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AVHRR-Based Spectral Vegetation Index for Quantitative Assessment of Vegetation State and Productivity: Calibration and Validation

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Abstract

The goal of the work was to estimate, quantitatively, vegetation state and productivity using AVHRR-based Vegetation Condition Index (VCI). The VCI algorithm includes application of post-launch calibration to visible channels, calculation of NDVI from channels' reflectance, removal of high-frequency noise from NDVI's annual time series, stratification of ecosystem resources, and separation of ecosystem and weather components in the NDVI value. The weather component was calculated by normalizing the NDVI to the difference of the extreme NDVI fluctuations (maximum and minimum), derived from multi-year data for each week and land pixel. The VCI was compared with wheat density measured in Kazakhstan. Six test fields were located in different climatic (annual precipitation 150 to 700 mm) and ecological (semi-desert to steppe-forest) zones with elevations from 200 to 700 m and a wide range of NDVI variation over space and season from 0.05 to 0.47. Plant density (PD) was measured in wheat fields by calculating the number of stems per unit area. PD deviation from year to year (PDD) was expressed as a deviation from median density calculated from multi-year data. The correlation between PDD and VCI for all stations was positive and quite strong ($r^2 > 0.75$) with the Standard Errors of Estimates (SEE) of PDD less than 16 percent; for individual stations, the SEE was less than 11 percent. The results indicate that VCI is an appropriate index for monitoring weather impact on vegetation and for assessment of pasture and crop productivity in Kazakhstan. Because satellite observations provide better spatial and temporal coverage, the VCI-based system will provide efficient tools for management of water resources and the improvement of agricultural planning. This system will serve as a prototype in the other parts of the world where ground observations are limited or not available.

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Introduction

Over the past decade, spectral vegetation indices, particularly those derived from the Advanced Very High Resolution Radiometer (AVHRR) on board NOAA polar-orbiting operational satellites, have shown excellent potential for monitoring vegetation, environmental parameters, and phenomena (Tucker *et al.*, 1985; Holben, 1986; Marlingreau, 1986; Prince *et al.*, 1986; Townshend and Justice, 1986; Tucker and Sellers, 1986; Justice *et al.*, 1986; NOAA, 1988; Ohring *et al.*, 1989; Rao *et al.*, 1990; Kogan, 1990; Kogan, 1997). A considerable amount of AVHRR-based data is now archived and made available to the global community (Ohring *et al.*, 1989; Los *et al.*, 1994; Townshend, 1994; Goward *et al.*, 1994; Gutman *et al.*, 1995; Kidwell, 1997).

Among these data sets, the Global Vegetation Index (GVI), developed by NOAA in 1985 from the Global Area Coverage (GAC) product (NOAA, 1988; Kidwell, 1997), has a special place because it showed excellent utility for a wide range of applications. More importantly, unlike other data sets, the GVI was comprehensively validated against ground data. This helped to develop a number of products widely used for estimation of vegetation health, monitoring drought, analysis of thermal and moisture conditions of land surface, diagnosis of crop production and pasture biomass, estimation of irrigation acreage, monitoring vector-borne diseases, fire risk, ENSO (El Niño—Southern Oscillation) impacts on land ecosystems, etc. (Kogan, 1995; Hayas and Decker, 1996; Liu and Kogan, 1996; Kogan, 1997; Unganai and Kogan, 1998; Seiler *et al.*, 2000; Kogan, 2001; Liu and Kogan, 2002; Dabrowska-Zielinska *et al.*, 2002).

Successful application of the GVI expanded in the 1990s when the new tools for data processing, analysis, interpretation, and dissemination were developed and tested in many countries (the U.S.A., Mexico, Poland, Russia, China, India, Zimbabwe, Morocco, Republic of South Africa, Argentina, and Brazil), including major agricultural producers. Following these achievements, the United States Agency for International Development (US AID) provided funds to investigate possible applications of the new tools in Kazakhstan, a new country separated from the former USSR. This work included quantitative validation of the new AVHRR-based indices in ecological environment of this country and their calibration against ground data (Gitelson *et al.*, 1998). These objectives were set

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up because Kazakhstan is a huge agricultural country (wheat and cattle producer) where agriculture accounts for a large share in the total country's budget. Its dry climate is incompatible with agricultural goals, thus limiting agricultural production. Moreover, in recent years, the weather network, which provides data for assessment of weather impacts on agricultural crops, shrank considerably and the quality of observations deteriorated, which jeopardized the environmental services. This paper presents comprehensive results of a quantitative comparison and analysis of AVHRR-based indices with ground observations in Kazakhstan's wheat fields.

Strategy

To quantitatively validate AVHRR-based algorithms, we focused on

- A large area with diversified ecosystem resources,
- An entire growing season in order to reflect the vegetation response at different stages of vegetation growth,
- Multi-year analysis of weather impact on vegetation condition and productivity,
- An area where vegetation is an important part of the population wellbeing, and
- Quantitative estimation of the vegetation state and production.

Target Area

Kazakhstan, located in the southern part of the former Soviet Union, satisfies the identified strategy quite well. Pastures occupy 87 percent and crops 13 percent of Kazakhstan's total area (Figure 1). The climate of Kazakhstan is arid and semi arid. Annual precipitation changes from nearly 50 mm in the desert (south) to 300 to 450 mm in the steppe zone in the north; only a small area in the southeast receives around 1000 mm. Annual potential evapotranspiration in the northern principal agricultural areas is between 500 and 700 mm, exceeding the amount of precipitation two-fold. In the south, potential evapotranspiration (700 to 900 mm) exceeds the annual precipitation four to seven times. Vegetation zones change from desert in the south to steppe and forest-steppe in the north.

Agriculture is important for the well-being of Kazakhstan's population, and agricultural productivity is highly dependent on climate and weather. Most of Kazakhstan's crops and pastureland are located in arid and semi arid zones. Rainfall fluctuations are large during the growing season and from year to year, putting additional constraints on agriculture. Drought is the most typical phenomenon of the Kazakhstan climate, occurring every two to four years. Extreme droughts occur every 7 to 10 years, leading to considerable losses in agricultural production.

Data

Satellite Data

Radiances measured by the AVHRR on board the NOAA 9, 11, and 14 polar-orbiting satellites were used in the study. These data were collected from the GVI data set (1985–1994), which includes radiance in the following bands: visible (Ch1), near-infrared (Ch2), and two thermal channels (Ch4 and Ch5), the Normalized Difference Vegetation Index, NDVI = (Ch2 − Ch1)/(Ch2 + Ch1); and solar and satellite angles. The GVI was sampled over space from 1 to 16 km resolution and over time from one day to one-week composites.

Ground Data

The ground data included plant density (PD) measured in spring wheat fields at six weather stations from 1985 through 1994. The PD measurements included calculation of a number of stems per unit area inside the selected field, every 10 days during the growing season (WMO, 1972). Following the standard procedure, PD for each station was measured in the representative spring wheat field (normally a 20- to 100-hectare size) not far from a weather station. In four locations in each field, the total number of plants (per one square meter of an area) was counted. These locations were well marked for continuity of observations. The PD for the field was calculated from the four one-square-meter samples.

The PD measurements are standard agrometeorological observations used to characterize plant conditions and productivity (WMO, 1972). In the earlier stages (up to tillering) of

Figure 1. Map of Kazakhstan with the locations of the six weather stations selected for VCI validation.

wheat growth, each plant consists of one stem, and density increases with an improvement (more plants emerge) and decreases with a deterioration (some plants die) of environmental conditions. From the tillering (or shooting) stage, each plant is potentially able to produce up to six additional stems (grown from the nodal buds), and each of them is potentially able to produce an ear with grains. The number of additional stems and their productivity depend on moisture and thermal conditions; good moisture supply and warm temperature stimulate stems' appearance and survival and higher PD.

Therefore, the PD is an indirect measure of vegetation density and productivity (both biomass and amount of grain; other characteristics such as leaf area index, biomass, etc., are not measured in Kazakhstan). Because PD depends on moisture and thermal conditions prior to and during the shooting stage, this parameter is an appropriate indicator of weather impacts on wheat biomass and production (Ulanova, 1975; Paulsen, 1978; FAO, 1986). Most of Kazakhstan's ecosystems and climate zones from semi-desert to steppe/steppe-forest (Figure 1) were represented in this study.

Methods

The processing of the satellite data included

- Calibration of Ch1 and Ch2 radiance using post-launch calibration to eliminate noise related to sensor degradation and, partially, to satellite orbit drift and calculation of albedo (Rao *et al.*, 1995; Kidwell, 1997);
- Completion of noise suppression to eliminate high-frequency temporal variations from the NDVI time series (van Dijk *et al.*, 1986; Kogan, 1990); this is a very important procedure because noise sources are multiple degrading the data (Goward *et al.*, 1991; Gutman, 1991); and
- Calculation of the NDVI-based Vegetation Condition Index (VCI).

The VCI was derived from NDVI by normalizing to NDVI's multi-year maximum and minimum values (Kogan, 1990; Kogan, 2001): i.e.,

$$VCI_{ywjk} = (NDVI_{ywjk} - NDVImin_{wjk})/(NDVImax_{wjk} - NDVImin_{wjk}). \quad (1)$$

Here NDVImin and NDVImax are the lowest and the highest weekly values observed during the 1985 to 1994 period for each pixel, respectively; y is year number, w is the week number (between 1 and 52), j is the latitude (between 55°N and 75°S), and k is the longitude (between 180°W and 180°E). For example, for the end of June 1991, station 1 will have the following values: $y = 1991$, $w = 26$, $j = 49.53°$, and $k = 69.31°$ (the latter two should be converted to row and column of the global data set, following a selected map projection).

The VCI concept was designed to extract the weather component from NDVI values (Kogan, 1990). The fact is that NDVI represents two environmental signals: ecosystem, which explains long-term changes in vegetation (driven by climate, soils, vegetation type, topography, etc.), and weather (short term), explaining intra- and inter-annual variations in each ecosystem in response to weather fluctuations. Because the weather component is much smaller than the ecosystem component, the algorithm was developed to enhance the weather component. This procedure was based on three environmental laws: law-of-minimum, law of tolerance, and the principle of carrying capacity (Hardin, 1986). These laws provide the basis for determining the lowest and the highest potentials of an ecosystem's resources in response to the environment. Basically, extreme NDVI values during the years 1985 through 1994 were calculated for each week and pixel. The resulting multi-year maximum and minimum NDVI were used as the criteria for estimating the upper (favorable weather) and the lower (unfavorable weather) limits of the ecosystem resources in response to extreme weather conditions. These limits characterize the "carrying capacity" of each pixel. Because the minimum and maximum values in the annual cycle delineate the contribution of the ecosystem component in the NDVI for the most extreme weather cases, the area between these curves largely approximates the weather-driven component of NDVI. The VCI is invariant of ecological background and depends on weather condition only; it was validated against ground data (Hayas and Decker, 1996; Kogan, 1997; Unganai and Kogan, 1998; Kogan, 2001).

To compare with ground measurements, VCI was aggregated from 3- by 3-GVI pixels around the selected stations. Some concerns might be raised regarding matching space-aggregated GVI with 100-meter transects of ground data. We made a preliminary comparison of NDVI measured from NOAA satellite data and from hand-held radiometer data near one of the selected sites. Although the ground-measured NDVI was higher, the time series of both values had similar dynamics (Gitelson *et al.*, 1995). These results are also supported by identical studies in the wetter climate of Poland (Dabrowska-Zielinska *et al.*, 2002). Cereal crops (mostly wheat) in Kazakhstan occupy around 18 million hectares. Individual fields spread to thousands and more hectares and are comparable to the spatial resolution of GVI data. For much smaller non-irrigated fields represented by a mixture of wild vegetation and crops, it has already been proven that in drought/non-drought years, vegetation responds similarly to the surrounding areas, by reduced/increased greenness, vigor, density, biomass, and yield (Decker and Hyas, 1996; Unganai and Kogan, 1998; Dabrowska-Zielinska *et al.*, 2002).

During the 1985 through 1994 growing period, wheat's PD was measured each 10 days as the number of plants per square meter. Following the previous discussion, wheat's PD has some seasonal cycle, showing a density increase around the tillering stage and a decrease thereafter. Because the goal of this research was to explore weather-related variations, the PD was normalized using the approach similar to VCI approximation; we used multi-year median values of density for each 10-day period of the growing season (PDmed) and also multi-year minimum (PDmin), and maximum (PDmax) values. Then, the corresponding VCI values were compared with the difference between the measured density and the multi-year median density (PD − PDmed), normalized to the difference between the maximum and minimum densities. The resulting PD deviations (PDD) are expressed as

$$PDD_{ywjk} = (PD_{ywjk} - PDmed_{wjk})/(PDmax_{wjk} - PDmin_{wjk}) \quad (2)$$

where y, w, j, and k are the same as in Equation 1.

Results and Discussion

The NDVI in the 1991 and 1992 growing seasons were quite similar in some locations and different in others. Figure 2 shows that the 1991 and 1992 NDVI dynamics for stations 1, 2, and 3 were low and fairly similar during the entire growing season, while the NDVI values in 1992 were higher. For stations 4 and 5, the difference in NDVI was 0.02 to 0.03 in the early season (weeks 18 to 26); for station 6, the maximum difference occurred at midseason (weeks 25 to 30). While the NDVI shows mainly seasonal vegetation dynamics, the VCI shows changes in the vegetation condition in the range minimum to maximum multi-year NDVI values. A typical example is shown for station 6 where in 1991 the NDVI increased at the beginning of the growing season (weeks 18 to 20), reached the maximum in the middle, and dropped at the end. The VCI showed the opposite tendency, indicating good vegetation conditions at the beginning and end of the growing seasons and bad conditions in the middle.

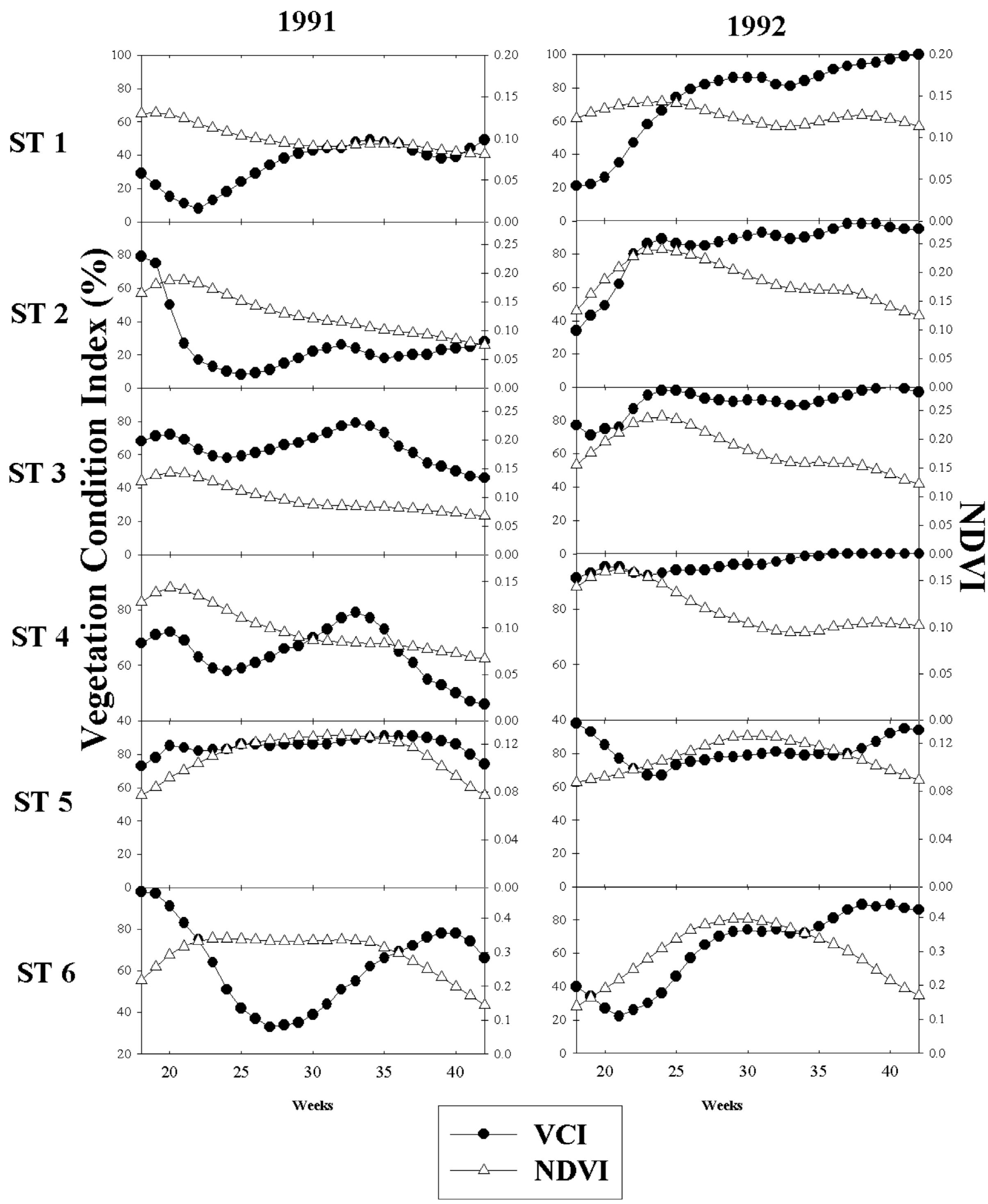

Figure 2. Comparison of NDVI and VCI aggregated for 3- by 3-GVI pixels: 1991 (dry conditions) and 1992 (favorable conditions). Stations 1 and 5, Almaty region; 3 and 4, Jeskazgan; and 2 and 6, Akmola (Figure 1).

The VCI values in 1991 and 1992 were quite different. Following the VCI estimates at stations 1 and 2, the 1992 growing season was more favorable (VCI values 70 to 90 percent) than 1991 (VCI values 20 to 50 percent). During weeks 22 to 24 in 1991, the VCI showed considerable deterioration of conditions, while changes in the NDVI were not as pronounced. Conversely, the NDVI values differed considerably for station 3; the difference in the VCI was not very significant (about 20 percent). At station 4, temporal VCI dynamics were extremely different between the years. In 1991, the changes during the growing season were between 50 and 80 percent with a minimum for week 24, while in 1992, the VCI was high (90 percent) from the beginning to the end of the season. Different VCI dynamics could also be seen at station 6, where considerable reduction occurred between weeks 25 and 30 in 1991, while in 1992, the VCI reached 75 percent by week 30.

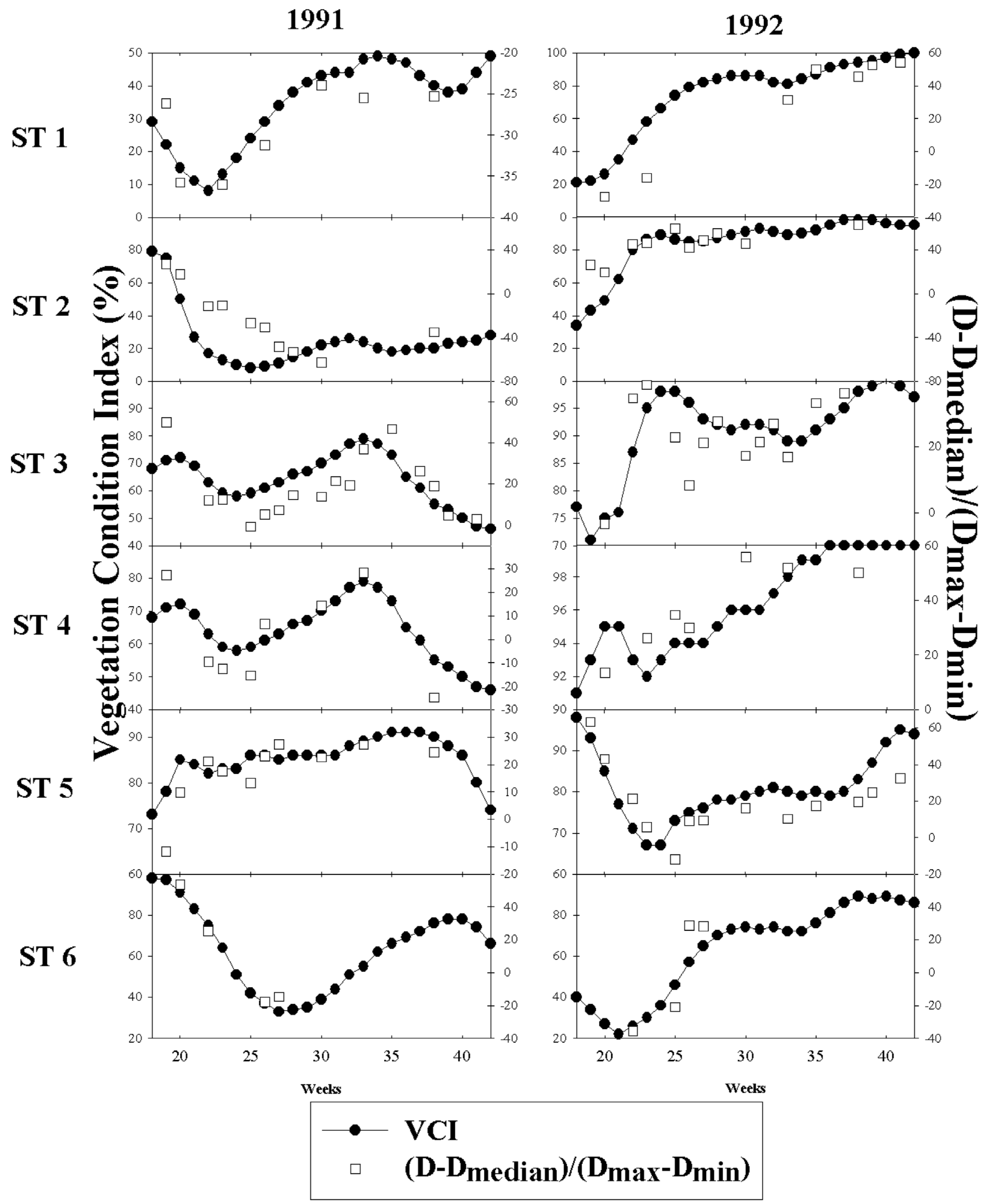

Figure 3. Seasonal dynamics of the VCI and deviation of wheat plant density (PDD) in 1991 and 1992. Station locations shown in Figure 1.

Figure 3 shows temporal variation of VCI and wheat's PDD in 1991 and 1992. As shown, there is a good match between the temporal behavior of the VCI and PDD for all ecosystems and for both favorable and stressed vegetation conditions. Station 1 shows the closest correspondence between VCI and PDD for both years. It should be noted that these years had quite different weather conditions. The year 1991 had severe drought, which was reflected in both VCI (below 40 percent) and PDD (below 20 percent). On the other hand, during mostly favorable 1992, both the VCI and PDD were very high, 70 to 90 percent and 30 to 60 percent, respectively. It is notable that the dynamics of the VCI and PDD were similar, changing from a reduction during weeks 18 to 22 to an increase thereafter. In general, the dynamics of the VCI and PDD matched quite well. The only two stations where some shifts occurred in 1991 were stations 2 (weeks 22 to 28) and 3 (weeks 25 to 33).

Figure 4 shows the scatter plot of VCI versus PDD for each station. The correlation was strong with $R^2 = 0.7$ to 0.8, except station 5 ($R^2 = 0.47$), where both VCI and PDD were high with low variation inside and between the years. Following these relationships, VCI values around 50 percent characterize near-normal vegetation conditions. They corresponded to a near-zero deviation of PD from the multi-year median values. VCI values below 30 percent, which specify strong drought conditions (Kogan, 1995), corresponded to a reduction of PDD below 20 percent. The highest PDD recorded in this study was around 60 percent, which corresponded to a VCI value around 15 percent, indicating exceptional drought. For a VCI over 60 percent, the density of the vegetation exceeds the median value, indicating that conditions are favorable for the development of healthy vegetation.

Although selected stations were located in different climatic and ecological zones and had considerable variation in elevation (200 to 700 m) and NDVI values (0.05 to 0.47), the

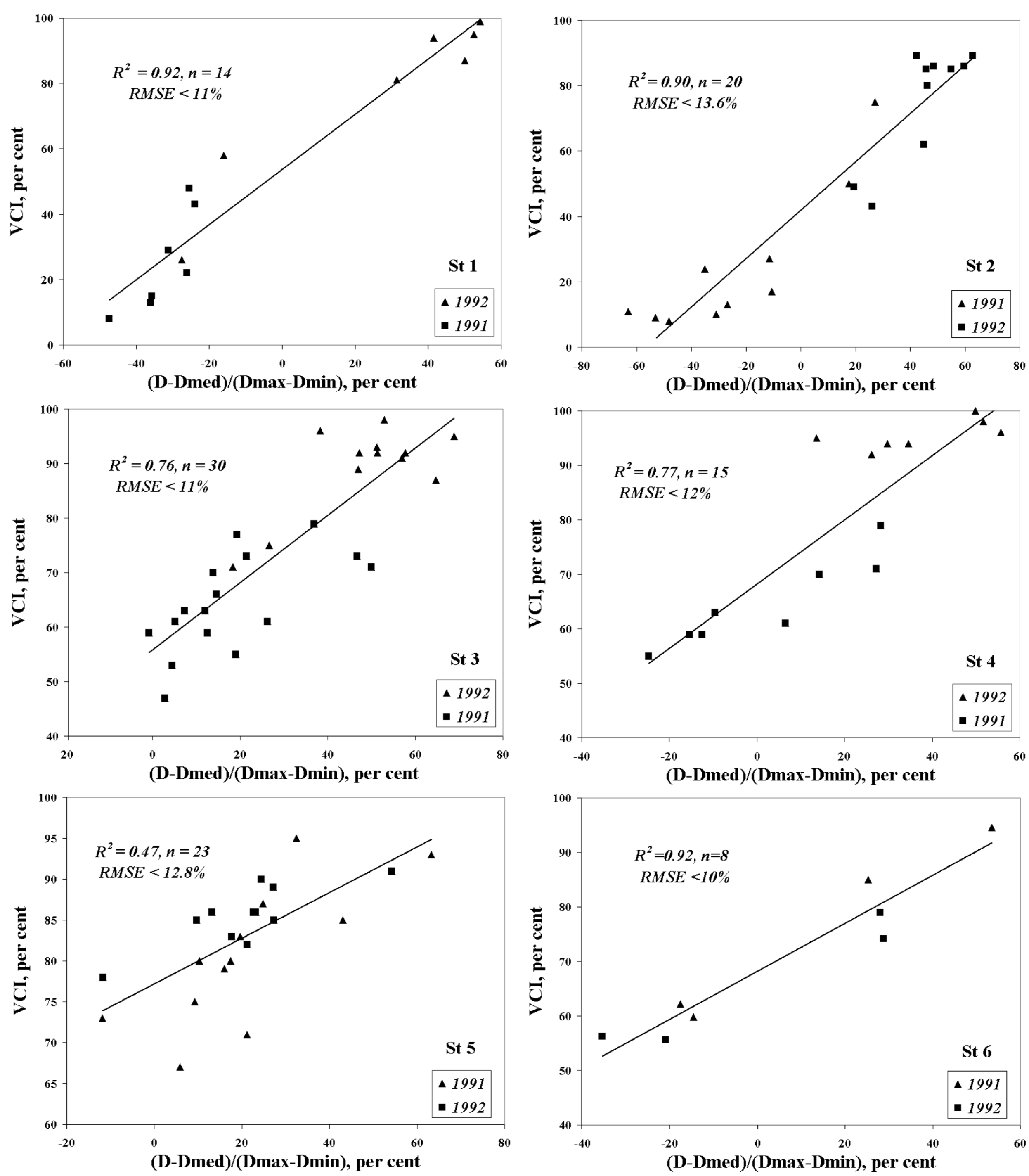

Figure 4. Scatter plot of VCI versus wheat plant density (PDD). The RMSE of plant density estimation for each station was less than 13.6 percent.

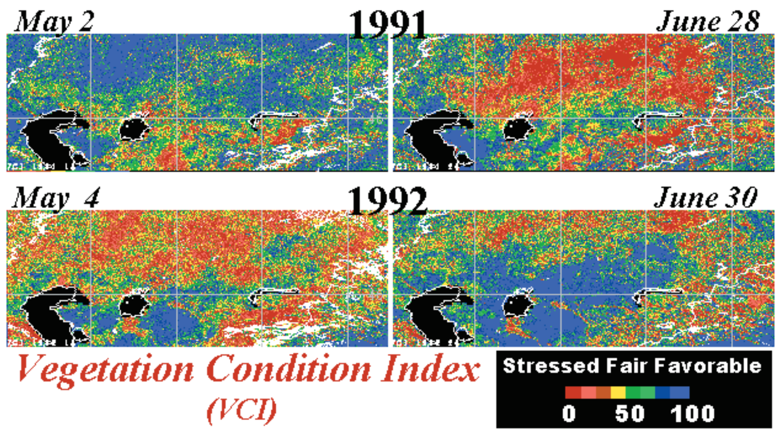

Plate 1. Color-coded maps of VCI-based vegetation conditions in May and June 1991–1992. Drought is shown in red, normal conditions in yellow and green, and favorable in blue.

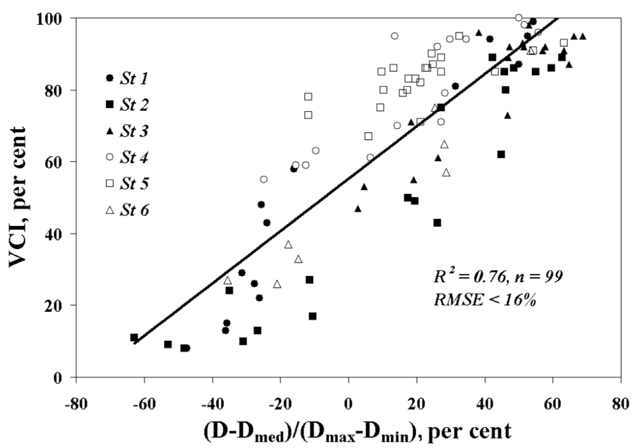

Figure 5. Scatter plot of VCI versus wheat PDD (all stations together).

all-station VCI versus PDD correlation (Figure 5) was quite strong ($R^2 = 0.76$) with an SE of the PDD estimation of less than 16 percent, considering that the variation in vegetation density was large (between −60 and 70 percent). The RMSE was smaller for a low density, indicating a higher accuracy in estimation of VCI-derived drought conditions. Thus, AVHRR-derived VCI maps shown in Plate 1 can be interpreted in terms of both wheat conditions and its density deviation from the multi-year median density (Plate 1).

Conclusions

A satellite-derived vegetation condition index was validated based on ground measurements of wheat density in the very different climatic conditions of Kazakhstan. VCI dynamics during the growing season matched well with plant density both in direction and values. The deviation of plant density was shown to be correlated strongly with VCI. Similar to previous research with crop yield and pasture biomass in different parts of the world, VCI once again was shown to be a good indicator of weather impact on vegetation and, correspondingly, vegetation condition, health, and productivity. It provides a fairly accurate assessment of unfavorable vegetation conditions, especially those related to drought impact. The next step should include quantitative calibration of the VCI against large area biomass, yield, and production measurements of various crops and pastures in different ecosystems of Kazakhstan. Also, further research will include combining NDVI-based estimates of conditions with thermal conditions estimated from infrared channels.

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