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THE SOIL-ADJUSTED VEGETATION INDEX FOR SOIL SALINITY ASSESSMENT IN UZBEKISTAN

ABSTRACT

Soil salinization, as one of the threats of land degradation, is the main environmental issue in Uzbekistan due to its aridic climate. One of the most vulnerable areas to soil salinization is Sirdarya province in Uzbekistan. The main human-induced causes of soil salinization are the insufficient operation of drainage and irrigation systems, irregular observations of the agronomic practices, and non-efficient on-farm water use. All of these causes considerably interact with the level of the groundwater, leading to an increase in the level of soil salinity. The availability of historical data on actual soil salinity in agricultural lands helps in formulating validated generic state-of-the-art approaches to control and monitor soil salinization by remote sensing and geoinformation technologies. In this paper, we hypothesized that the Soil-Adjusted Vegetation Index-based results in soil salinity assessment give statistically valid illustrations and salinity patterns. As a study area, the Mirzaabad district was taken to monitor soil salinization processes since it is the most susceptible territory of Sirdarya province to soil salinization and provides considerably less agricultural products. We mainly formulated this paper based on the secondary data, as we downloaded satellite images and conducted an experiment against the in-situ method of soil salinity assessment using the Soil-Adjusted Vegetation Index. As a result, highly saline areas decreased by a factor of two during the studied period (2005–2014), while non-saline areas increased remarkably from a negligible value to over 10 000 ha. Our study showed that arable land suitability for agricultural purposes has been improving year by year, and our research held on this district also proved that there was a gradual decrease in high salt contents on the soil surface and land quality has been improved. The methodology has proven to be statistically valid and significant to be applied to other arid zones for the assessment of soil salinity. We assume that our methodology is surely considered as a possible vegetation index to evaluate salt content in arable land of either Uzbekistan or other aridic zones and our hypothesis is not rejected by this research.

KEYWORDS: soil salinity, remote sensing, Soil Adjusted Vegetation Index, p-test, Uzbekistan

INTRODUCTION

The interrelationships between human-being and the environment are still not calling appropriate policy attention in Uzbekistan. Over the past few years, the research and action community concerned with the consequences of land and soil degradation, and the need for sustainable land management has significantly taken place on the agenda of land management policies [Nkonya *et al.*, 2011].

Soil salinization, as one of the threats of land degradation, is the main environmental issue in Uzbekistan due to its aridic climate [Platonov *et al.*, 2015]. According to the latest information,

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derived from the Land Reclamation Monitoring Service of the State Committee for Land Resources, Geodesy, Cartography and State Cadasters (hereinafter Uzgeodezkadastr), it presents that more than 46,6 % of Uzbekistan's irrigated land is affected by salinization in some degree, with 2,5 % strongly saline ($EC_e = 8-16$ dS/m), 13,3 % moderately saline ($EC_e = 4-8$ dS/m) and 30,9 % slightly saline ($EC_e = 2-4$ dS/m)¹.

One of the most vulnerable areas to soil salinization is Sirdarya province in Uzbekistan. The main human-induced causes of soil salinization are the insufficient operation of drainage and irrigation systems, irregular observations of the agronomic practices, and non-efficient on-farm water use [Akramova, 2008; Akrmakhanov *et al.*, 2011; Ivushkin, 2014]. All of these causes considerably interact with the level of the groundwater, leading to an increase in the level of soil salinity. To ameliorate the actual soil quality of salt-affected arable land across the republic, such reactive land reclamation measures (i.e., time-efficient inventory of saline fields and sustainable salt leaching) have in-time to be applied to decrease the severity of soil salinization and lessen the negative consequences of soil salinization to crop yield [Elhag, Bahrawi, 2017]. Innovative soil salinity assessment approaches to assist in speeding up the inventory processes of salt-affected areas and is highly required to enable proper decision making on preparing proactive measures against soil salinization. The availability of historical data on actual soil salinity in agricultural lands helps in formulating validated generic state-of-the-art approaches to control and monitor soil salinization. However, an alternative approach to soil salinity assessment, conventional method, is exceptionally slow and expensive, since arranging sampling methods and conducting soil sampling is inefficient on time and requires more labor [Eltazarov, 2016]. On the other hand, using the advantages of the Geo-information systems (GIS) tools and Remote Sensing (RS) technologies in soil salinity assessment as an innovative approach, we consider, it makes the assessment procedure more financially efficient and more rapid.

In Uzbekistan, numerous studies have been undertaken on the use of appropriate spectral RS vegetation indices to characterize soil salinity, considering the soil-plant relations [Akramkhanov *et al.*, 2011; 2012; Platonov *et al.*, 2013; Ivushkin *et al.*, 2017] and vegetation canopies. One of the most commonly used RS indices to evaluate soil salinity during these studies is the Normalized Difference Vegetation Index (NDVI) because these scientists perceived that vegetation is a good proxy, accurately reflecting the level of soil salinity, and this proxy can be captured by the NDVI. However, Huete [1988], Bannari *et al.* [1995] and Xue and Su [2017] also found an opposite soil brightness effect on the Perpendicular Vegetation Index (PVI) and the Soil-Adjusted Vegetation Index (SAVI) such that brighter soils resulted in higher index values for a given quantity of incomplete vegetation cover.

Considering all the above, we hypothesized that the SAVI-based results in soil salinity assessment give statistically valid illustrations and salinity patterns. In this article, we aimed at analyzing remotely sensed images of the Sirdarya province to comparatively conduct monitoring on soil salinization dynamics in several years concerning the years when the governmental institutions of Uzbekistan have carried out in-situ soil salinity assessments.

MATERIALS AND METHODS OF RESEARCHES

Study area

Sirdarya province (fig. 1) is one of the agricultural regions of Uzbekistan, located in the center of the country on the left bank of the Syrdarya River. The province shares borders with Kazakhstan, Tajikistan, and Tashkent and Jizakh provinces of Uzbekistan. Sirdarya province covers an area of 4 300 km² and the Mirzachul Steppe takes a large bulk of the province's total area. Sirdarya province is divided into 9 administrative districts. One of the districts, Mirzaabad, was

¹ Uzgeodezkadastr. State Committee for Land Resources, Geodesy, Cartography and State Cadasters of the Republic of Uzbekistan. Annual National Reports, 2006–2019. Tashkent, Uzbekistan (in Uzbek language)

taken to monitor soil salinization processes since it is the most susceptible territory of the province to soil salinization and provides a considerably less agricultural product in contrast to the other districts.

In Mirzaabad District, anthrosol, solonetz, and solonchak soils are widespread and its total area of arable land accounts for 144 752 ha. The texture of the irrigated soils of the district is as follows: clay — 1.9 %, heavy loamy — 11.7 %, medium loamy — 49.6 %, lightly loamy soils — 30.0 %, sandy soils — 6.2 %, and desert — 6 % [Atlas of Uzbekistan, 2017].



Fig. 1. Location of the study area

Materials

In this paper, we used satellite images, acquired from Landsat TM 5 and Landsat OLI 8 from open sources (glovis.usgs.gov and earthexplorer.usgs.gov) in August because the maximum growing season of cotton can be observed in this month [Khamidov et al., 2009]. As we discussed above, the vegetation indices are highly sensitive to the crop type. The field soil salinity assessments in this district were performed in October and November after the vegetation period of the agricultural calendar. The brief information about the satellite data acquisition from sensors is given in table 1.

Table 1. Dates of field soil salinity assessments and analyzed satellite images

No	Name of sensors and data acquisition of satellite images		Month of in-situ soil salinity assessments by the governmental institutions (Uzgeodezkadastr, 2015)
1	Landsat TM 5	13/08/2005	October, 2005
2	Landsat TM 5	15/08/2009	November, 2009
3	Landsat OLI 8	10/08/2014	October, 2014

As a secondary data to compare our results, the Soil Quality Index (SQI) values (fig. 2) determined in the indicated years in table 1 were chosen. Mean values of SQI were taken out of three massives (polygons) of the district, given in the annual reports of the governmental institutions (Uzgeodezkadastr, 2006–2015) and were mapped in the ArcMap (ver. 10.6) software to enhance better visualization. The SQI values, ranging from 0 (completely unsuitable) to 100

(perfectly suitable) denote for the actual soil condition of arable land, determining how the soil is ready for agricultural purposes, against different criteria (i.e., soil salinity level, erodibility, and actual soil organic matter).

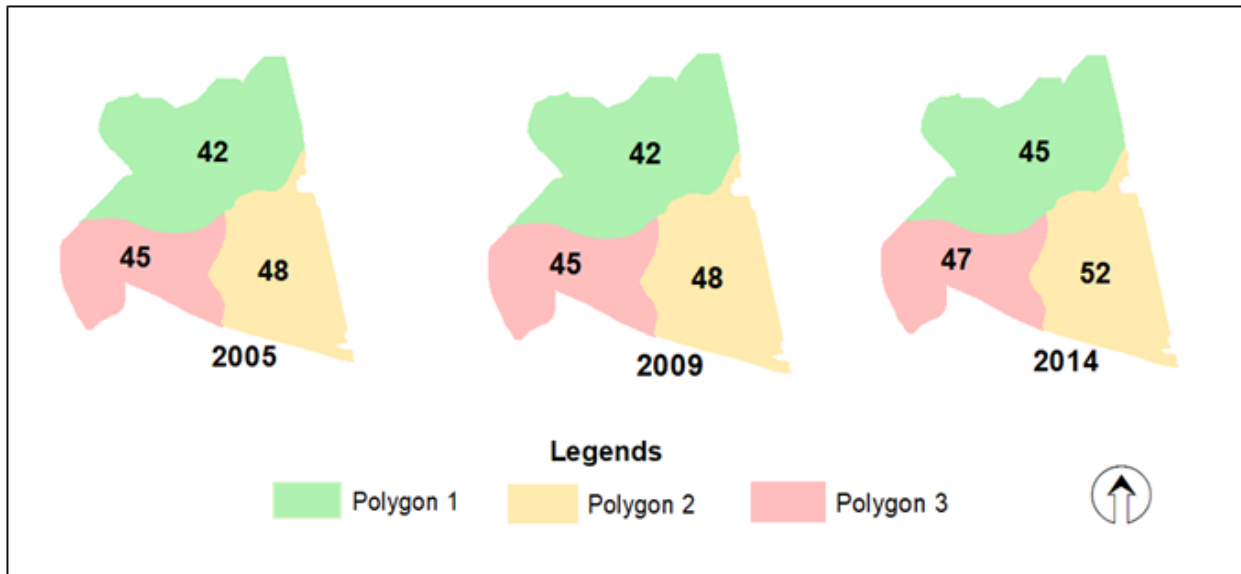


Fig. 2. Soil Quality Index values in different reference years in three massives of Mirzaabad district

Methods

After having downloaded remotely sensed images, some pre-processing steps for satellite images such as atmospheric and geometric corrections were executed according to the principles of Hadjimitsis et al. [2010]. We next applied and tested the SAVI how it works on soil salinity assessment concerning the aridic climate of Uzbekistan. The originality of this index lies in the development of a simple model that allows describing concisely the soil-vegetation system. The SAVI can be defined by the following Equation 1 [Huete, 1988]:

$$SAVI = \frac{NIR-RED}{NIR+RED+L} (1+L) \quad (1)$$

where, *NIR* is the near infrared band of the satellite image; *RED* is the red band of the satellite image and *L* is a soil adjustment factor.

Based on a simplified radiative transfer model, Huete [1988] has shown that a value, standing for $L = 0.5$, permits the best adjustment, i.e., to minimize the secondary backscattering effect of canopy-transmitted soil background reflected radiation. The range of the SAVI is between -1.5 and 1.5. On the condition that the *L* value is zero ($L = 0$), the SAVI is equal to the NDVI [Bannari et al., 1995], so, we took *L* in this study with the optimal (0.5) value and the proposed classification of the SAVI was detailed in table 2 below [Mobasheri et al., 2010; Poggio et al., 2013; Yoshino et al., 2015; Zeraatpisheh et al., 2017].

In such areas where canopy cover is low (i.e., < 40 %) and the soil surface is bare, the reflectance of bright in the red and near-infrared spectra can significantly impact vegetation index values [Bannari et al., 1995]. This is especially difficult when contrasts are being made across dissimilar soil types that may imitate diverse uncertain quantities of light in the red and near-infrared wavelengths while applying the NDVI. The SAVI was developed as a modification of the NDVI to correct for the effect of soil brightness when canopy cover is low [Huete, 1988].

We above determined the proposed RS vegetation index for soil salinity assessment and accomplished the pre-processing steps of satellite image analysis, after having successfully stacked

band layers in the Erdas Imagine 2014 software. During processing the satellite images, ignoring zero in statistics has to be ticked. In this way, either the calculation of no-data or the number, which is equal to zero, is ignored and isolated in the analysis.

The next step is calculating the SAVI in the Erdas Imagine software. One of the main advantages of this software is that most of the vegetation indices are automatically calculated upon saving much time and more simply rather than the ArcGIS software.

Table 2. SAVI classification range in regards to the level of soil salinity

Range	SAVI classification
-1.5....0	Water
0.01-0.37	High salinity
0.38-0.76	Moderate salinity
0.77-1.10	Weak salinity
1.11-1.50	No-salinity

The adjacent operation was selecting an appropriate *L* value. The range of this value is between 0 and 1, and we discussed above, $L=0.5$ is more promising and commonly used for SAVI calculations. Prior to running the calculation process, ignoring zero value in statistics is important. Once we have calculated the SAVI for each downloaded remotely sensed images in Erdas Imagine, the SAVI images were then processed in the ArcGIS program. Through the ‘*extract by mask*’ function, we snipped the study area of interest and three massives were also allocated from the study area. The allocation of three massives of the study area from the SAVI images enabled us to derive average SAVI values to make a comparison between our results and the reference in-situ data. To validate our comparison, we applied statistical analysis at the end of the results part.

RESULTS OF RESEARCHES AND THEIR DISCUSSION

Concerning the used methodology to analyze the Landsat images of three years (2005, 2009 and 2014), we found out that continuous improvement of the soil quality, which was the same as the in-situ results, has been occurring throughout the selected time period. We created SAVI maps for each year to visually track the patterns (fig. 3). In a glance at these maps, a decrease in the high salt content on topsoil can be noticed over 10 years.

As we plotted the dynamics of soil salinization over the ten years in fig. 3, we then quantified the actual territory of each soil salinity class. Fig. 4 below demonstrates detailed numeric information about the dynamics of soil salinity levels in the Mirzaabad District.

Generally summarizing the analyzed data on the dynamics of saline areas in the Mirzaabad district, we can see that highly saline areas decreased by a factor of two over the decade, while non-saline areas remarkably rose from the negligible point of the chart to just over 10 000 ha. Interestingly, oscillatory trends for weak and moderate saline areas were fairly uncertain throughout the period due to the significant changes in the non-saline and highly saline areas.

We analyzed remotely sensed images of Mirzaabad district, and in regards to our secondary data to examine our results, hinged on the SQI values of arable land determined by the governmental in-field soil survey, three massives characterized three different SQI values of arable land in the Mirzaabad District in different years. Visually, we identified similar patterns as in the results of the in-situ soil survey in our SAVI-based soil salinity maps. Specifically, according to the result of governmental soil survey, it was revealed that arable land suitability for agricultural purposes has been improving year by year, and our research held on this district also proved that there was a gradual decrease on high salt contents on the soil surface and land quality has been ameliorated.

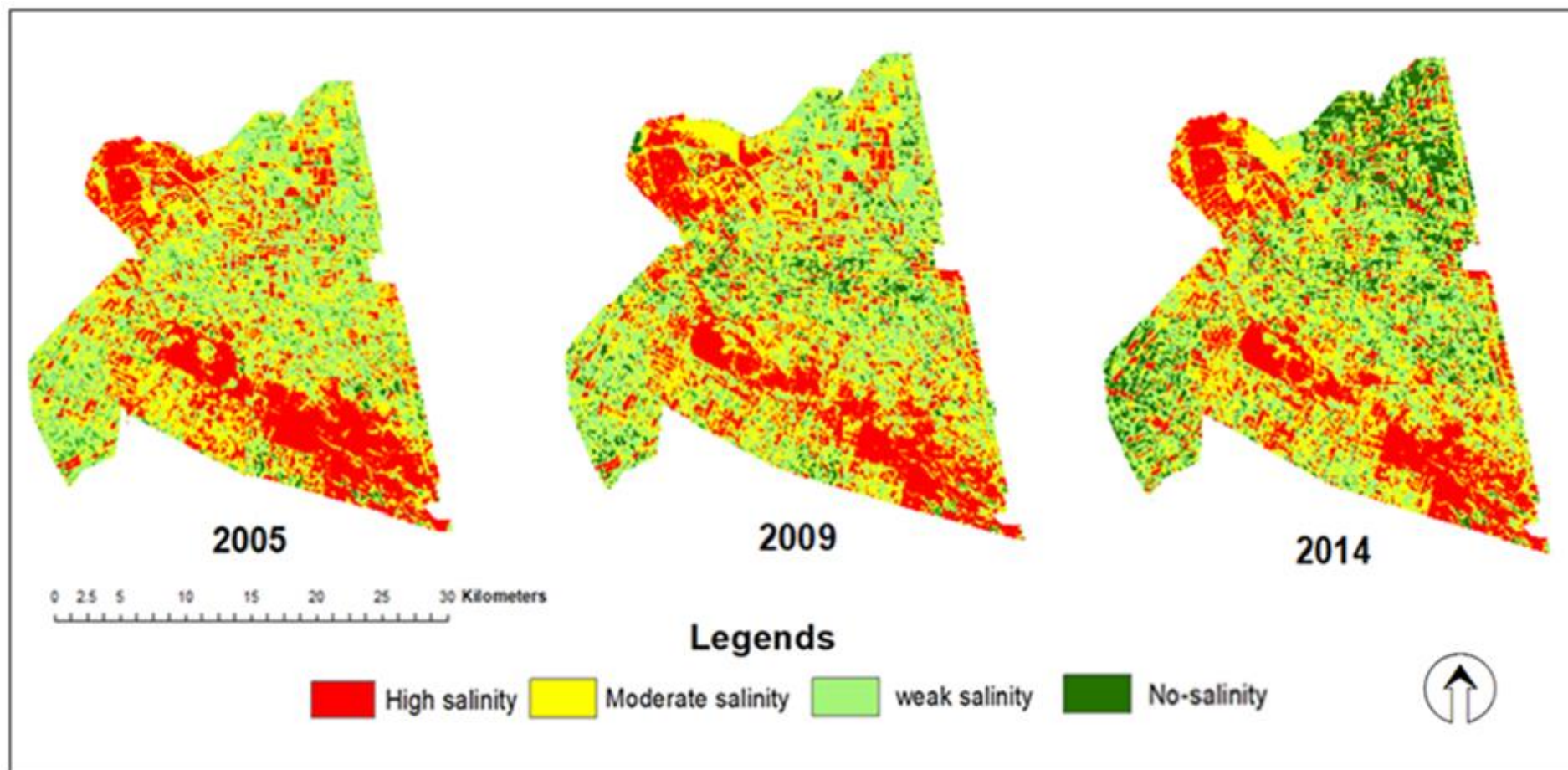


Fig. 3. SAVI-based soil salinity maps of Mirzaabad district in different years

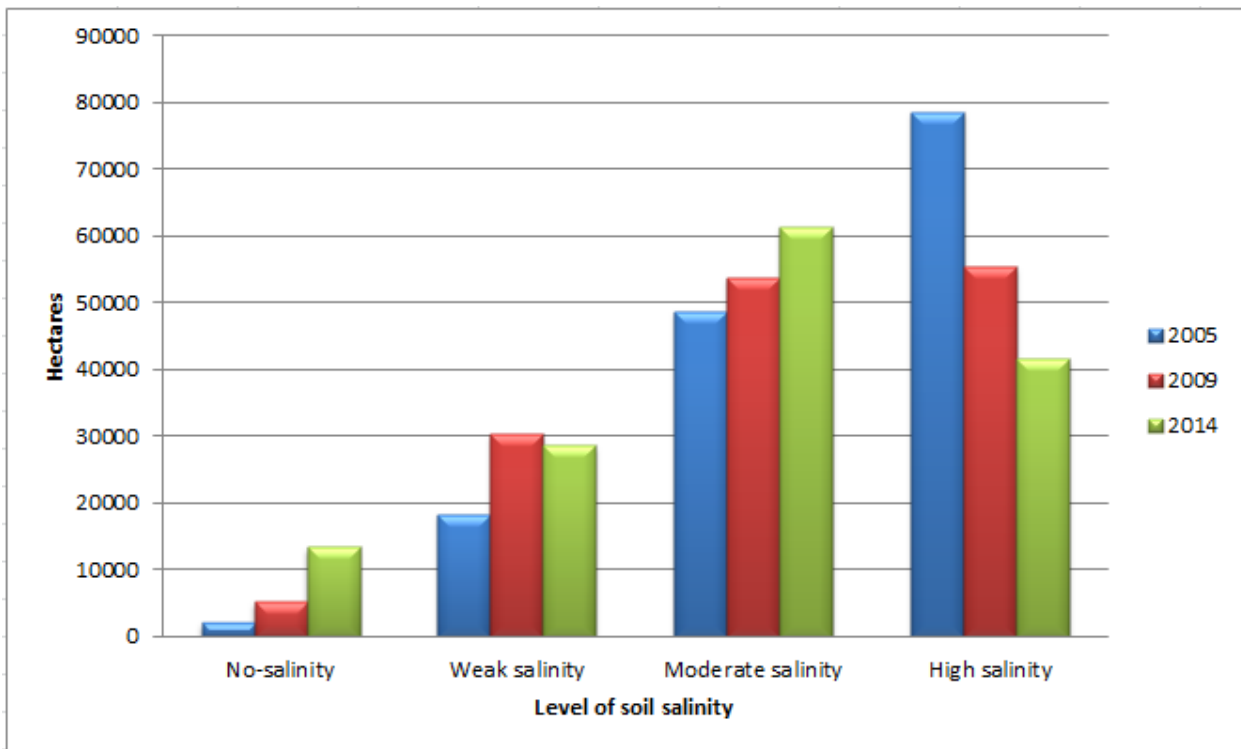


Fig. 4. Dynamics of salt-affected areas over time in Mirzachel Mirzaabad district, in hectares

To make appropriate evidence to support our research results, some statistical analyses were carried out in this paper. The point of interest by performing the statistical analysis was to correlate the SAVI to the SQI values and to check the statistical significance of our findings. However, the simple linear regression analysis (R^2) gave an unexpected value, accounting for $R^2 = 0.09$ (fig. 5).

In addition to fig. 5, below we attached a full output of the regression statistics (table 3). Despite having insignificant values to produce a higher R^2 , we then tested how these insignificant values can make our findings statistically significant using a *p-test*.

Prior to running the *p-test*, we selected the SQI values as the variable against the average SAVI values. Also, unexpectedly, the *p-test* proved our findings in comparing the SAVI-based soil salinity assessment to the in-situ governmental soil survey outputs statistically significant ($p < 0.05$) and the results of the *p-test* were given in table 4.

The R^2 value that we derived was considerable low, but the *p*-value statistically validates it. In this case, we assume that as the primary reason for the results of less R^2 reflected on either the complicated atmospheric and geometric corrections in the pre-processing steps of satellite images.

“All models are wrong”, says George E.P. Box. Based on this quote, we consider that some errors may occur, which significantly impact the outcome of the statistical analysis, since the pre-processing steps of satellite images are built on the models. Inaccurate processed satellite data may reflect the waves differently, leading to misclassifying the values, serving to derive the SAVI maps [Tokotoko et al., 2018]. Regarding the time-related issues as the source of error for the R^2 , this comes after using different spatial patterns that were taken on different days of each reference year.

Soil salinity assessment studies by using different types of RS vegetation indices have still not been well investigated and validated. The widespread and common method for this assessment is the NDVI. The NDVI does not consider the soil characteristics while processing the satellite image, whereas the SAVI is adjusted to the soil reflectance [Huete, 1988]. Ivushkin et al. [2017]

validated that there is a significant correlation between satellite-derived canopy temperature and soil salinity levels, using MODIS satellite thermal images together with the NDVI, the Enhanced Vegetation Index and a traditional soil salinity map. Other studies have also been conducted on soil salinity assessment using the NDVI, a lack of a statistical test for significance is disabling these studies fully explored [Akramova, 2008; Eltazarov, 2016; Platonov, 2015]. On the other hand, the application of the SAVI for the arid zone to assess desert extension based on the soil relations in Uzbekistan has already been investigated by Khasanov [2019]. However, the application of the SAVI to soil salinity assessment is still lacking in past studies.

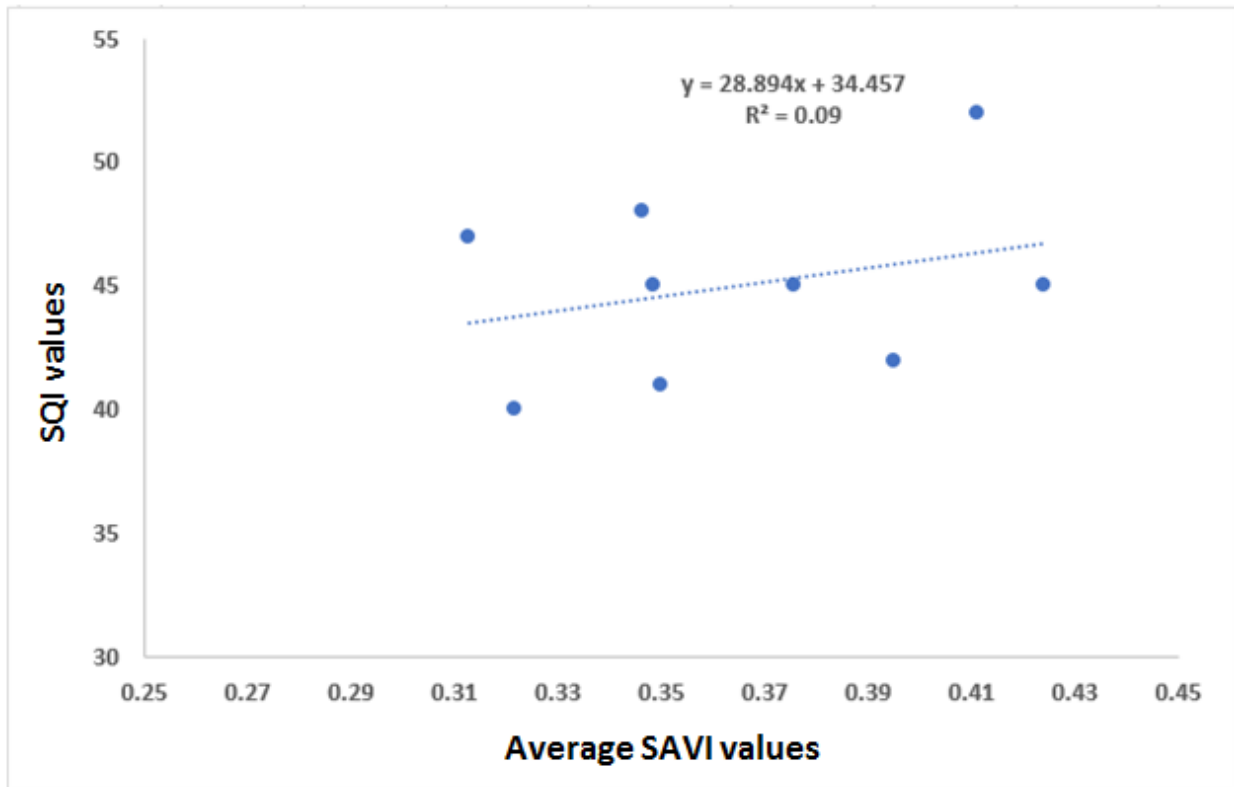


Fig. 5. Output of the simple linear regression analysis

Table 3. Detailed output of the regression analysis

Regression statistics	
Multiple R	0.30006
R Square	0.09004
Adjusted R Square	0.03995
Standard error	3.81568
Observation	9

Table 4. Output of the p-test

	Standard error	t-Stat	p-value
SQI values	12.73211	2.70631	0.03036

The SAVI is usually calculated to understand the extent of healthy vegetation cover in the area. Additionally, to enhance the differentiation of saline areas, suppressing the vegetation, two indices, for example, the Salinity Index and the Normalized Difference Salinity Index is calculated depending on the spectral response of salt-affected soils [Ivushkin, 2014].

In the case of vegetation indices, Elnaggar and Noller [2009] found that vegetation indices had a weak correlation with the electrical conductivity measurements and suggested that halophytes could not be used to identify salt-affected soils under vegetation cover. However, with the SAVI, soil salinity mapping can be performed considering the proposed classification for saline areas. This mapping method, in this study, is statistically tested and valid ($p > 0.05$) to disseminate to other aridic regions across the republic.

CONCLUSIONS

Salt affected soils are widespread over the world, especially semi-arid and arid regions. Soil salinity can be occurred by natural or human-induced processes and is a major environmental risky hazard. Recent advances in remote sensing technologies have opened new techniques to conduct inventories, characterization, and monitoring of degraded soils. Especially, the vegetation indices allow us time-efficient monitoring and assessment of soil salinity in multiple saline zones simultaneously.

Thus, in this paper, we used satellite images to map saline areas of the Mirzaabad district and compared our results with the governmental in-situ soil salinity assessment results which have executed by Uzgeodezkadastr in several years. Both results prove that there is an improvement in the arable land quality for agricultural purposes. Despite having a weak significance of derived values from the SAVI-based analysis according to the simple regression analysis, we continued our statistical analysis in the p-test which proved our experiment as significant. Using the SAVI for validation of the results of remote sensing analysis is a good option as far as this index is not as so rapidly changing as salinity is. In the opposite, we can see that remote sensing data give more detailed information about the salinity status of soils. We assume that the methodology, the SAVI, is considered as a possible vegetation index to evaluate salt content in arable land of either Uzbekistan or other aridic zones, and our hypothesis is not rejected.

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