Land surface phenology, climatic variation, and institutional change: Analyzing agricultural land cover change in Kazakhstan

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Abstract

Kazakhstan is the second largest country to emerge from the collapse of the Soviet Union. Consequent to the abrupt institutional changes surrounding the disintegration of the Soviet Union in the early 1990s, Kazakhstan has reportedly undergone extensive land cover/land use change. Were the institutional changes sufficiently great to affect land surface phenology at spatial resolutions and extents relevant to mesoscale meteorological models? To explore this question, we used the NDVI time series (1985–1988 and 1995–1999) from the Pathfinder Advanced Very High Resolution Radiometer (AVHRR) Land (PAL) dataset, which consists of 10 days maximum NDVI composites at a spatial resolution of 8 km. Daily minimum and maximum temperatures were extracted from the NCEP Reanalysis Project and 10 days composites of accumulated growing degree-days (AGDD) were produced. We selected for intensive study seven agricultural areas ranging from regions with rain-fed spring wheat cultivation in the north to regions of irrigated cotton and rice in the south. We applied three distinct but complementary statistical analyses: (1) nonparametric testing of sample distributions; (2) simple time series analysis to evaluate trends and seasonality; and (3) simple regression models describing NDVI as a quadratic function of AGDD.

The irrigated areas displayed different temporal developments of NDVI between 1985–1988 and 1995–1999. As the temperature regime between the two periods was not significantly different, we conclude that observed differences in the temporal development of NDVI resulted from changes in agricultural practices.

In the north, the temperature regime was also comparable for both periods. Based on extant socioeconomic studies and our model analyses, we conclude that the changes in the observed land surface phenology in the northern regions are caused by large increases in fallow land dominated by weedy species and by grasslands under reduced grazing pressure. Using multiple lines of evidence allowed us to build a case of whether differences in land surface phenology were mostly the result of anthropogenic influences or interannual climatic fluctuations.

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1. Introduction

Recent studies of land cover/land use change (LCLUC) have focused on data derived from spaceborne sensors with spatial resolutions < 100 m acquired across several years (e.g., Brown et al., 2000; Peterson & Aunap, 1998). While much information can be gained by parsing the dynamics of decision-making in landscapes in this manner (Geoghegan et al., 1998), the observational scale occurs at too fine a resolution and too slow a tempo to expect significant linkages with the atmospheric boundary layer (Lambin, 1996).

The boundary layer is the lower portion of the troposphere where the atmosphere can be directly influenced by the planetary surface. The atmospheric boundary layer plays an important role in numerical weather prediction models. Observations of land surface phenology at coarser spatial resolutions (1–16 km) have shown linkages with boundary layer dynamics (Lim & Kafatos, 2002; Schwartz & Reed, 1999; White et al., 2002). However, the seasonality of surface vegetation in temperate climates and the interannual variation in onset, duration, and intensity of the growing season pose formidable challenges to LCLUC studies since it is necessary to distinguish between weather-induced variation and enduring changes. Given an image time series that has both the sufficient temporal density to characterize seasonality and the temporal depth to characterize interan-

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nual variability, how should we analyze changes in land surface phenology? LCLUC occurs on many different spatial and temporal scales and in multiple forms ranging from alterations in crop type to changes in land use category, e.g., from cultivated to residential. Here, we are interested in using land surface phenology as a means to detect changes in agricultural land cover and land management practices. Land surface phenology could change because of changing climate, leading to phenomena such as the earlier onset of spring (Myneni et al., 1997; Zhou et al., 2001) or earlier senescence. However, land surface phenology could also change as a result of shifts in land cover proportions or alterations in land management practices.

Change analysis of image time series can be decomposed into four steps: (1) change detection to identify differences between images; (2) change quantification to determine the character, magnitude, and extent of the differences; (3) change assessment to decide whether the observed differences are significant; and (4) change attribution to identify possible causes associated with the observed changes.

Most change detection strategies commonly used in remote sensing studies were developed in an era of image scarcity and thus focus on comparing just a few scenes (Jensen, 1996). In an era of intensive earth observation, something more is required for change analysis. What sufficed for handfuls of data is inadequate when confronted with a “data tsunami”. Coarser spatial resolution satellites (e.g., AVHRR, MODIS, MERIS) are capable of observing broad regions in every overpass, resulting in a much higher temporal data record than for finer resolution satellites. Change analysis methods applicable to images with sparse temporal sampling may not provide efficient or effective analysis when applied to dense image time series where coherent, quasi-periodic spatio-temporal patterns may be observable. For example, when operational remote monitoring of the terrestrial environment is to contribute near-realtime data flows for assimilation into numerical weather prediction models (Champeaux et al., 2000; Ehrlich et al., 1994), there is the need to determine whether “significant” change has occurred since the last data acquisition. Whether a detected change is “significant” depends on the research question. A similar question addresses whether there are significant trends in timing of the onset of boreal spring (Myneni et al., 1997; Shabanov et al., 2002; Tucker et al., 2001; Zhou et al., 2001).

Kazakhstan has been the setting for several notable anthropogenic transformations of the planetary surface during the 20th century. Well known is the dramatic recession of the Aral Sea resulting from the upstream diversion of water to agriculture (Bos, 1995). Less familiar, perhaps, is the largest land cover change event in the 20th century—Khrushchev’s “Virgin Lands” program. More than 13 million hectares of native steppe were plowed and sown to spring wheat during 1954–1956. To support this colossal effort, more than a million people immigrated to the region, which transformed Kazakhstan into the only Soviet state in which the native population was a numerical minority (McCausley, 1976). From a traditional economy, based largely on nomadic pastoralism, Kazakhstan was rapidly transformed into a principal provider of grain to the Soviet Union, supplying 27% of USSR’s demand for wheat (Kaser, 1997). The total cultivated area for all crops increased from 11.4 million hectares in 1954 to 30.8 million hectares a decade later (McCausley, 1976). Besides grains, Kazakhstan also exported large quantities of wool and meat (FAO, 2003; Suleimenov & Oram, 2000). The exceptionally strong emphasis on grain production had a large damaging effect on the environment in Kazakhstan. Excessive use of fertilizers and pesticides and large irrigation projects caused soil pollution, desertification, and deterioration of water quantity and water quality (Grote, 1998).

Following the collapse of the Soviet Union in 1991, Kazakhstan gained independence and became the second largest country cleaved from the USSR and the world’s ninth largest country in land area. Independence caused myriad economic dislocations, including the end of the highly regulated Soviet trading bloc, centralized agricultural planning, and the political interest in agriculture in general. The political changes resulted in extremely high inflation, scarcity of food and other products, and a precipitous decline in production of exports such grain, wool and meat (Alaolmolki, 2001).

The question motivating our analysis is this: Given abrupt, sweeping changes in political, social, and economic institutions and the subsequent reallocation of land use decisions, are the consequences of change observable in land surface phenology at spatial resolutions relevant to interactions with the atmospheric boundary layer? To be relevant to boundary layer processes, any land surface transformation must be observable and significant at resolutions that are very coarse relative to conventional LCLUC studies. To quantify and assess change in the presence of high interannual variation in weather and NDVI response, we employ a suite of complementary statistical analyses and test hypotheses for significant differences in land surface phenology among different study areas and periods contained within a standard NDVI dataset.

We used the Pathfinder Advanced Very High Resolution Radiometer (AVHRR) Land (PAL) dataset to analyze the land cover dynamics of seven agricultural areas in Kazakhstan before and after institutional change and to place this episode in the larger context of climate variability and landscape dynamics. The Pathfinder AVHRR Land (PAL) data are frequently used in change detection studies (Borak et al., 2000; Shabanov et al., 2002; Tucker et al., 2001; Young & Wang, 2001). To minimize clouds and atmospheric contaminants, maximum-value NDVI composites (Holben, 1986) have been generated for 10-day periods (dekads) by selecting the maximum NDVI value from the daily data during a dekad. Although there are numerous problems with the PAL data, such as satellite orbital drift and lack of correction for scattering and water vapor absorption, these data are still...
very attractive for change analysis because the data are global in extent, frequent in recurrence, long in duration, and freely available in a standard form. Filtering techniques have been developed to attenuate remaining cloud contamination (Lovell & Graetz, 2001), and other atmospheric conditions degrading the data (Shabanov et al., 2002). Kaufmann et al. (2000) concluded however that, despite the orbital drift and sensor changes, the data still could be used for research about interannual variability. Numerous studies have been performed to estimate crop yields from AVHRR satellite data. Labus et al. (2002) developed a model to estimate wheat yield with AVHRR data and concluded that NDVI data from AVHRR can provide good estimators of regional yields at the end of the growing season.

Retrospective analyses can be fraught with ambiguities that result from a lack of clear experimental manipulation. As in the case for accuracy assessment of small-scale land cover maps (Merchant et al., 1994), a multiple lines of evidence approach is preferred over reliance on a single type of analysis. Here, we focus on seven agricultural areas in Kazakhstan, ranging from grassland and dryland agricultural areas in the north to irrigated intensive agriculture in the south, because it is exactly in the agriculture sector—where centralized control and subsidies abounded—that repercussions of institutional change ought to be observable. To investigate changes in seasonality and interannual variation independent of variations in the bioclimatic regime, we apply to each study area three distinct but complementary statistical analyses: (1) nonparametric testing of sample distributions to investigate for difference in means for NDVI and growing degree-days (GDD); (2) simple time series analysis to evaluate trends and seasonality; and (3) simple regression models describe NDVI as a quadratic function of accumulated growing degree-days (AGDD). The methods proceed from simple to more involved, both in terms of implementation and interpretation. Method 1 is a basic comparison of the mean structure of the dataset performed to detect obvious average differences between the two time periods. Method 2 is a trend analysis performed to identify temporal trends. In method 3, the AGDD and NDVI are linked using simple quadratic models to identify any changes in NDVI that are not attributable to changes in AGDD. The remainder of the paper is organized into six sections: description of the study areas, description of data, methods, presentation of the results, discussion, and conclusions. Section 5 has been divided into three parts to allow separate discussions of the three analytical approaches. Section 6 is divided in four sections discussing similar regions in one section. The discussion is followed by a general conclusion.

2. Study areas

With an area of 2.72 million km², Kazakhstan roughly equals one-third of the conterminous U.S. or one-quarter of China. It is sparsely populated with only 16.7 million people (Grote, 1998). As a landlocked country, Kazakhstan borders Turkmenistan, Uzbekistan, and Kyrgyzstan to the south, Russia to the north, China to the east, and the Caspian Sea to the west. Kazakhstan covers about 15 degrees of latitude from 40°N to 55°N and 35 degrees of longitude from 50°E to 85°E (Fig. 1).
The climate is strongly continental. Annual precipitation ranges from about 250 mm in the north to 450 mm in the mountain ranges in the south, with much lower levels in the low-lying deserts in the west and southwest. Temperature fluctuates widely with large variations between subregions. Average temperature in January ranges from $-20\degree C$ in the north and central regions to $-5\degree C$ in the south; average July temperature reaches $+18\degree C$ in the north and $+29\degree C$ in the south (Lydolph, 1965). Kazakhstan consists of many ecoregions but the principal biomes are, in order of increasing aridity, wooded steppe, steppe, semi-desert, and desert. Roughly 60% of the territory of Kazakhstan (179.9 million hectares) is desertified. Dominant cultivated crops are wheat, oats, barley, crown flax, and sunflower. In the arid south, the irrigated crops include cotton, rice, sugar beet, and yellow tobacco. Kazakhstan’s share in global grain production is a little more than one percent. Grain and its products are the main agricultural exports, accounting for 5.5% of its total in 2000 (World Bank, 2003); the main export products are fuel and oil products (52.8%) and ferrous metals (12.9%).

Spring wheat is mostly cultivated in northern Kazakhstan with some winter wheat cultivated under irrigation in the south (Meng et al., 2000). Before the institutional changes of the 1990s, a few very large state-owned companies dominated agricultural production. Most privatization occurred between 1994 and 1997 and, by the beginning of 1998 almost 98% of farms were privately owned (Suleimenov & Oram, 2000). However, small individual farms were typically not viable due to a lack of machinery and money, which resulted in the establishment of larger production cooperatives. The production cooperatives function on the basis of a joint ownership and there has been hardly any fragmentation of cropping areas (Baydildina et al., 2000). With the institutional changes following independence, significant constraints on productivity in the agricultural sector emerged: dissolution of trading agreements; decrease in regional demand for feed and food grains; higher, unsubsidized prices for fertilizers and pesticides; a paucity of farm credit for private farms; decaying structure for transportation and storage; minimal governmental investment in agricultural research and development; and the lack of extension networks and services for technology transfer to the new private farms and cooperatives (Meng et al., 2000). These factors combined led to declines in the area under cultivation, the production of grains (Baydildina et al., 2000; Meng et al., 2000) as well as in the size of livestock herds (Suleimenov & Oram, 2000; Fig. 2).

Spring wheat and barley are the principal crops grown using a dryland cultivation strategy of rotation with fallow every 3–4 years and interspersed with grazed grasslands (Morgounov et al., 2000). Reliance on dryland cropping means that the region’s frequent droughts reduce the productivity and increase interannual variability in crop yields (Doraiswamy et al., 2002). In general, the crops are planted in late May (Doraiswamy et al., 2002; Morgounov et al., 2000). Rice and cotton are the most common crops in irrigated regions (Lydolph, 1965).

We selected seven representative agricultural areas for intensive study. The first area is located in the north of Kazakhstan near the city of Petropavlovsk ($54^\circ 31'48''$N, $69^\circ 7'48''$E). The average yearly temperature is $1.5\degree C$ and the average precipitation is 366 mm. The dominant land cover consists of a cropland/woodland mosaic (51%) (Table 1) followed by dryland cropland and pasture.

Table 1

<table>
<thead>
<tr>
<th>Land cover (%) per study area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Description</td>
</tr>
<tr>
<td>Dryland cropland and pasture</td>
</tr>
<tr>
<td>Irrigated cropland and pasture</td>
</tr>
<tr>
<td>Cropland/woodland mosaic</td>
</tr>
<tr>
<td>Grassland</td>
</tr>
<tr>
<td>Shrubland</td>
</tr>
<tr>
<td>Deciduous broadleaf forest</td>
</tr>
<tr>
<td>Deciduous needleleaf forest</td>
</tr>
<tr>
<td>Mixed forest</td>
</tr>
<tr>
<td>Water bodies</td>
</tr>
<tr>
<td>Other</td>
</tr>
<tr>
<td>1    2     3     4    5    6    7</td>
</tr>
<tr>
<td>37.0 21.6 48.9 6.5 2.7 5.1 1.4</td>
</tr>
<tr>
<td>1.4</td>
</tr>
<tr>
<td>51.4 27.4 23.1 1.9</td>
</tr>
<tr>
<td>1.4 18.8 9.9 38.7 55.9 21.4 27.8</td>
</tr>
<tr>
<td>8.1 21.2</td>
</tr>
<tr>
<td>1.4 41.2 2.5</td>
</tr>
<tr>
<td>2.0</td>
</tr>
<tr>
<td>8.9</td>
</tr>
<tr>
<td>2.4 2.5 1.1 3.7 6.0</td>
</tr>
<tr>
<td>4.4 3.3 5.9 5.6 1.8 0.8 2.9</td>
</tr>
</tbody>
</table>

Values in bold indicate the largest proportions within each study area. Data from Brown et al. (1998).
(37%). The second area is located in the east of Kazakhstan on the foothills of the Altai Mountains. The main city in this region is Öskemen (49°59’38N, 87°51’39E) and this is the only region in the study with more than half (52%) of its land cover in forest. The remaining land cover is a mixture of dryland cropland and grasslands. The average annual temperature is just under 1 °C and the average precipitation is 313 mm. The third region is located in the north of Kazakhstan just southwest of the Syr-Darya in the south of Kazakhstan, centered on Kyzylorda (44°51’10N, 65°30’33E). The average annual temperature is 2.8 °C and the average precipitation is 324 mm. This region occurs in Kazakhstan’s primary wheat belt and consists of dryland cropland and pasture (49%) and a mosaic of cropland and woodland (27%). The fourth area is located in northern Kazakhstan in the triangle between Kostanai, Astana, and Torghai (51°38’44N, 66°8’13E), also in the wheat belt. Most of the region (57%) consists of cropland mixed with either grasslands or woodlands and 39% is grasslands. The average annual temperature is a bit cooler than in the third region (1.8 °C) and the area is slightly drier at 308 mm. The fifth region is an elongated area in the western part of Kazakhstan, bordering Russia. There are vast amounts of grasslands in this region (56%) while the remaining areas are filled with cropland (43%). The main city in this region is Aktobe (50°17’53N, 57°10’53E). The average annual temperature is 4.6 °C and the average precipitation is 310 mm. The last two regions are irrigated areas in southern Kazakhstan. The sixth region forms a strip of irrigated desert land on the Syr-Darya (46°48’0N, 75°6’0E). The average annual temperature, 5.6 °C, is slightly cooler than in the sixth region and it has comparable average annual precipitation (154 mm).

3. Data

3.1. Satellite sensor data

The Pathfinder AVHRR Land (PAL) data were used to characterize the spatio-temporal dynamics of the land surface. The maximum value compositing method can create a relatively cloud-free dataset (Holben, 1986). The AVHRR scanner records near infrared and red radiance in two broad channels. The Normalized Difference Vegetation Index (NDVI) is calculated as the ratio of the difference between the near infrared and red divided by the sum of near infrared and red. Active green vegetation reflects near-infrared radiation much more strongly than red radiation, resulting in $0 < \text{NDVI} < 1$. In contrast, the NDVI of unvegetated surfaces or senesced vegetation is closer to zero than green vegetation (Jensen, 1996).

The idea of selecting agricultural regions is that those are the most susceptible to institutional change. To select the subsets for analyses, the number of composites with an NDVI value above 0.35 has been counted for every year. These counts have been summarized into an average number of composites above 0.35, standard deviation, and skewness for the total time period, which are plotted to a false color composite (not shown). Based on this image, the subsets are chosen to be as homogeneous as possible while still being distinct from each other. The selected subsets are of sufficient size to avoid the possibility of capturing only one land cover class and to attenuate variability due to image misregistration. The study areas range from 3768 to 65,942 km². The average annual NDVI ranges from 0.28 in the grassland dominated areas (4 and 5) to 0.56 in the mostly forested area (2). The coefficient of variation of NDVI within each area is about 6% with a higher coefficient of variation in area 1 (13.3%). The interannual coefficient of variation of NDVI ranges around 30% for each region.

Since our aim was to select different agricultural regions within Kazakhstan to investigate land cover changes following institutional change, we do not directly compare the selected study areas. Rather, we applied the same set of techniques to each study area to characterize the land surface phenology. The size of the study areas does not differ between the time periods and, therefore, the different sizes do not have an influence on the final results.

3.2. Surface temperature data

Surface temperature data serves here as a surrogate for available photosynthetically active radiation, since surface temperature in temperate grasslands during the growing season is highly correlated with insolation. Due to the sparseness of the weather monitoring network prior to independence and its general collapse thereafter, ground station data records are spotty and scarce. To solve this lack of data we used daily minimum and maximum temperature data from the NCEP/NCAR CDAS/Reanalysis Project (Kalnay et al., 1996). Since temperature gradients are generally smooth in the absence of steep altitudinal gradients, we assumed that the spatial resolution of the Reanalysis Project temperature data—roughly 2°—was sufficient for this study. These data are measured in °K. We calculated daily growing degree-days (GDD) using a base of 0 °C as follows:

$$\text{GDD} = \frac{(T_{\text{max}} + T_{\text{min}})}{2} - 273.3$$
We accumulated daily GDD over the growing season by simple summation when GDD exceeded the base of 0 °C:

\[
\text{if } \text{GDD}_t > 0 \text{ then } \\
\text{AGDD}_t = \text{AGDD}_{t-1} + \text{GDD}_t \\
\text{else } \\
\text{AGDD}_t = \text{AGDD}_{t-1}
\]

(2)

where GDD, is the daily increment of growing degree-days at day \(t\) and AGDD, is the growing degree-days accumulated from the beginning of the time period till day \(t\). The final accumulated growing degree-days (AGDD) are summarized into 10-day composites.

3.3. Data preparation

To assess for changes in the phenology of the land surface before and after independence, we used the image time series of two AVHRR sensors, NOAA-9 and NOAA-14. NOAA-9 recorded data from 1985 until 1988. NOAA-14 collected data from 1995 until 1999. In a separate study (de Beurs & Henebry, 2004), we demonstrated that there are no significant differences between the NDVI data from those two satellites. Using a series of statistical tests to compare the data from those satellites for a desert region in Kazakhstan, we concluded that not only are there no significant differences in the NDVI data, but there are also no trends during either of the sensor periods. Therefore, in this study, we assumed that satellite artifacts would not affect a comparison of the NDVI data from those two periods. We used the data from the last dekad in April to the last dekad in September, resulting in a dataset with 144 images, 64 for the first time period and 80 for the second time period. (The complete growing season dataset from 1982 to 1999 consists of 330 images and can be downloaded from the project website: http://www.calmit.unl.edu/kz/)

4. Methods

4.1. Exploratory data analysis

We want to test the null hypothesis that the mean NDVI from the NOAA-9 and NOAA-14 AVHRRs is equivalent. First, it is necessary to determine if the data follow a normal distribution. In case of normality, the data can then be submitted to the regular \(t\)-test with unequal variances to test for differences between the two groups. In case the data are not normally distributed, the data are submitted to the nonparametric Wilcoxon rank-sum test. This procedure was repeated for both the NDVI and GDD data in every study area.

4.2. Time series trend analysis

Similar to the analysis of hydrological time series (Hirsch & Slack, 1984) or other seasonal time series (Dietz & Killeen, 1981), testing for trends in the PAL NDVI data is complicated by the non-normality, seasonality, and serial dependence intrinsic to the data. When the data are dependent on processes that are serially correlated (which is also referred to as autocorrelation among the residuals), standard statistical tests for trends will fail to give reliable results; therefore, it is preferable to use a formal trend test that is corrected for serial dependence. Temporal autocorrelation occurs in most climatic data (von Storch & Navarra, 1999) and also in the PAL NDVI data. Thus, we have chosen to apply the nonparametric seasonal Mann–Kendall test corrected for serial dependence (Hirsch & Slack, 1984). The seasonal Mann–Kendall is completely rank-based and, therefore, is robust against non-normality, missing values, seasonality, and if corrected, against serial dependence as well. For each study area and period, we tested the null hypothesis that the observations are randomly ordered versus the alternative hypothesis of a monotonic trend (de Beurs & Henebry, 2004).

4.3. Bioclimatological modeling

For each study area and time period, we fitted a second-order polynomial model of the NDVI data to the accumulated growing degree-days (AGDD): 

\[
\text{NDVI} = a + \beta \times \text{AGDD} + \gamma \times \text{AGDD}^2
\]

We calculated the model fit parameters \(R^2\), \(R^2_{\text{adj}}\), the coefficient of variation (CV%) of the residuals, and the root mean squared error (RMSE) of the model. Student’s \(t\)-test was used to test for significant differences in model parameters between the two periods (Zar, 1984). The model parameters were tested sequentially: first, the quadratic term \(\gamma\); next, the linear term \(\beta\); and then the intercept \(a\). If the two quadratic terms were evaluated as not significantly different, then these parameters were averaged and the model for each period was refit using the averaged quadratic parameter \(\gamma_{\text{avg}}\). The process was repeated, if needed, with the linear and then with the intercept parameters of the revised models (Zar, 1984). The estimated models were influenced by positive auto-

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### Table 2

<table>
<thead>
<tr>
<th>Growing degree-days</th>
<th>NDVI</th>
<th>p-values</th>
<th>Growing degree-days</th>
<th>NDVI</th>
<th>p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 137.84 134.78</td>
<td>0.439</td>
<td>0.10</td>
<td>2 95.32 98.48</td>
<td>0.268</td>
<td>0.01</td>
</tr>
<tr>
<td>3 151.29 148.94</td>
<td>0.79</td>
<td>0.77</td>
<td>4 113.03 117.80</td>
<td>0.374</td>
<td>0.01</td>
</tr>
<tr>
<td>4 113.03 117.80</td>
<td>0.77</td>
<td>0.77</td>
<td>5 181.18 176.39</td>
<td>0.302</td>
<td>0.01</td>
</tr>
<tr>
<td>6 227.16 224.04</td>
<td>0.316</td>
<td>&lt;0.001</td>
<td>7 194.97 193.77</td>
<td>0.382</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>7 194.97 193.77</td>
<td>0.88</td>
<td>0.10</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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correlation in the residuals. To correct for autocorrelation, we fitted autoregressive models with a one period lag factor. These models resulted in slightly higher standard errors, smaller $t$-values, and smaller $R^2$. However, the differences in magnitude between the parameters estimated by ordinary least squares (OLS) and the parameters estimated by the autoregressive models are very small, with no change in significance. Therefore, we suggest that the OLS method results in sufficiently precise models and that a separate correction for autocorrelation between the observations is unnecessary. However, it is important to recognize that the regression models are developed here only for exploratory analysis, not prediction.

What is the range of possible model behaviors? There are three parameters for the quadratic model. If only the intercept terms change, then there are two possibilities: either the intercepts increase or decrease between periods. We designate this situation as type A model behavior. If both the intercept and linear parameters can change between periods, then there are four possible combinations (type B model behavior). If we assume that all three parameters can change, then there are eight distinct behaviors (type C model behavior). In sum, there are 14 possible combinations of change in the models spread across 3 types (type A = 2 + type B = 4 + type C = 8). Finally, there is the 15th possibility of no change between periods.

5. Results

5.1. Exploratory data analysis

Average NDVI and GDD values were compared for the periods before and after institutional change. Table 2 reports the mean NDVI and mean sum of GDD per dekad of each study area and each period together with the $p$-values for the difference between the periods. Notice that every region shows a higher mean NDVI after institutional change; however, the increase is significant only in study areas 5, 6, and 7. Five regions have a slightly lower sum of GDD after institutional change but nowhere are there significant differences. To summarize: tests indicate higher average NDVI values following institutional change but not as a result of changes in GDD.

5.2. Time series trend analysis

The $p$-values of the seasonal Mann–Kendall test are reported in Table 3. Only irrigated area 7 shows a trend in the NDVI after institutional change. This trend cannot be explained by a trend in GDD during the same time period. The area 3 before and area 5 after institutional change show a trend in GDD, although this trend is absent in the NDVI. The areas 5 and 7 exhibit trends in the earlier period in both the NDVI and GDD. The trend in the NDVI may result from the GDD trend, but not necessarily.

5.3. Bioclimatological modeling

Table 4 reports the final quadratic models with the adjusted coefficient of determination ($R^2_{adj}$), RMSE, and

<table>
<thead>
<tr>
<th>Area</th>
<th>Period</th>
<th>Model</th>
<th>$R^2_{adj}$</th>
<th>RMSE</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>B</td>
<td>NDVI = 0.145 + 6.681E $^{-4}$ AGDD $^{-1}$ + 2.705E $^{-2}$ AGDD $^{2}$</td>
<td>0.73</td>
<td>0.072</td>
<td>B</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>NDVI = 0.215 + 6.301E $^{-4}$ AGDD $^{-1}$ + 2.705E $^{-2}$ AGDD $^{2}$</td>
<td>0.73</td>
<td>0.079</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>B</td>
<td>NDVI = 0.247 + 1.080E $^{-3}$ AGDD $^{-1}$ + 6.199E $^{-2}$ AGDD $^{2}$</td>
<td>0.78</td>
<td>0.080</td>
<td>B</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>NDVI = 0.327 + 1.037E $^{-3}$ AGDD $^{-1}$ + 6.199E $^{-2}$ AGDD $^{2}$</td>
<td>0.69</td>
<td>0.097</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>B</td>
<td>NDVI = 0.109 + 5.830E $^{-4}$ AGDD $^{-1}$ + 2.106E $^{-2}$ AGDD $^{2}$</td>
<td>0.76</td>
<td>0.067</td>
<td>B</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>NDVI = 0.190 + 5.199E $^{-4}$ AGDD $^{-1}$ + 2.106E $^{-2}$ AGDD $^{2}$</td>
<td>0.69</td>
<td>0.073</td>
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</tr>
<tr>
<td>4</td>
<td>B</td>
<td>NDVI = 0.166 + 4.171E $^{-4}$ AGDD $^{-1}$ + 2.322E $^{-2}$ AGDD $^{2}$</td>
<td>0.53</td>
<td>0.061</td>
<td>A</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>NDVI = 0.199 + 4.171E $^{-4}$ AGDD $^{-1}$ + 2.322E $^{-2}$ AGDD $^{2}$</td>
<td>0.61</td>
<td>0.065</td>
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</tr>
<tr>
<td>5</td>
<td>B</td>
<td>NDVI = 0.273 + 4.935E $^{-4}$ AGDD $^{-1}$ + 2.940E $^{-2}$ AGDD $^{2}$</td>
<td>0.24</td>
<td>0.066</td>
<td>C</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>NDVI = 0.279 + 1.356E $^{-4}$ AGDD $^{-1}$ + 6.112E $^{-2}$ AGDD $^{2}$</td>
<td>0.46</td>
<td>0.069</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>B</td>
<td>NDVI = 0.049 + 2.636E $^{-3}$ AGDD $^{-1}$ + 5.741E $^{-2}$ AGDD $^{2}$</td>
<td>0.81</td>
<td>0.037</td>
<td>A</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>NDVI = 0.096 + 2.636E $^{-3}$ AGDD $^{-1}$ + 5.741E $^{-2}$ AGDD $^{2}$</td>
<td>0.86</td>
<td>0.034</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>B</td>
<td>NDVI = 0.056 + 3.946E $^{-3}$ AGDD $^{-1}$ + 1.012E $^{-2}$ AGDD $^{2}$</td>
<td>0.86</td>
<td>0.039</td>
<td>A</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>NDVI = 0.109 + 3.946E $^{-3}$ AGDD $^{-1}$ + 1.012E $^{-2}$ AGDD $^{2}$</td>
<td>0.84</td>
<td>0.044</td>
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</table>

Type A models have a significantly different intercept; type B models have significantly different intercepts and linear parameters; and in type C models, all parameters are significantly different between periods.

type of model behavior. The intercepts were always found to be significantly higher after institutional change for every study area. Fig. 3 displays the final models for each time period and study area. Area 5 stands out as having poor model performance with $R_{adj}^2 = 0.24$ in the earlier period and 0.6 after institutional change. All other models exhibit moderate to excellent fits with $R_{adj}^2$ ranging from 0.53 in the grassland-dominated area 4 to 0.86 in the irrigated area 7.

Although there are 14 possible combinations of models, we only find 3 options in the data. Type A model behavior shows an increase in intercepts for the second model, while the timing of the phenological sequence is unaltered. An increased intercept indicates a higher NDVI observed for an equivalent quantity of growing degree-days. Type B model behavior involves equal quadratic behavior but declined linear parameters and increased intercepts. The NDVI peak occurs at fewer growing degree-days, which can be inter-

Fig. 3. Model behavior of each study area. Model performance was moderate to good for every area except #5. Each study area exhibits one of the three model behaviors described in Fig. 4.
interpreted as earlier green-up. All the parameters are different in type C behavior. The quadratic parameter is larger, the linear parameter is smaller and the intercept parameter is increased. This causes an earlier green-up, a higher peak NDVI, and a longer duration of greenness (Fig. 4).

The grassland-dominated area 4 and the two irrigated areas (6 and 7) display Type A model behavior in which only the intercept is significant different. The shape of the curve describing the NDVI phenology as a function of AGDD is similar in both periods for all three study areas; however, after the institutional change, the intercept is higher. In both periods the peak of the model occurs at the same AGDD. In area 4, the peak NDVI at AGDD = 898. The peak NDVI value for 1985–1988 is 0.353 versus 0.386 for 1995–1999, which represents 9% increase that is not significantly different. Area 6 peaks at AGDD = 2296, while area 7 peaks earlier at AGDD = 1950. In area 6, there is a 13.6% increase in peak NDVI values (0.345 vs. 0.392). The higher peak values in area 7 show a 12% increase (0.429 vs. 0.482).

Study areas 1–3 exhibit type B model behavior, indicating equivalent quadratic parameters between periods but differing linear parameters and intercepts. In these three areas the linear parameter is smaller after institutional change, which leads to an earlier green-up, e.g., peak NDVI at lower AGDD. The advancement of the NDVI peak following institutional change is 70 GDD for area 1, 35 GDD for area 2, and 140 GDD for area 3. The increase in the peak NDVI value is about 4%, 34%, and 6% for areas 1, 2, and 3, respectively. The corresponding increases of the intercepts are 48%, 32%, and 74%, respectively, which indicates that there is a much larger increase in the NDVI at the beginning of the growing season than later on. Area 2 shows least shift toward earlier AGDD and the least increase in intercept; this area has the largest forest cover (>50%). The study area with the greatest shift to earlier AGDD and the greatest increase in intercept is region 3 in northern Kazakhstan, which has the most area in agriculture (~50%) and cropland mosaics (~30%).

Area 5 exhibits Type C model behavior; all model parameters are significantly different for the two periods. The model performance is very poor in the first period and not much better in the second. The AGDD is not able to explain a significant proportion in the variation in the NDVI data for this region. This region has ~56% of grassland area and about 38% of cropland/grassland mosaic. Although the cover mosaics are comparable to region three and four, it has much larger grassland areas.

6. Discussion

The seven study areas are distributed across an area greater than 1.6 million km² and are located in eight different ecoregions as delineated by the World Wildlife Fund (Olson et al., 2001). They have distinct temperature and precipitation regimes, different native land cover types and land uses. However, they share the same historical events associated with institutional change in Kazakhstan. To assess significant differences between the periods on either side of the institutional change in these seven areas, we have demonstrated three ways (average comparison, seasonally adjusted time series trend analysis, bioclimatological modeling using growing degree-days) to analyze NDVI image time series. Multiple analyses provide multiple lines of evidence to help build the case of whether differences in the tempo and rhythm of land surface phenology
are mostly the result of anthropogenic influences or interannual climatic fluctuations.

The time series we analyzed have sufficient temporal density to characterize interannual variability. In six regions, it was possible to detect changes in land surface phenology, quantify their magnitude, and assess their statistical significance. Further, it was possible to rule out climatic variations as the source of the observed changes and to attribute these differences instead to anthropogenic influences. Only in area 5 did a difficulty arise due to the poor fit of the bioclimatological model. This lack of fit could be the result of the influence of another climatic parameter such as precipitation, which we could not consider due to lack of data. It is the combination of techniques that enables the identification of the changes in the other regions and a causal construction of the events leading to those changes. The explanatory data analysis and the trend analysis can point to certain differences between the time series, but they are not sufficient on their own.

The bioclimatological models enable the comparison of basic phenological structures for the two time series. Of the 14 possible parameter combinations, the bioclimatological modeling revealed only 3 specific types of model behavior in the transition from the first to the second period: type A, in which the intercept diminishes and the other parameters stay unchanged; type B, in which the linear parameter diminishes while the intercept increases; and type C, in which the quadratic parameter increases, the linear parameter diminishes, and the intercept increases.

6.1. Northern grain belt: study areas 1 and 3

The analysis and interpretation of the data from the region of dryland cultivation in northern Kazakhstan is a challenge. The northern study areas cover a spatially heterogeneous mosaic of pastures, active and fallow fields near Petropavlovsk and Kostanai. The NDVI phenologies are strongly influenced by the precipitation regime in addition to temperature, which results in high interannual variability. Crop yields also show very high interannual variability (Fig. 2), due to frequent drought, late frosts, and strong winds, in addition to institutional factors. Trend analyses of the seasonally adjusted time series failed to reveal trends in the NDVI or in growing degree-days. The parametric tests showed no differences in mean NDVI values following institutional change. The bioclimatological modeling performs reasonably well for both periods. Both models behave as type B: significantly different intercepts and linear parameters. After independence, the increase in the intercept and the decrease in the slope during the beginning of the growing season indicate that the NDVI is higher at the end of April and that it does not increase as much by the end of June as before independence. The increase of intercept NDVI is 48% in area 1 and about 74% in area 3. Crops in the grain belt are planted in mid to late May (Doraswamy et al., 2002); thus, this change in land surface phenology is not due to variation in the crop type or crop development. The NDVI peak is advanced by about 70 GDD or about 4 days in area 1 and 140 GDD or about 7 days in area 3.

One consequence of independence was a lack of investment by the new government in institutional structures to minimize the shocks of the socioeconomic transition in the agricultural sector (Baydildina et al., 2000; Meng et al., 2000; Morgounov et al., 2000; Suleimenov & Oram, 2000). The removal of governmental subsidies to production inputs, for instance, forced farmers to increase efficiency by removing marginal lands from production. The area sown for all crops in Kazakhstan was reduced by 37.9% through the mid-1990s, with a reduction in grains of 33% (Suleimenov & Oram, 2000). This large increase in fallow lands led to significant increases in the regional growth of weedy species, which, in turn, hindered production due to the steep reduction in the use of herbicides (Meng et al., 2000). Furthermore, most of the land dropped from production was not added to rangeland, due in large part to the collapse of livestock production following independence, which also reduced the intensity of grazing in grasslands and pastures across the country (Suleimenov & Oram, 2000).

The higher intercept and lower slope in our bioclimatological models at the beginning of the growing season following independence point to agricultural de-intensification in the northern grain belt, a phenomenon that runs counter to global patterns of intensifying agricultural production (Matson et al., 1997). Based on extant socioeconomic studies and our model analyses, we conclude that the changes in land surface phenology observed in the NDVI image time series of northern Kazakhstan are caused by large increases in the area dominated by weedy species as well as in native grassland vegetation under reduced grazing pressure (Meng et al., 2000). Since the more northerly area 1 was more favorable for wheat cultivation than the more southerly, drier area 3, the difference in phenology is more pronounced in latter than in the former.

6.2. Forest: study area 2

The bulk of Kazakhstan’s forests are located in the mountains north of the Ertisch river in the northeast. Area 2 consists of young pines with pine undergrowth and dry larch forests. There are cedar forests on the rocks of the southern slopes of the Altai Mountains and the growing conditions are dry (Arkhipov et al., 2000). This is our only study area where the majority of the land cover is considered natural vegetation. There is no significant trend within periods for either the NDVI or GDD; furthermore, there is no significant difference in the NDVI between periods. The NDVI peak advanced only 35 GDD and the intercept increased by 32%. Although there was an increase in the incidence of forest fires following independence with a peak in 1997 (Khaidarov & Arkhipov, 2001), there is no significant change observed in the land surface phenology. Due to planned and natural reforestation of bare and timbered areas, there is a slight increase in
forested areas in Kazakhstan (Grote, 1998). This may explain the increase in the model intercept.

6.3. Grasslands and pastures: study areas 4 and 5

Study areas 4 and 5 are located furthest south in the Kazakh Steppe and the Kazakh deserts. Area 4 shows a 9% overall increase in the NDVI but the phenology did not change between periods. Area 4 is natural grassland region that has been used mostly for livestock grazing. Following the collapse of the Soviet Union, the costs of producing meat, wool, and milk have increased dramatically (Kerven & Behnke, 1996). Furthermore, globalization has increased international competition in wool, which has led to sharp decline in the market value of wool. The collapse of livestock production following independence (Fig. 2) reduced the intensity of grazing in grasslands and pastures across the country (Suleimenov & Oram, 2000). The reduction in herd size has decreased vegetation loss due to trampling and pasture production has even improved since the early 1990s (Grote, 1998). Finally, we have no reason to suspect changes in crop type or land cover in this area. Therefore, we conclude that the significant increase in the NDVI intercept (type A behavior) is a consequence of the improved pasture production.

Area 5 posed a challenge to our modeling efforts. It shows a significant overall increase of NDVI after independence, further, there are significant ($p = 0.02$) trends both in GDD and in the NDVI during the first period. The second period shows a trend in GDD but not in the NDVI. Furthermore, the AGDD does not account for a significant proportion of the variation in NDVI (Table 4). The phenology of this arid grassland located within the Kazakh desert is driven substantially by available soil moisture and thus by precipitation. This strong dependence on the precipitation regime leads to great interannual variability including drought events. In the absence of adequate precipitation data, we found it not possible to model the land surface phenology in area 5 properly using AGDD alone.

6.4. Intensive irrigation: study areas 6 and 7

In the arid south, cultivation must rely exclusively on irrigation because precipitation during the growing season is minimal in the desert climate. Accordingly, we assumed that the irrigated croplands do not suffer from water stress and, therefore, the region’s normal precipitation patterns do not appreciably influence the NDVI phenology in the croplands. A nonparametric test showed significantly higher mean NDVI values after institutional change. The bioclimatological model performs well for both periods with only the intercept parameters differing significantly between periods (Type A model behavior). The intercept is larger following institutional change and, as the other model parameters are equivalent, the NDVI is larger. In a related study (Henebry et al., 2002), we found that the spatial dependence structure of the NDVI, measured as correlation length (Henebry, 1993), was significantly less variable in southern Kazakhstan following institutional change. The correlation length is a measure for the spatial dependence among pixels within a region. A decrease in the variability of the spatial dependence structure indicates that there is less variability between neighboring pixels, indicating less variation between fields and thus suggesting better land management.

Multiple lines of analysis of the NDVI time series point to significant changes in NDVI phenology in the irrigated croplands after independence. What may account for these changes? While it is outside the present scope to investigate change attribution, the difficult fourth phase in change analysis, we can point to a possible avenue of explanation. Economic research on agricultural production in socialist countries has shown that the interannual variation of crop production under centralized planning can be significantly greater than under private ownership and market economies (Brada, 1986). Moreover, the variability of efficiencies on state farms is significantly greater than on private farms, even though the average efficiencies of state and private farms are similar (Brada & King, 1993, 1994). Thus, we suggest that changes observed in the NDVI time series result from institutional changes that enabled the newly decentralized agricultural decision-making in the intensively managed irrigated croplands of southern Kazakhstan to respond to market forces.

7. Conclusion

In this study we analyzed image time series with high temporal density for changes due to institutional change. We focused on the processes of change quantification and change assessment of the land surface phenology in seven areas across Kazakhstan. We presented three distinct but complementary statistical analyses to test for significant differences before and after institutional change. Testing of average NDVI values revealed significant differences between the two periods for three areas. Simple time series analysis demonstrated positive trends over two periods from two areas. The bioclimatological modeling was very successful in revealing period differences. Whereas the first two techniques test for differences between two datasets, the latter method was shown to be of greater value in understanding the phenological behavior embedded in noisy data. Were the observed changes in phenology solely attributable to climate change, then we would expect only one type of model behavior. However, we have demonstrated here that there are at least three distinct types of phenological change, which are explainable from events within the regions. Our multiple lines of analysis yield multiple lines of evidence that indicate the disestablishment of the Soviet agricultural sector has led to such widespread de-intensification of agriculture in Kazakhstan that there have been significant
changes in the land surface phenology throughout much of the country.

Shifts in land surface phenology have implications for the predictive reliability of numerical weather prediction models by affecting, among other things, the fractional green vegetation cover (Gallo et al., 2001; Gutman & Ignatov, 1998; Zeng et al., 2000). Reliance on land surface “climatologies” rather than current and recent dynamics may lead to significant predictive biases (Crawford et al., 2001). Socioeconomic studies have suggested several institutional influences that may be responsible for the observed changes in phenology. Incorporation of the effects of institutions, policies, and market forces on LCLUC remains an open research question; however, we have demonstrated here that some traction is possible through the careful partitioning of multiple influences on variation in land surface phenology.

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References


