (see Table 4). These two land cover classes are highly intermixed (see also de Beurs and Henebry, 2004), which causes the strong oscillation of mean annual NPP north of 48°N (see Fig. 4). The higher NPP values (around 300 g C m^{-2}) correspond to agricultural areas while grassland has lower NPP values (about 160 g C m^{-2}). In the zone between 48°N and 46°N, the NPP values are lower (about

Table 3
Average mean annual NPP for different land cover types for 2003–2011.

Class name	% of Area of Kazakhstan	ø Mean annual NPP [g C m^{-2}]
Irrigated agriculture	1.6	337.9
Broadleaved trees	1.3	264.1
Needleleaved trees	1.5	263.8
Rain-fed agriculture	10.7	224.5
Closed shrubland	1.5	205.1
Grassland	43.7	140.0
Sparse vegetation	13.8	119.9
Open shrubland	11.8	112.0
Bare area	4.2	73.0
Bare area with salt flats	4.0	65.4
Artificial, ice and snow, water bodies	6.0	–

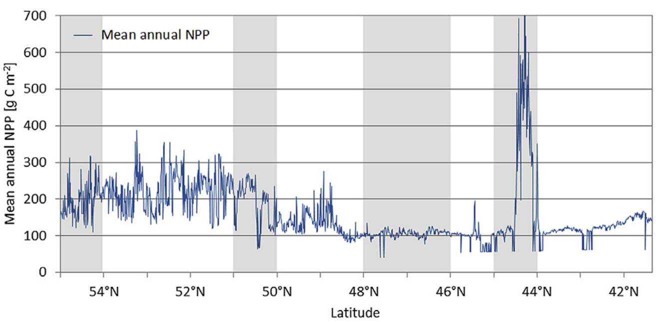


Fig. 4. Profile of mean annual NPP for 2003–2011 along the 67°E longitude transect from North to South. The highlighted latitudinal zones correspond to the highlighted columns in Table 4.

100 g C m^{-2}) and show a rather smooth behaviour. This region is characterized by a homogeneous land cover of mainly grassland with small strips of sparse vegetation and open shrubland. The NPP of grassland between 48°N and 46°N is considerably lower than that of grassland between 54°N and 51°N. After crossing a transitional zone with open shrubland and grassland, the transect line reaches the Syr Darya River. In this zone, north of and about 44°N, very high NPP values with maxima up to 700 g C m^{-2} can be observed, which show the high productivity of the irrigated agricultural areas along the Syr Darya River. The abrupt rise and decline clearly show the sudden change in land cover. South of the Syr Darya region, land cover turns to sparse vegetation with relatively low NPP values (Fig. 4).

3.3. Mean monthly NPP – intra-annual NPP patterns

Fig. 5 depicts the mean monthly NPP for the relevant months of vegetation growth from March to October. The monthly NPP indicates the beginning of vegetation activity in March in South Kazakhstan. Especially irrigated agriculture starts to grow early with an average NPP of 8 g C m^{-2} in March and already 30 g C m^{-2} in April. Further North, vegetation growth begins later, mainly in April or May. The growth of forests in the Altay Mountains in eastern Kazakhstan is also hindered by low temperature before May. The rain-fed agricultural areas in North Kazakhstan do not show a strong vegetation activity before June. Natural steppe vegetation at the same latitude has already reached about 80% of its maximum productivity in May (see Table 5). These findings correspond to observations by Doraiswamy et al. (2002), who found a difference in NDVI during April and May between rangeland and cropped areas in northern Kazakhstan. They state that crops are planted in late May and crop growth can be observed from June on in this region.

The maximum vegetation productivity is reached in June throughout the country for all vegetation classes except sparse vegetation, for which NPP is slightly higher in May (see Table 5). Vegetation productivity for agricultural areas and woody vegetation classes stays high in July (>50 g C m^{-2} for agriculture and >60 g C m^{-2} for forests), while the productivity of steppes and semi-deserts already decreases. In July and August, the agricultural areas are clearly identifiable with high NPP values in Fig. 5: rain-fed cultivation in northern Kazakhstan and irrigated agriculture along the rivers in southern Kazakhstan. Especially irrigated agriculture shows a high mean NPP through all months from May on as temperature conditions in southern Kazakhstan are convenient and water availability is no limiting factor due to water management (de Beurs and Henebry, 2004). In September, the vegetation activity drops throughout the country and in October, only minor NPP can be observed in the Syr Darya valley and other irrigated areas.

3.4. NPP anomalies – inter-annual NPP patterns

NPP anomalies were calculated for each individual month between March and October for 2003–2011. NPP anomalies provide important information for identification of areas most strongly affected by changing meteorology. From the monthly anomalies, the number of months showing anomalies for each year was derived. Two datasets were separately calculated, one for positive anomalies and one for negative anomalies, as presented in Appendices 1 and 2.

The region with most positive anomalies is located in central northern Kazakhstan. In this region, NPP was especially high in

Table 4
Dominant land cover along the 67°E longitude transect within latitudinal zones from North to South. 1: primary vegetation class (>45% of pixels); 2: secondary vegetation class (>25% but < 45% of pixels); 3: secondary vegetation class (>10%, but <25% of pixels); +: scarce minor vegetation class (<10% of pixels).

Class name	>54°	54°–51°	51°–50°	50°–48°	48°–46°	46°–45°	45°–44°	44°-<42°
Rain-fed agriculture	1	1	1	3				
Irrigated agriculture							2	+
Broadleaved trees	+							
Sparse vegetation			+		3	+	1	1
Grassland	1	2	3	1	1	3	+	+
Closed shrubland	+							
Open shrubland					3	1		+
Bare area (with salt flats)					+	+	3	+

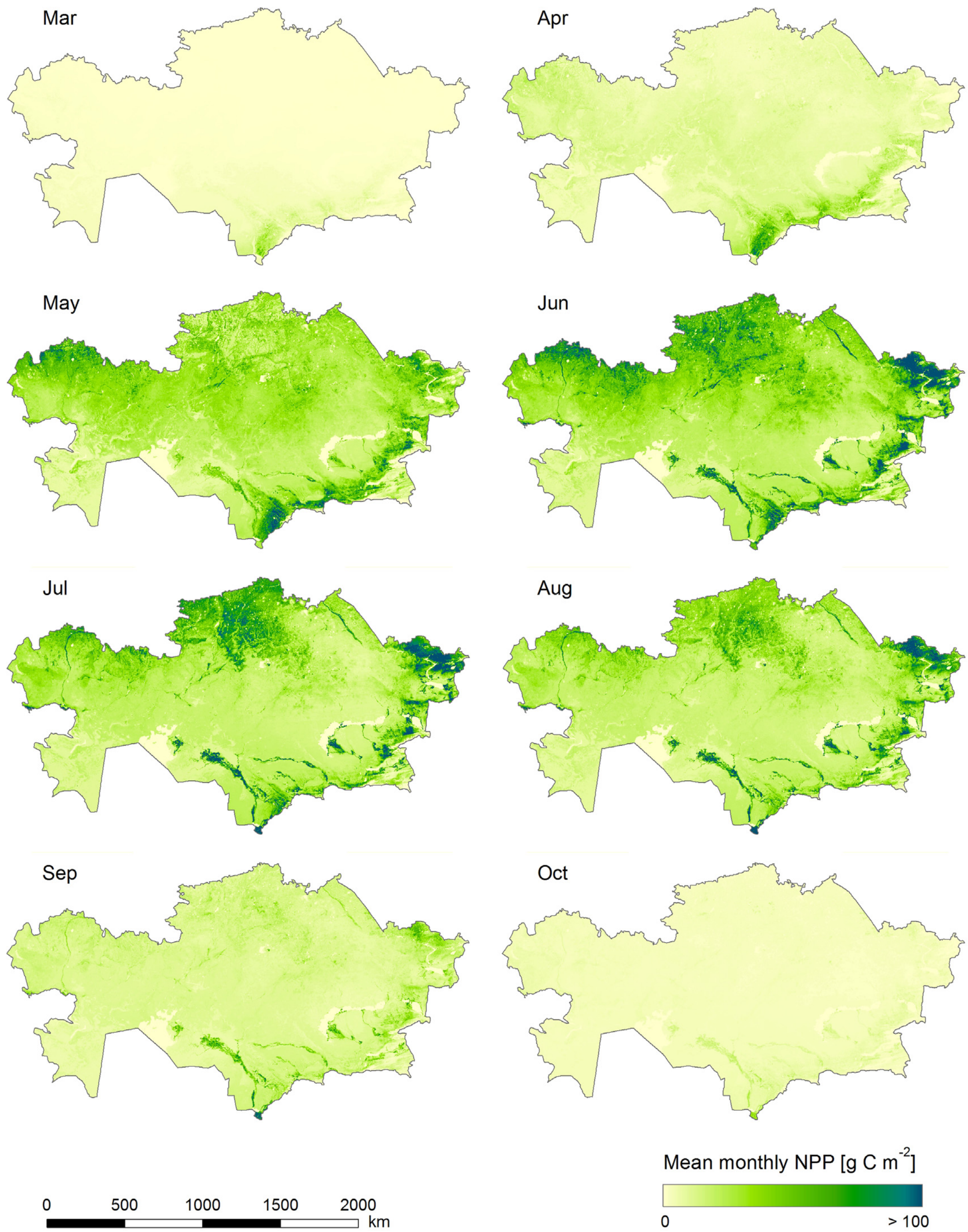


Fig. 5. Mean monthly NPP for Kazakhstan (March to October for the time period 2003–2011).

2003, 2005, 2008, and 2011 (Appendix 1). In north-eastern Kazakhstan, positive anomalies occurred in 2008, 2010, and 2011, and in the north-western part of the province Aktobe significant positive anomalies can be observed for 2003, 2007, and 2008.

The number of months with negative NPP anomalies during 2003–2011 is lower than for positive anomalies, but the regions in which most months with negative anomalies occurred are located in similar regions (Appendix 2): the most northern parts of central and western Kazakhstan (mainly 2004 and 2009), and north-eastern Kazakhstan (2006 and 2009). The high mountainous regions of the Tian Shan also show positive or negative anomalies in some years.

Anomalies for the period 2003–2011 in Kazakhstan have not been analyzed in other studies so far. However, Propastin et al. (2008) observed significant upward trends of NDVI in the period 1982–2003 in northern Kazakhstan. Though their study covered a different time period and focused on a different phenomenon, their findings indicate stronger changes in vegetation activity in northern Kazakhstan than in other regions of the country. This supports our findings. High variability in vegetation activity for northern

Table 5
Mean monthly NPP values for 2003–2011 for individual vegetated land cover classes within Kazakhstan.

Class name	Mean monthly NPP [g C m^{-2}]							
	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
Rain-fed agriculture	0.4	7.7	37.4	61.1	52.7	43.0	16.2	3.8
Irrigated agriculture	8.2	29.8	63.1	66.6	55.9	57.9	35.4	11.5
Needleleaved trees	0.6	6.9	37.2	69.1	61.6	59.6	26.1	4.9
Broadleaved trees	1.1	6.9	35.8	68.6	64.7	54.4	24.5	5.6
Sparse vegetation	3.5	12.7	23.6	23.1	20.8	18.5	11.9	4.6
Grassland	0.9	8.2	29.8	36.0	27.0	23.1	11.9	3.4
Closed shrubland	1.8	9.9	33.9	48.4	44.2	38.5	20.8	6.3
Open shrubland	1.9	9.3	23.2	24.5	20.3	17.9	10.8	3.9
Bare area	1.6	6.5	14.0	14.9	13.3	11.5	7.6	3.2
Bare area with salt flats	1.8	5.7	10.9	12.7	12.6	10.7	7.4	3.4
All land areas in Kazakhstan	0.9	8.3	24.4	34.6	31.4	27.9	13.5	3.5

Kazakhstan was also reported by Lioubimtseva et al. (2005), de Beurs and Henebry (2004), and Doraiswamy et al. (2002).

3.5. Annual NPP variability

The mean annual NPP variability for the 2003–2011 period is displayed in Fig. 6. It gives information on how strong NPP varies from year to year. The results indicate that 39% of the area of Kazakhstan have low annual NPP variability below 10%, 61% of the area have a variability higher than 10%, 11% show a variability higher than 20%, and only 2% of the area varies more than 30%.

Highest NPP variability can be observed in some agricultural areas in North Kazakhstan, which might be caused by changing crop cultivation. In the mountainous areas of the Altay, the Zhungar Alatau, and the Tian Shan also high NPP variability occurs, which might be due to strong variability of meteorology in mountainous environments (von Wehrden et al., 2010) and variability of snow cover duration (Dietz et al., 2013). Further, high NPP variability was detected along rivers and next to water bodies, which can be attributed to differing water discharge in rivers (Propastin et al., 2008).

Our finding of high variability in rain-fed agriculture in northern Kazakhstan is supported by de Beurs and Henebry (2004), who observed high inter-annual variability in crop yields in northern Kazakhstan. According to Doraiswamy et al. (2002), frequent droughts in northern Kazakhstan might explain the high variability in this region.

3.6. Relation between NPP and meteorological parameters

To analyze the relation between NPP and the meteorological parameters temperature, PAR, and precipitation, the correlation (linear Pearson correlation coefficient) between monthly NPP and monthly meteorological parameters for March–October for 2003–2011 was calculated. For every spatial location, 72 data pairs were considered for each parameter. The results are shown in Fig. 7. For temperature and PAR, a strong positive correlation ($r > 0.6$ for 90% of the land area) can be observed to NPP of the same month. The correlation between NPP and temperature is highest in southern Kazakhstan except the most south-eastern part at the border to Kyrgyzstan (see Fig. 7). For 38% of the land area of Kazakhstan, the correlation coefficient between NPP and temperature is higher than 0.8. The correlation to PAR is very strong ($r > 0.8$) for 66% of the land area. Exceptions are again the very Southeast and some agricultural areas in the North.

The correlation between NPP and precipitation of the same month was mostly not significant or negative (see Fig. 7). Therefore, correlation to cumulative precipitation of one to three previous months was analyzed. The best overall correlation can be observed when NPP is correlated to precipitation sums of the two previous months. The time lag can be explained by the fact that

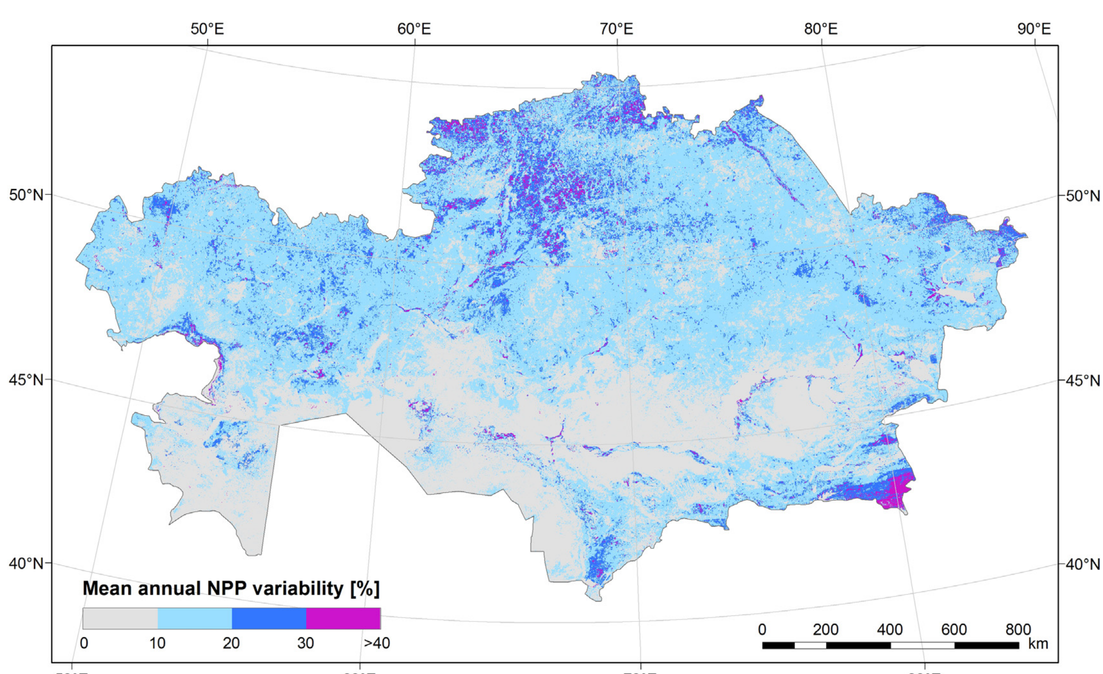


Fig. 6. Mean annual NPP variability for Kazakhstan for 2003–2011. Mean percentage variability is calculated from absolute annual values of percentage deviation from the 2003–2011 mean per year.

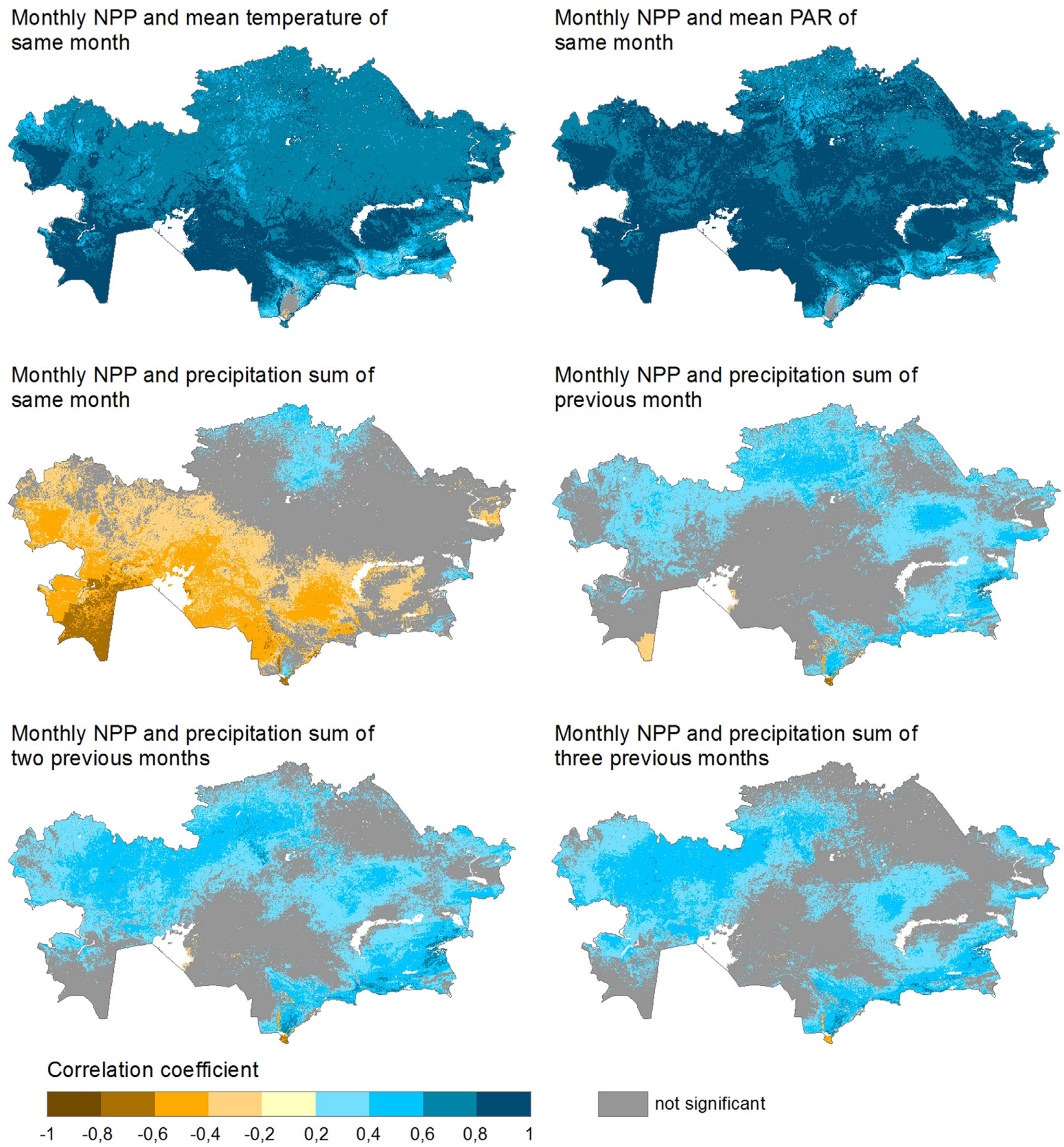


Fig. 7. Linear Pearson correlation coefficients between monthly NPP and monthly meteorological parameters (temperature, PAR, and precipitation) for 2003–2011.

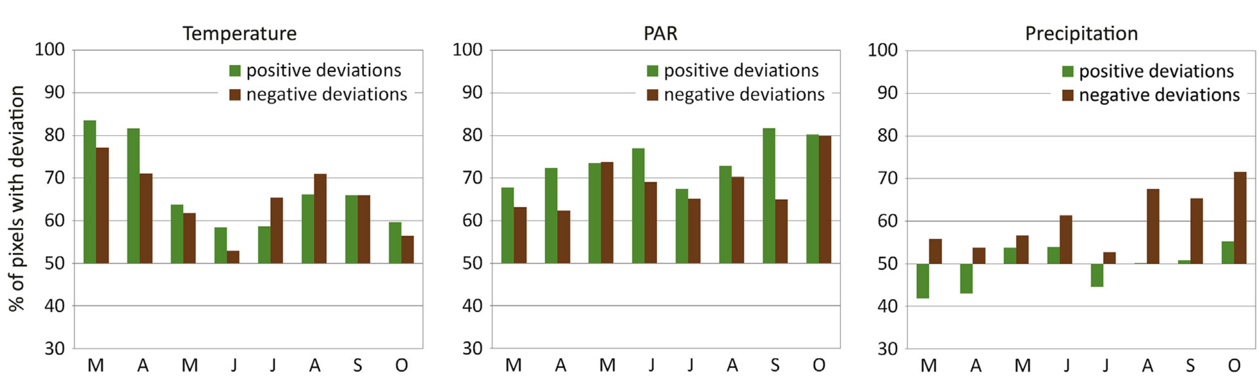


Fig. 8. Percentage of pixels with a positive monthly NPP deviation > 10% that also had a positive deviation in the meteorological parameter (green), and percentage of pixels with a negative monthly NPP deviation > 10% that also had a negative deviation in the meteorological parameter (brown) for the parameters: temperature (left), PAR (middle), and precipitation (right), for March to October in 2003–2011. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

precipitation does not directly condition vegetation growth, but first infiltrates into the soil and is then available to plants as soil water. A temporal lag of 1–3 months between precipitation anomalies and vegetation response, particularly in semiarid and arid regions with 100–400 mm of annual precipitation, has also been observed by Gessner et al. (2013). The correlation of an integrated productivity measure and previous months accumulated precipitation was also observed by Mendez-Barroso et al. (2009) in another semiarid region.

Significant correlation between NPP and precipitation sum of the two previous months can be observed in the north-western part of the country, in the Kazakh Highland, and the mountainous regions in the East and Southeast. Furthermore, correlation to precipitation is relatively high (r of 0.4–0.8) in the Southeast, where correlation to temperature and PAR is lowest. Large areas of Kazakhstan show no significant correlation to precipitation (Fig. 7). This was also reported by Robinson et al. (2002), who found poor rainfall–biomass relationships for Kazakhstan in general and no significant rainfall–biomass relationship for semi-desert regions.

To better understand the intra-annual variation of the influence of meteorological conditions on vegetation growth, we analyzed how the monthly deviations from mean values are correlated. The comparison of monthly NPP deviations and deviations of the meteorological parameters (temperature, PAR, and precipitation) allows investigation of the influence of the climatic characteristics on the calculated NPP.

The diagrams in Fig. 8 show the percentage of pixels with a positive or negative NPP deviation, which also had a positive or negative deviation in the meteorological parameters. The percentages above or below 50% are plotted, as >50% indicates a mainly positive correlation and <50% a mainly negative correlation. For precipitation, sums of the two previous months were considered. For each month, all land pixels of Kazakhstan from 2003 to 2011, which show NPP deviations higher than 10% were included in the analysis. Thus, pixels that feature a very low monthly deviation were excluded. At average, 71% of the land area of Kazakhstan was considered for the analysis.

For more than 80% of the pixels with higher NPP in March and April, the temperature was also higher than the mean. For negative NPP deviations in March and April, lower temperatures explain for 77% and 71% of pixels (Fig. 8). The results indicate that differences in vegetation productivity at the beginning of vegetation growth are most likely to be caused by varying temperature in different years. During summer months, deviations in NPP and temperature show a lower correlation. This can be expected as we are close to the optimum temperature for vegetation growth of 25 °C (Knorr and Heimann, 2001; Lioubimtseva et al., 2005). In August and September, temperature deviation explains again for 65–70% of NPP deviation. In these analyses we present mean values for Kazakhstan. Meteorological parameters might explain even better NPP deviations on a regional basis.

The combination of NPP and PAR deviations reveals a more stable relation than for NPP and temperature (Fig. 8). PAR deviation explains between 65% (March) and 80% (October) of the NPP deviation. This mirrors the high importance of PAR, which is an essential driver for photosynthesis on vegetation growth throughout the year.

The relation between NPP deviation and deviation of the sum of precipitation from the two previous months is not as obvious as for temperature and PAR. Especially positive NPP deviation does not seem to be caused by higher precipitation (see Fig. 8). However, in the months August to October, a clear relation can be observed between negative NPP and precipitation deviations. About 70% of the area with low NPP also shows low precipitation.

4. Conclusions

In this study, the model BETHY/DLR was applied for NPP modelling in Kazakhstan for the period 2003–2011. The NPP results were analyzed regarding spatial, monthly, and inter-annual variations. The derived datasets provide information about spatial distribution and temporal variation of vegetation productivity for the arid and semiarid environments in Kazakhstan.

The regions that experienced most months with anomalous NPP in the 2003–2011 period were mainly located in the semiarid North of Kazakhstan. These regions seem to be most strongly affected by changes in meteorology and are likely to be especially vulnerable to global change. For further research, analysis of longer time-periods would be of interest, especially for these areas. This might allow identification of trends, for example, regarding degradation or strength and frequency of extreme events.

Analyses of annual NPP variability showed that the regions in the North of the country that are used for agriculture have the strongest NPP variability. Regarding more natural environments, semiarid zones generally show less stable productivity within the observed time period than arid regions. This leads to the conclusion that differences in annual meteorology are higher in the semiarid areas, or that variation in meteorological conditions has stronger effects on semiarid vegetation than on vegetation in the more arid environments.

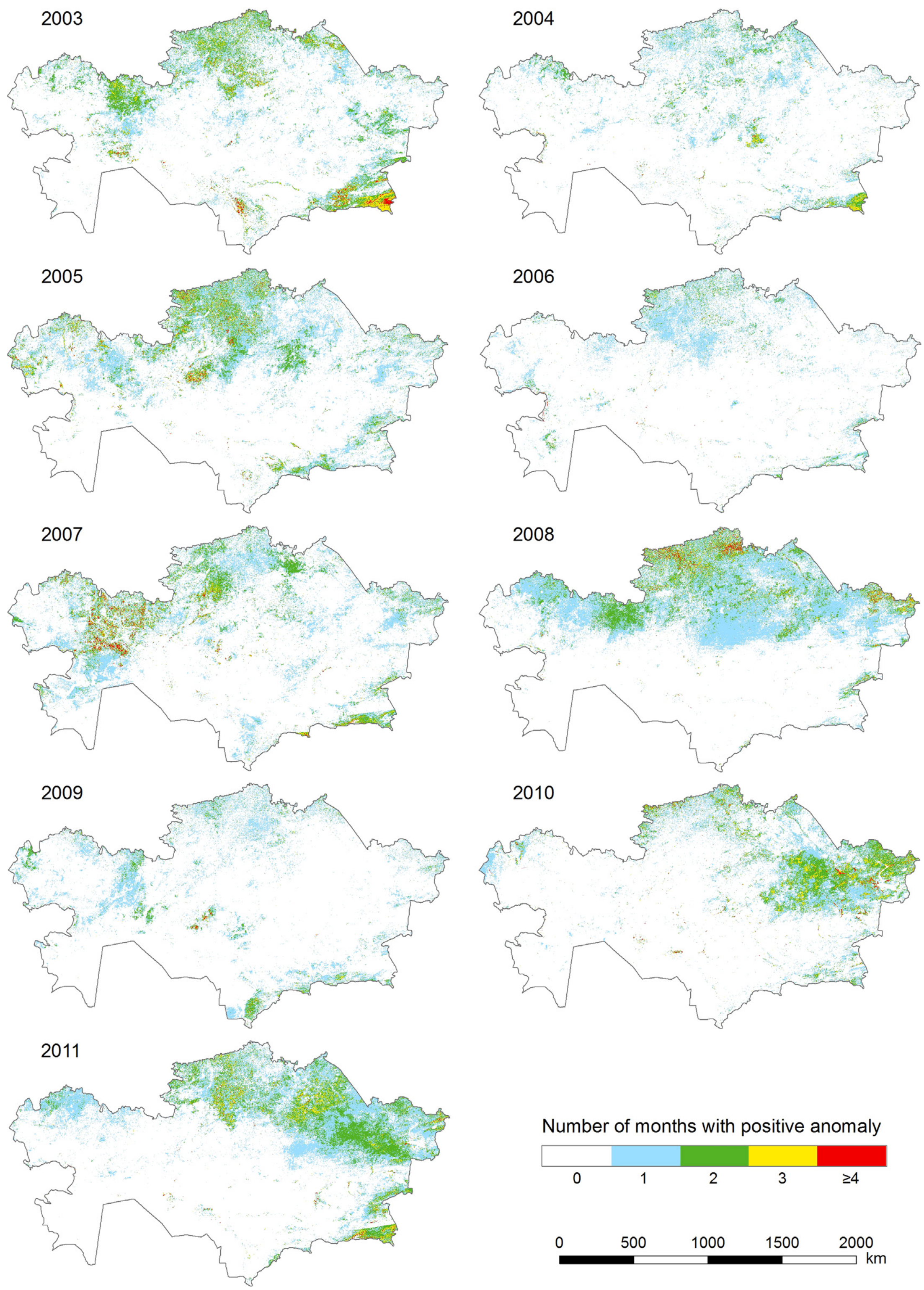
For areas with low variability, NPP values of individual years are predicted quite well by the 9-year mean. Thus, NPP modelling may provide valuable information for ecosystem and rangeland management in terms of prediction of possible carbon sequestration and available biomass for livestock in the arid and semiarid regions of Kazakhstan. This is important information for sustainable land management.

Comparison of monthly NPP and meteorological parameters revealed differing influences of temperature, PAR, and precipitation on vegetation productivity. Our observations indicate that low precipitation in early summer causes low vegetation productivity in the months August to October. This may be explained by the drying out of the soil during summer in the arid to semiarid environment. The relation between negative NPP and precipitation deviations is weaker at the beginning of the growing period because melting snow adds to the available soil water content (Dietz et al., 2013). Overall, NPP deviations seem to be more strongly influenced by temperature and PAR than by precipitation. Deviations in temperature most strongly influenced vegetation productivity in spring.

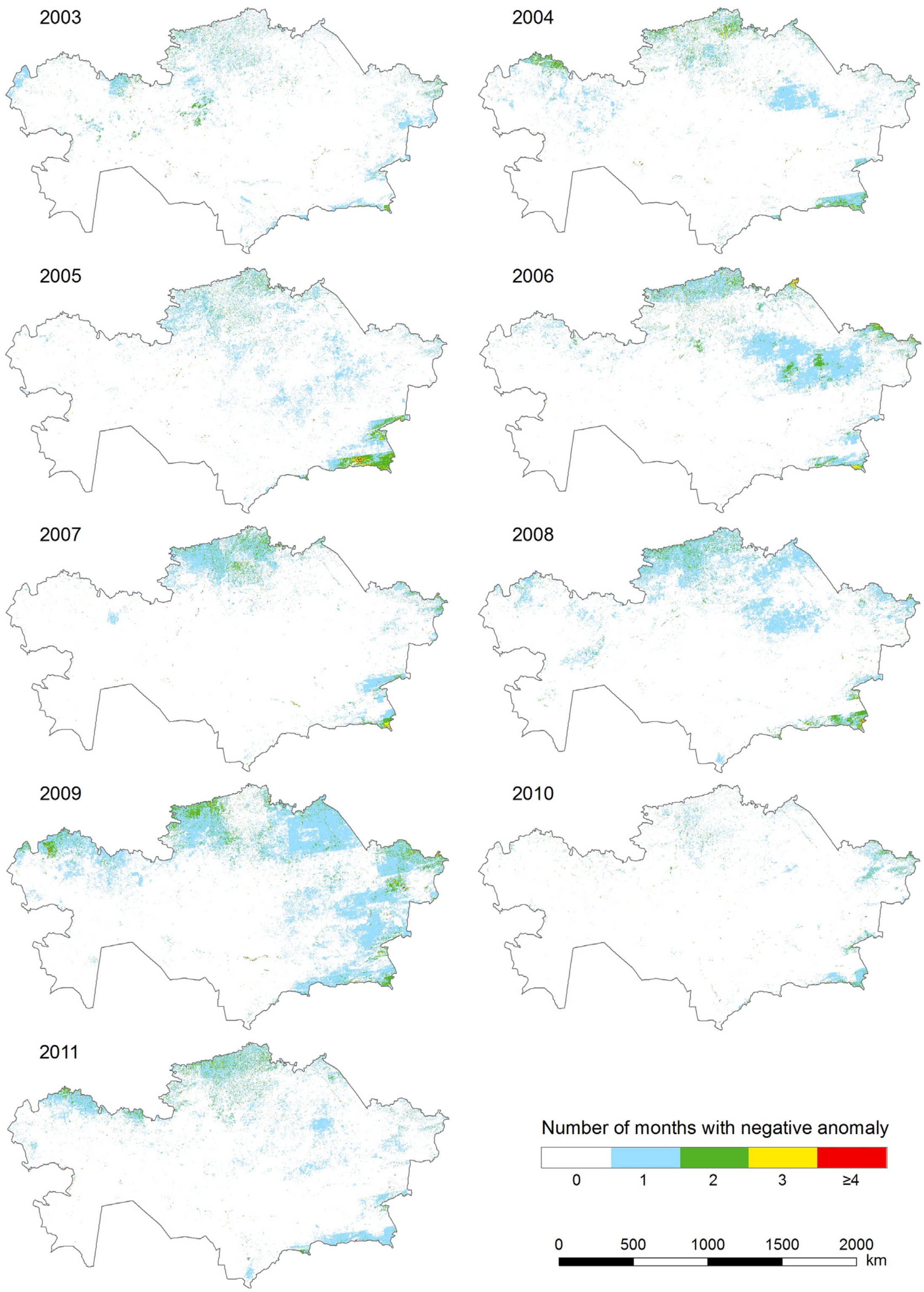
Regarding possible effects of climate change, this leads to the conclusion that possible changes in temperature at the beginning of vegetation growth will strongly affect NPP in this cold arid and semiarid environment. If Central Asia is becoming warmer during the coming decades as projected (Lioubimtseva and Henebry, 2009) this might lead to an increase in productivity at the beginning of vegetation growth. A further shift to an earlier season would also be likely as already observed in the past (e.g. de Beurs and Henebry, 2004; Propastin et al., 2008).

The monthly analysis of NPP and precipitation deviations indicated that vegetation growth is especially sensitive to lower precipitation in summer and autumn. The projected decrease in precipitation for summer and autumn (Lioubimtseva and Henebry, 2009) would, thus, likely lead to a decrease in productivity in the period August to October.

The analyses of this study show that detailed analyses of NPP data allow derivation of valuable information for land management in arid regions and identification of areas most vulnerable to global change. These analyses could be extended to other arid environments to identify similarities and differences in response of vegetation productivity to climate conditions.



Appendix 1. Number of months per year with positive NPP anomalies (March–October considered). A positive anomaly is defined if the monthly NPP is higher than the 2003–2011 mean NPP for that month plus two standard deviations.



Appendix 2. Number of months per year with negative NPP anomalies (March–October considered). A negative anomaly is defined if the monthly NPP is lower than the 2003–2011 mean NPP for that month minus two standard deviations.

Acknowledgements

We thank ECMWF, USGS, and IIASA for providing data. The study by C. Eisfelder was funded via the DLR-DFD Network EOS (Integrated Earth Observation System) PhD Program. The authors are grateful to the anonymous reviewers for their constructive comments.

References

ADB, 2010. Central Asia Atlas of Natural Resources. Asian Development Bank, Manila, Philippines. ISBN 978-971-561-886-1.

Berg, L.S., 1959. Die geographischen Zonen der Sowjetunion, Band 2. B.G. Teubner, Leipzig (in German).

Berrisford, P., Dee, D., Poli, P., Brugge, R., Fielding, K., Fuentes, M., Kallberg, P., Kobayasha, S., Uppala, S., Simmons, A., 2011. The ERA-interim archive. In: ERA Report Series, No. 1, Version 2.0. ECMWF, Reading, UK.

Calvão, T., Palmeirim, J.M., 2004. Mapping Mediterranean scrub with satellite imagery: biomass estimation and spectral behaviour. Int. J. Remote Sens. 25 (16), 3113–3126.

CGER, 2000. Ecological Indicators for the Nation. National Academy Press, Washington, D.C.. Available online at: http://www.nap.edu/openbook.php?record_id=9720&page=66 (accessed 27.09.12.).

Collatz, G.J., Ribas-Carbo, M., Berry, J.A., 1992. Coupled photosynthesis–stomatal conductance model for leaves of C_4 plants. Aust. J. Plant Physiol. 19 (5), 519–538.

de Beurs, K.M., Henebry, G.M., 2004. Land surface phenology, climatic variation, and institutional change: analyzing agricultural land cover change in Kazakhstan. Remote Sens. Environ. 89 (4), 423–433.

Dee, D.P., Uppala, S.M., Simmons, A.J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M.A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A.C.M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A.J., Haimberger, L., Healy, S.B., Hersbach, H., Hólm, E.V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A.P., Monge-Sanz, B.M., Morcrette, J.-J., Park, B.-K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J.-N., Vitart, F., 2011. The ERA-interim reanalysis: configuration and performance of the data assimilation system. Q. J. R. Meteorol. Soc. 137 (545), 553–597.

Dietz, A., Kuenzer, C., Conrad, C., 2013. Snow cover variability in Central Asia between 2000 and 2011 derived from improved MODIS daily snow cover products. Int. J. Remote Sens. 34 (11), 3879–3902.

Doraiswamy, P., Muratova, N., Sinclair, T., Stern, A., Akhmedov, B., 2002. Evaluation of MODIS data for assessment of regional spring wheat yield in Kazakhstan. In: Proceedings of International Geoscience and Remote Sensing Symposium, IGARSS. 24–28 June 2002, Toronto, Canada, pp. 487–490.

Eisfelder, C., Kuenzer, C., Dech, S., 2012. Derivation of biomass information for semi-arid areas using remote sensing data. Int. J. Remote Sens. 33 (9), 2937–2984.

Eisfelder, C., Kuenzer, C., Dech, S., Buchroithner, M.F., 2013. Comparison of two remote sensing based models for regional net primary productivity estimation – a case study in semi-arid Central Kazakhstan. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 6 (4), 1843–1856.

Eswaran, H., Lal, R., Reich, P.F., 2001. Land degradation: an overview. In: Bridges, E.M., Hannam, I.D., Oldeman, L.R., Pening de Vries, F.W.T., Scherr, S.J., Sompatpanit, S. (Eds.), Responses to Land Degradation, Proceedings of the 2nd International Conference on Land Degradation and Desertification, Khon Kaen, Thailand. Oxford Press, New Delhi, India, pp. 20–35.

Fartuschina, M.M., 1986. Produktivnost Senokosov I Pastbistch. Nauka, Novosibirsk, pp. 74–77 (in Russian).

FAO, 1989. Arid Zone Forestry: a Guide for Field Technicians. Available online at: http://www.fao.org/docrep/T0122E/t0122e03.htm (accessed 17.09.12.).

FAO, et al., 2009. Harmonized World Soil Database (Version 1.1). FAO/IIASA, Rome, Italy/Laxenburg, Austria.

Farquhar, G.D., Caemmerer, S., Berry, J.A., 1980. A biochemical model of photosynthesis in leaves of C3 species. Planta 149 (1), 78–90.

Feng, X., Liu, G., Chen, J.M., Chen, M., Liu, J., Ju, W.M., Sun, R., Zhou, W., 2007. Net primary productivity of China's terrestrial ecosystems from a process model driven by remote sensing. J. Environ. Manag. 85 (3), 563–573.

Gessner, U., Naeimi, V., Klein, I., Kuenzer, C., Klein, D., Dech, S., 2013. The relationship between precipitation anomalies and satellite-derived vegetation activity in Central Asia. Global Planet. Change 110 (A), 74–87.

Hiernaux, P., Mougin, E., Diarra, L., Soumaguel, N., Lavenu, F., Tracol, Y., Diawara, M., 2009. Sahelian rangeland response to changes in rainfall over two decades in the Grouma region. Mali. J. Hydrol. 375 (1-2), 114–127.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978.

Huth, J., Kuenzer, C., Wehrmann, T., Gebhardt, S., Vo Quoc, T., Dech, S., 2012. Land cover and land use classification with TWOPAC: towards automated processing for pixel- and object based image classification. Remote Sens. 4, 2530–2553.

IPCC, 2006. 2006 IPCC guidelines for national greenhouse gas inventories. In: Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.), Prepared by the National Greenhouse Gas Inventories Programme. IGES, Japan. Available online: http://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html (accessed 10.05.12.).

Klein, I., Gessner, U., Kuenzer, C., 2012. Regional land cover mapping and change detection in Central Asia using MODIS time series. Appl. Geogr. 35 (1), 219–234.

Knorr, W., 1997. Satellite Remote Sensing and Modelling of the Global CO_2 Exchange of Land Vegetation: a Synthesis Study (PhD dissertation). Max-Planck-Institute for Meteorology, Hamburg.

Knorr, W., Heimann, M., 2001. Uncertainties in global terrestrial biosphere modeling 1. A comprehensive sensitivity analysis with a new photosynthesis and energy balance scheme. Glob. Biogeochem. Cycles 15 (1), 207–255.

Knyazikhin, Y., Glassy, J., Privette, J.L., Tian, Y., Lotsch, A., Zhang, Y., Wang, Y., Morisette, J.T., Votava, P., Myneni, R.B., Nemani, R.R., Running, S.W., 1999. MODIS Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation Absorbed by Vegetation (FPAR) Product (MOD15). In: Algorithm Theoretical Basis Document. Version 4.0.

Köchy, M., Mathaj, M., Jeltsch, F., Malkinson, D., 2008. Resilience of stocking capacity to changing climate in arid to Mediterranean landscapes. Reg. Environ. Change 8 (2), 73–87.

Kuenzer, C., Bartalis, Z., Schmidt, M., Zhao, D., Wagner, W., 2008. Trend analyses of a global soil moisture time series derived from ERS-1/-2 scatterometer data: floods, droughts and long term changes. Int. Arch. Photogramm., Remote Sens. Spat. Inf. Sci. 37, 1363–1368.

Kuenzer, C., Zhao, D., Scipal, K., Sabel, D., Naeimi, V., Bartalis, Z., Hasenauer, S., Mehl, H., Dech, S., Wagner, W., 2009. El Niño southern oscillation influences represented in ERS scatterometer-derived soil moisture data. Appl. Geogr. 29 (4), 463–477.

Lioubimtseva, E., Adams, J.M., 2004. Possible implications of increased carbon dioxide levels and climate change for desert ecosystems. Environ. Manag. 33 (1), 388–404.

Lioubimtseva, E., Cole, R., Adams, J.M., Kapustin, G., 2005. Impacts of climate and land-cover changes in arid lands of Central Asia. J. Arid Environ. 62 (2), 285–308.

Lioubimtseva, E., Henebry, G., 2009. Climate and environmental change in arid Central Asia: impacts, vulnerability, and adaptations. J. Arid Environ. 73, 963–977.

Makarowa, L.I., 1971. Tyrsovaya formacia w basseyne ozera Tchelkar. In: Materialy Po Flore I Rastitelnosti Severnogo Prikaspiya. Wsesojuz. geogr. obstch., Leningrad, pp. 179–186 (in Russian).

Mendez-Barroso, L.A., Vivoni, E.R., Watts, C.J., Rodriguez, J.C., 2009. Seasonal and interannual relation between precipitation, surface soil moisture and vegetation dynamics in the North American Monsoon region. J. Hydrol. 377, 59–70.

Moleele, N., Ringrose, S., Arnberg, W., Lunden, B., Vanderpost, C., 2001. Assessment of vegetation indexes useful for browse (forage) prediction in semi-arid rangelands. Int. J. Remote Sens. 22 (5), 741–756.

Niemeijer, C., 2002. Developing indicators for environmental policy: data-driven and theory-driven approaches examined by example. Environ. Sci. Policy 5 (2), 91–103.

Niklaus, M., Eisfelder, C., Tum, M., Günther, K.P., 2012. A remote sensing model based land degradation index for the arid and semi-arid regions of southern Africa. In: International Geoscience and Remote Sensing Symposium, IGARSS 2012. 22–27 July 2012, Munich, Germany.

Olson, D.M., Dinerstein, E., Wikramanayake, E.D., Burgess, N.D., Powell, G.V.N., Underwood, E.C., d'Amico, J.A., Itoua, I., Strand, H.E., Morrison, J.C., Loucks, C.J., Allnutt, T.F., Ricketts, T.H., Kura, Y., Lamoreux, J.F., Wettengel, W.W., Hedao, P., Kassem, K.R., 2001. Terrestrial ecoregions of the world: a new map of life on earth. Bioscience 51 (11), 933–938.

Perschina, M.N., Yakovlewa, M.E., 1960. Biologitcheskiy Krugovorot W Zone Sukhich Stepey SSSR. In: Dokl. Sov. Potchwowedov K VII Mezschdunar. Kongr. Potchwowedov W USA. AN SSSR, Moscow, pp. 116–123 (in Russian).

Propastin, P.A., Kappas, M., Muratova, N.R., 2008. Inter-annual changes in vegetation activities and their relationship to temperature and precipitation in Central Asia from 1982 to 2003. J. Environ. Inf. 12 (2), 75–87.

Propastin, P.A., Kappas, M.W., Herrmann, S.M., Tucker, C.J., 2012. Modified light use efficiency model for assessment of carbon sequestration in grasslands of Kazakhstan: combining ground biomass data and remote-sensing. Int. J. Remote Sens. 33 (5), 1465–1487.

Robinson, S., Milner-Gulland, E.L., Alimaev, I., 2002. Rangeland degradation in Kazakhstan during the Soviet-era: re-examining the evidence. J. Arid Environ. 53, 419–439.

Schimel, D.S., 1995. Terrestrial biogeochemical cycles: global estimates with remote sensing. Remote Sens. Environ. 51 (1), 49–56.

Schweiger, A.J., Zhang, J., Lindsay, R.W., Steele, M., 2008. Did unusually sunny skies help drive the record sea ice minimum of 2007? Geophys. Res. Lett. 35, L10503, 6 pp.

Shackleton, W.G., 1986. Economic and Applied Geology: an Introduction. Croom Helm, New Hampshire, USA, ISBN 0-7099-3387-8, p. 227.

Tyurmenco, A.N., 1975. Biologitcheskiy krugovorot zolnych elementov pod celinnoy i culturnoy rastitelnostyu w zone sukhich i polupustynnych stepey. In: Genesis, Swoystwa I Plodorodiye Potchw. Izd. Kazan. Universiteta, Kazan', pp. 135–176 (in Russian).

UN, 1994. Elaboration of an International Convention to Combat Desertification in Countries Experiencing Serious Drought and/or Desertification, Particularly in Africa. UN General Assembly. A/AC.241/27. Available online at: http://www.unccd.int/convention/text/pdf/conv-eng.pdf (accessed 17.03.10.).

UN, 2004. A More Secure World: Our Shared Responsibility. Report of the Secretary-General's high-level Panel on Threats, Challenges and Change. Published by the United Nations Department of public Information. DPI/2367, December 2004. Available online at: http://www.un.org/secureworld/report2.pdf (accessed 17.03.10.).

UNEP, 1999. National Action Programme to Combat Desertification in Republic of Uzbekistan. Tashkent. Available online at: http://www.unccd.int/actionprogrammes/asia/national/1999/uzbekistan-eng.pdf (accessed 17.03.10.).

USGS, 1996. GTOPO30, Global 30-Arc-Second Elevation Data Set. U.S. Geological Survey, EROS Data Center, Sioux Falls, South Dakota. Available online at: http://eros.usgs.gov/#/Find_Data/Products_and_Data_Available/GTOPO30 (accessed 01.10.12.).

Vellinga, M., Wood, R.A., 2002. Global climatic impacts of a collapse of the Atlantic thermohaline circulation. Clim. Change 54, 251–267.

Verstraete, M.M., 1986. Defining desertification: a review. Clim. Change 9 (1–2), 5–18.

von Wehrden, H., Hanspach, J., Ronnenberg, K., Wesche, K., 2010. The interannual climatic variability in Central Asia – a contribution to the discussion on the importance of environmental stochasticity in drylands. J. Arid Environ. 74, 1212–1215.

Wißkirchen, K., 2005. Modellierung der regionalen CO_2-Aufnahme durch Vegetation (PhD dissertation). Faculty of Math and Science, University of Bonn, Germany (in German).
Wißkirchen, K., Tum, M., Günther, K.P., Niklaus, M., Eisfelder, C., Knorr, W., 2013. Quantifying the carbon uptake by vegetation for Europe on a 1 km^2 resolution using a remote sensing driven vegetation model. Geosci. Model Dev. 6, 1623–1640.
Yu, D., Shi, P., Shao, H., Zhu, W., Pan, Y., 2009. Modelling net primary productivity of terrestrial ecosystems in East Asia based on an improved CASA ecosystem model. Int. J. Remote Sens. 30 (18), 4851–4866.