10 An Approach to Monitoring of Salt-Affected Croplands Using Remote Sensing Data

The Case Study in the Nukus District (Uzbekistan)

*Maria Konyushkova, Alexander Krenke,
Gulchekhra Khasankhanova, Nizamatdin
Mamutov, Victor Statov, Anna Kontoboytseva
and Yevgenia Pankova*

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10.1 INTRODUCTION

Soil salinity is one of the main threats to agriculture in the arid zones of Central Asia, especially in Uzbekistan and Turkmenistan, where salt-affected soils comprise the substantial part of these countries (Figure 10.1). In Uzbekistan, the area prone to salinity in the upper meter of soil profile is 35% of the area of the country and reaches 50% of the area of irrigated cropland (Bucknall et al., 2003; Vargas et al., 2018).

FIGURE 10.1 Distribution of salt-affected soils in the countries of Central Asia.

The monitoring of soil salinity in Uzbekistan lies mainly under the responsibility of the Ministry of Water Resources and its regional hydrogeological expeditions.¹ The monitoring is organized within the irrigation zones relative to the network of water distribution (Water Users Associations, or WUA). As a result, each WUA in theory represents a small catchment, which manages the irrigation system in a proper way. More detailed information about WUAs is given in Yalcin and Mollinga (2007). Each WUA is sampled for soil salinity once per 3 years with the norm of sampling 100–170 sampling points (SP) per square kilometer for 1:2000 scale, 40–80 SP for 1:5000, and 20–35 SP for 1:10000 scale (Soil Survey for Amelioration Construction, 1985). The sampling depths are 0–25, 25–50, 50–75, 75–100, 100–150, and 150–200 cm. Such a sampling standard, if recalculated into the area justified by ground truth data, would give 80 × 80 m (for the maximum number of SP) to 225 × 225 m (for the minimum number of SP). Judging from the detailed spaceborne imagery (Figure 10.2), it is obvious that how the pattern of soil salinity within such an area can be complex. At present, even the minimum number of SP is usually not taken for a variety of reasons.

It is essential that remote sensing imagery be introduced into the system for monitoring soil salinity of the irrigated lands in Uzbekistan as it can give invaluable and prompt information about the pattern of soil salinity. The approaches to monitoring of soil salinity based on remote sensing data are abundant and well represented in the scientific literature (e.g., Ivushkin et al., 2019; Pankova et al., 2018; Rukhovich et al., 2016). Still, in Uzbekistan, there is a gap between science and practice which should be overcome in the near future. At present, Uzbekistan is passing through a

FIGURE 10.2 Soil heterogeneity within the area justified by one sampling point. (From minimum to maximum required amount of samplings.)

set of reforms in agriculture aimed at modernizing the whole agricultural system. So, now is the most appropriate time to introduce the digital technologies of soil monitoring based on remote sensing data and proximal soil sensing.

The goal of this study was to develop and justify the procedure of processing remote sensing data such from Landsat to integrate these or similar into the national system of soil monitoring including soil salinity monitoring. Such an approach can help achieve the sustainable management of irrigated lands in Uzbekistan.

10.2 MATERIALS AND METHODS

The test area was the Nukus district of the Republic of Karakalpakstan (Uzbekistan) which is located on the right bank downstream of the Amu-Darya river (Figure 10.3). This area is heavily prone to salinity and has 82% of salt-affected soils within the irrigated cropland. There is no rainfed cropland in this region. The predominant crops are monocultures of cotton and some paddy rice and winter wheat.

A set of 18 no-cloud Landsat 8 OLI scenes for the growing season of 2017–2019 were used, namely those collected on 10/05/17, 18/06/17, 04/07/17, 05/08/17, 06/09/17, 01/10/17, 04/05/18, 05/06/18, 07/07/18, 24/08/18, 02/09/18, 11/10/18, 07/05/19, 08/06/19, 03/07/19, 04/08/19, 28/09/19, and 14/10/19. The band numbers 2–7 of Landsat-8 OLI were taken for analysis.

Along with the reflectance in spectral bands of Landsat-8 imagery, the NDVI vegetation index (*formula 1*) and S4 salinity index (*formula 2*) were used for analysis. The spectral S4 index was calculated according to Abbas et al. (2013) and was used

FIGURE 10.3 Location of the study area. (Nukus district of Karakalpakstan.)

in our research as it proved to be well correlated with soil salinity both in the study of Abbas et al. (2013) in Pakistan and in our studies in Uzbekistan.

$$NDVI = \frac{NIR - R}{NIR + R} \quad (10.1)$$

$$S4 = \sqrt{B \times R} \quad (10.2)$$

where B , R , NIR are reflectance in blue, red, and near-infrared bands, respectively.

Most calculations were performed over the whole set of pixels within the Nukus district using STATISTICA software.

The map of croplands was downloaded from the LPDAAC GFSAD collection (<https://lpdaac.usgs.gov/products/gfsad30eucearumecev001/>) (Phalke et al., 2017).

The resulting map was compared with the data on the areas of salt-affected soils in WUAs of the Nukus district of Karakalpakstan as of 01/11/2017. These estimates were based on the chemical analysis of 1894 SP across the irrigated cropland of the Nukus district (22,930 ha), or 7–13 SP per km² (depending on WUA), or 1 SP per 8–15 ha.

10.3 METHODOLOGY

The whole procedure of processing the remote sensing data was aimed at the gradual dimensionality reduction² until the invariant feature space was found according to the approach described in Puzachenko (2009). A 3-year time span was taken to smooth the variations caused by different weather conditions. With 18 dates and 6 bands for each date, 108 variables in total were processed in this analysis.

The first stage was the principal component analysis (PCA) of 6 bands of one date. 1st and 2nd factors (components) described more than 90% of variability and were taken for further analysis. For 18 dates, 36 (i.e., 2×18) new variables were calculated as a result of this first stage.

At the second stage, one more PCA over these new 36 variables was performed. The 1st and 2nd factors (components) derived at this second stage described the invariant (intrinsic) state of the image pattern.

At the third stage, the *k*-means classification was performed using two variables (two first components) obtained at stage 2. Different metrics (Euclidean, Mahalanobis and Manhattan distances, scalar product, and others) were tested and that with maximum entropy was chosen as it reflected the most unbiased classification. Given the iterative nature of the selected classification method, the stop point for separation of further classes was chosen when the increment of entropy started to decrease. This method was dichotomic and produced 2-power number of classes (2, 4, 8, 16, etc.); the visual filtration of noisy classes was therefore performed and discriminant analysis was used to fill in the resulting gaps.

At the fourth stage, the discriminant analysis with the final classes obtained at stage 3 and all initial variables (in our case, 6 bands $\times$ 18 dates, or 108 in total) was performed. The resulting confusion matrix showed the performance of classification by discriminant functions. At this stage, the probability of correct classification of each pixel was visualized on the map. The pixels with high probability were correspondent with the cores of the classes whereas the pixels with low probability corresponded to the peripheries of the classes.

We supposed that the stable (invariant) classes derived in the end of the fourth stage of this procedure corresponded to agroecological groups of soils. As the main threat to soil productivity in this area is salinity, we expected that these classes would correspond well with the salinity status of soils.

At the last stage of our analysis, we performed the reverse analysis collecting the values of NDVI and S4 indices within each class to see what is happening with vegetation (NDVI) and surface behavior (S4).

10.4 RESULTS AND DISCUSSION

The resulting map of agroecological groups of soils at the irrigated cropland of the Nukus district of Karakalpakstan is shown in [Figure 10.4](#). As a result, nine stable classes were identified. Classes 1–4 were mainly found on cropland whereas classes 6–9 were located outside the cropland; they were therefore excluded from further analysis. Class 5 was found in both cropland and non-cropland.

The overall confusion matrix of class identification showed a very good performance of classification, 67.2%, especially for classes 1, 2, and 6–9 ([Table 10.1](#)).

In order to interpret the invariant classes (groups) of spaceborne imagery, the analysis of NDVI and S4 within classes 1–5 on the cropland was performed ([Figure 10.5](#)). It can be seen that despite the dynamic character of NDVI and S4 in time, the classes were organized in an ordinal manner, that is, the classes with higher NDVI and lower salinity index had higher NDVI and lower salinity irrespective of

TABLE 10.1
Confusion Matrix of Classification by Discriminant Functions. The Grey Color Marks the % of Correct Identifications, and the Light Grey Color Marks the % of Identification as a Neighboring Class

		Classifications: Rows (Observed) Columns (Predicted)									
Class	N	Percent	1	2	3	4	5	6	7	8	9
1	19275	64.4	64.4	33.8	0.9	0.2	0.4	0.12	0.05	0.00	0.0
2	138583	67.8	4.2	67.8	25.5	1.8	0.6	0.08	0.02	0.00	0.0
3	206363	56.9	0.5	18.5	56.9	20.9	3.0	0.29	0.04	0.00	0.0
4	201577	56.3	0.1	1.9	20.3	56.3	20.1	1.30	0.10	0.00	0.0
5	137290	56.6	0.0	0.2	1.9	23.1	56.6	17.32	0.69	0.05	0.0
6	91569	66.1	0.0	0.0	0.1	0.9	17.9	66.09	14.62	0.34	0.0
7	81478	73.0	0.0	0.0	0.0	0.1	0.9	17.49	72.98	8.49	0.1
8	75377	68.4	0.0	0.0	0.0	0.0	0.1	0.44	19.21	68.38	11.9
9	207680	93.7	0.0	0.0	0.0	0.0	0.0	0.01	0.33	5.92	93.7
Total	1159192	67.2

FIGURE 10.4 Map of agroecological groups of soils at the irrigated cropland of the Nukus district of Karakalpakstan derived from the Landsat data. The comments are given in the text.

FIGURE 10.5 Temporal dynamics of NDVI and S4 salinity index by agroecological groups of soils at the croplands of the Nukus district. Each date has a total of 2,711,070 pixels.

the season. Judging from Figure 10.5, group 1 was constant water. Groups 2 and 3 were very close to each other in terms of NDVI and salinity and they had highest biological productivity and lowest salinity. There was a slight difference in salinity between these two groups which allows us to conclude that group 2 was of nonsaline soils whereas group 3 had slightly saline soils. The slight degree of salinity does not influence the productivity of cotton, which is salt tolerant and can grow well on slightly saline soils. Group 4 is slightly different from groups 2 and 3 in terms of NDVI (less productive) but is very different in terms of S4 salinity index. We conclude that group 4 contains mainly medium saline soils which have some impact on cotton productivity. Group 5 has a substantially decreased biological productivity and highest values of salinity index comparing to all other groups.

As a result, the classes found on cropland were interpreted as:

- Group 1 – constant shallow water;
- Group 2 – most productive nonsaline soils;
- Group 3 – productive slightly saline soils;
- Group 4 – medium productive and medium saline soils;
- Group 5 – poorly productive strongly saline soils.

According to Landsat data, the worst situation with soil salinity and crop productivity is observed in the Kutankul WUA (northern part), and the Ornek, Darsan, and Kyzyl-ui WUAs. The best situation within Nukus district was observed in the Kerder, Shortanbay, Akterek, and Nukus WUAs.

The data on the proportions of different categories of soils according to the estimates of regional hydrogeological expedition and of our estimates based on Landsat data are given in Table 10.2. No statistically valid correlations were found between these estimates. However, the WUAs which were estimated as being in the worst state by remote sensing data (Kutankul, Ornek, and Kyzyl-ui, with the exception of Darsan) all had increased areas of medium and strongly saline soils. The WUAs with good situations according to the remote sensing data (Kerder, Akterek, and Nukus, with the exception of Shortanbay) all had increased areas of nonsaline soils.

TABLE 10.2

The Percentage of Different Categories of Saline Soils (according to Soil Salinity Survey Data as of 01.11.2017) and Agroecological Groups of Soils within WUAs of the Nukus District

WUA	Data from the Regional Hydrogeological Expedition as of 01.11.2017						Data from Landsat-8 OLI Multi-temporal Imagery (2017–2019)				
	Surveyed Area, ha	Nonsaline	Slightly Saline	Medium Saline	Strongly Saline	Extremely Saline	Surveyed Area, ha*	Group 2	Group 3	Group 4	Group 5
Akmangyt	1027	48.10%	48.30%	3.60%	0.00%	0.00%	2128	12.78%	35.80%	35.52%	13.62%
Akterek	764	63.74%	30.24%	5.24%	0.79%	0.00%	2229	20.93%	34.52%	26.68%	11.75%
Darbent	56	0.00%	0.00%	100.00%	0.00%	0.00%	95	4.00%	28.48%	36.19%	23.62%
Darsan	2468	62.28%	31.93%	5.79%	0.00%	0.00%	6903	10.91%	32.80%	38.03%	14.10%
Kattyagar	1790	47.21%	44.30%	8.49%	0.00%	0.00%	4135	14.63%	28.66%	33.09%	14.67%
Kerder	4859	55.19%	30.77%	12.93%	1.11%	0.00%	9168	21.39%	39.52%	26.12%	9.84%
Kutankul	1153	18.56%	41.11%	29.49%	9.63%	1.21%	4350	15.05%	30.85%	30.56%	16.36%
Kyzyl-ui	1049	49.48%	28.03%	20.97%	1.53%	0.00%	1767	18.11%	24.75%	28.94%	20.24%
Nukus	1664	64.24%	30.95%	4.81%	0.00%	0.00%	3077	18.97%	38.54%	31.87%	8.33%
Ornek	710	57.89%	28.87%	13.24%	0.00%	0.00%	1916	4.49%	26.67%	43.84%	18.95%
Shortanbay	4508	50.04%	41.75%	8.21%	0.00%	0.00%	8850	23.15%	37.40%	29.28%	8.09%

*As we used the areas of croplands derived from remote sensing data (LPDAAC GFSAD collection), the total area of the cropland studied with remote sensing data is higher than that given in statistical documents (31,022 ha).

10.5 CONCLUSION

Analysis of remote sensing data gives a good opportunity for the development of a national monitoring system of soil salinity to assess the spatial pattern of different categories of saline soils allowing better assessment and decision support in the management of soil and water in irrigated croplands.

On the basis of the resulting maps, different strategies can be chosen. The first strategy which has been used traditionally in this area is aimed at the unification of the quality of soil cover by abundant watering to flush the salts into the deeper soil layers. The economic costs of improving the quality of bad (marginal) lands are high and the return is low. Another strategy can be the differentiated management of this area which is inherently prone to salinization. In case of this approach, the main efforts should be focused on good lands, where the return on activities will be greatest, whereas the poor (marginal) lands should be used for low-cost agricultural activities. Both approaches require an economic assessment based on the sound information on the areas occupied by different agroecological groups of soils, as well as on planned activities.

We propose that at the worse categories of soils which constantly show the low NDVIs and high values of salinity index (groups 4 and 5 in our map) should be considered for use in saline farming, e.g., growing halophytes for cattle. The lands with good soils which constantly show high NDVIs and low salinity index should be monitored with higher attention so that their state does not deteriorate with time.

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ENDNOTES

1. The land in Uzbekistan is state-owned. The land users can rent the land for 30–50 years. Also, the small household farms (dehkans) can be possessed inheritably. More details can be found in Melniková and Havrland (2016).
2. “Dimensionality reduction is the transformation of high-dimensional data into a meaningful representation of reduced dimensionality. Ideally, the reduced representation should have a dimensionality that corresponds to the intrinsic dimensionality of the data. The intrinsic dimensionality of data is the minimum number of parameters needed to account for the observed properties of the data” (van der Maaten et al., 2009).

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