Remote sensing of soil salinity levels in irrigated cotton production systems in the Aral Sea Basin

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Introduction

Crop production in the Central Asian (CA) states has been increasing since the 1950s due to a construction of the large-scale irrigation and drainage systems and development of new areas for agricultural activities, irrigation had been increased from 5 mln ha to 8.5 mln ha in recent decades. However, human-induced soil salinization in the arid and semi-arid regions is a serious problem, jeopardizing agricultural sustainability and negatively affecting the livelihoods of farming population. In recent decades the agricultural land and crop yields have decreased in some regions of CA due largely to water shortage or worsened soil conditions, mainly in the form of soil salinization [2]. Therefore, accurate mapping and monitoring of salt-affected areas, identifying the spatial extent and magnitude of salinization become essential for land reclamation programs, sustainability of land productivity and prevention of continuing salinization for mitigating these negative impacts. Conventional monitoring of soil salinity by water management agencies is based on soil sampling with subsequent laboratory analyses. Conducted in autumn, such surveys plan to cover only 30% of the total irrigated area considering available time and resources. Remote sensing could offer a fast and efficient alternative for salinity mapping with suitable resolution [6,7], which has been assessed in this study.

Methods

To discriminate and map soil salinity with sufficient accuracy using remotely sensed data, it is important to compare/validate the estimation results with limited field measurements of salinity. For this study, soil salinity was sampled at random locations for, electrical conductivity (EC) and electromagnetic induction (EMI, Geonics Ltd) in transects. The measurements for EC and EMI were collected from 10 fields with an average size of 7 ha. Electromagnetic induction (EMI) measurements penetrating to a depth of 1.5 m vertical position of the EM-38 device should be treated as proxies of soil salinization and hence, must be calibrated against direct measurements of salinity. Therefore, limited EC samples were specifically collected at the EMI measurement locations for this purpose. Field data collection was conducted in 2008 through 2011 at various dates during April through October.

The Landsat images covering the study area (Path 160/Row 31), was atmospherically corrected using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) and included 22 time-series data (**Fig. 2**). Soil salinity has been classified using Random Forests (RF) algorithm introduced by Breiman (2001) and then examined by linear model (LM) and RF based on relationship between spectral response of plants combined with environmental covariates and soil salinity. The processing was conducted in the R modeling environment as shown in **Fig. 3**.

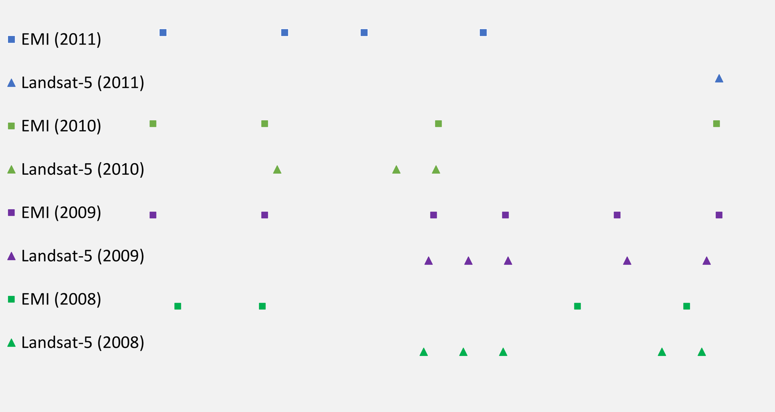


Figure 2: Acquisition of Landsat 5 images and corresponding EMI surveys during the vegetation period of 2008-2011 in Cotton Research Station (CRS) area.

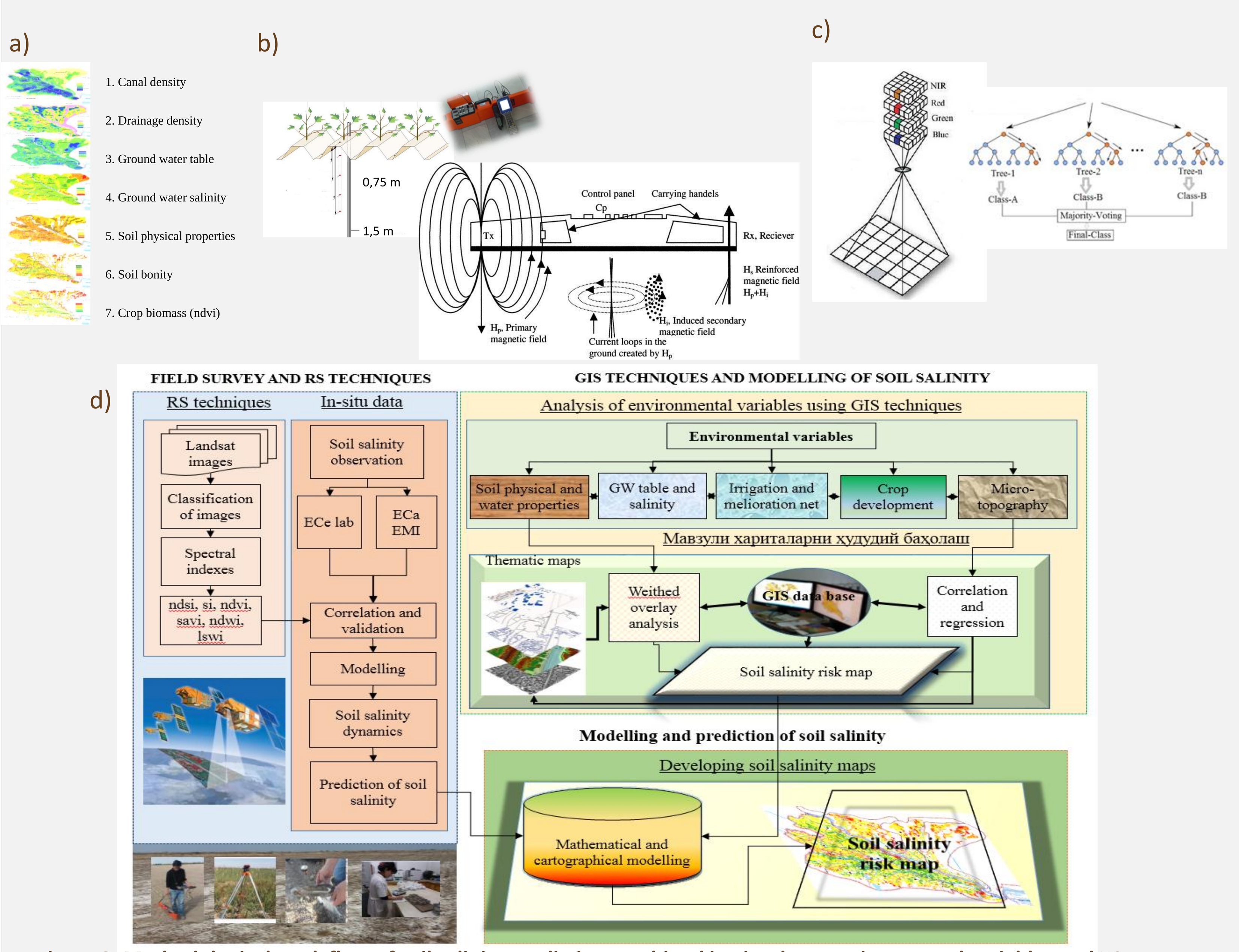


Figure 3: Methodological work flow of soil salinity prediction combined in-situ data, environmental variables and RS. a) Environmental variables, b) EMI techniques (Em38 MK2), c) Landsat images and classification algorithm RF, and d) Combined approach of discriminating soil salinity using RS, in situ soil EMI and environmental variables.

Study area

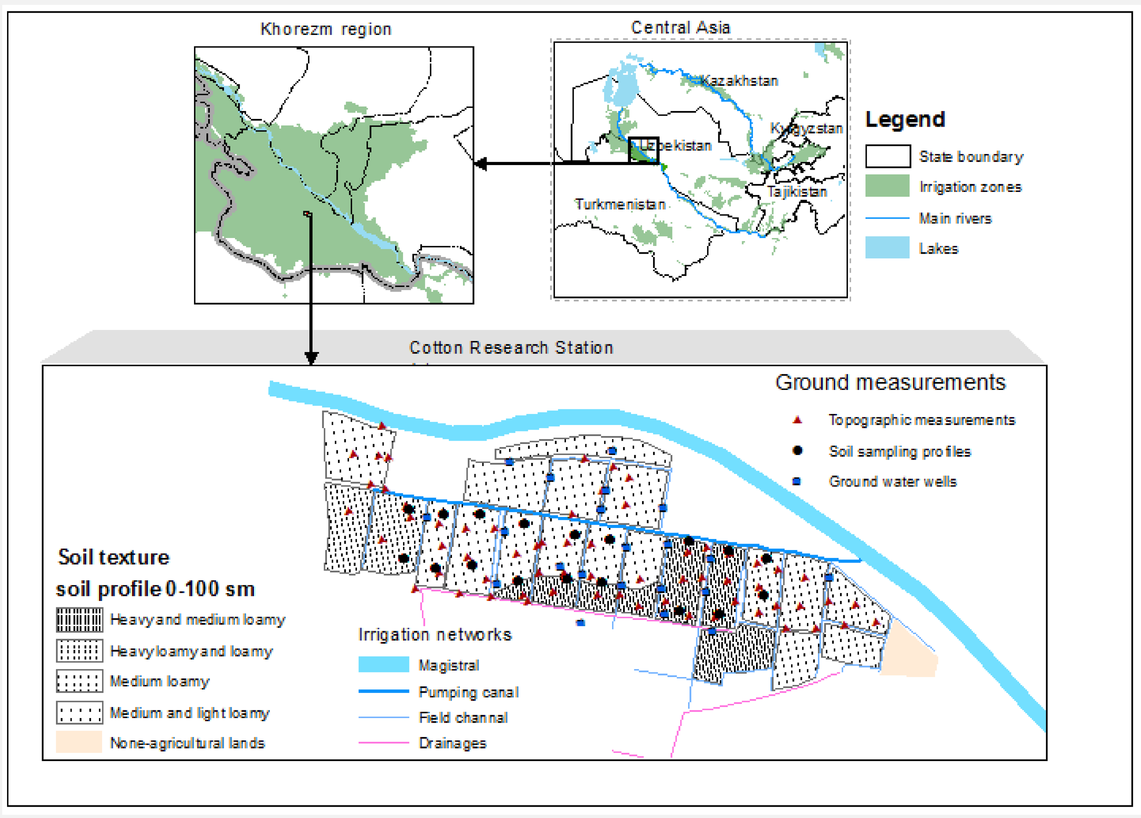


Figure 1: Location of the Khorezm province in the Aral Sea Basin (Central Asia) and the soil texture map of the focus area.

The Khorezm province is located in Uzbekistan, between 41°-42° N, 60°-61° E, 200 km from the Aral Sea (**Fig. 1**). The climate of the region is continental, annual ETp rates 1400 mm [3] highly exceeding precipitation 92 mm. Hence, agricultural production heavily relies on irrigation water. The annual water requirements of the province are 4.5 km³ for irrigation of 275,000 ha of cropland [3,8]. Of this volume, two thirds are utilized during the vegetation period, while one third is used for leaching of saline soils during pre-cropping periods in spring. Soils of the province are mostly silty loamy (occupying 55%), loamy (13%) and sandy loamy (12%) [1].

Cotton and winter wheat are the dominant crops in the province, accounting for 80 % of the agricultural areas. Cotton is usually grown from April through September, and may be followed by wheat. The peak irrigation period for all crops is June–August with 4-6 events, whereas irrigation of winter wheat starts in November and ends in May. The majority of cropped areas are irrigated through furrows (except for rice). Water is supplied through a complex-hierarchy, mostly unlined irrigation network. The irrigation of these water-intensive crops and seepage from the canal networks are the primary causes of the groundwater rise soil salinity in Khorezm [5].

Results

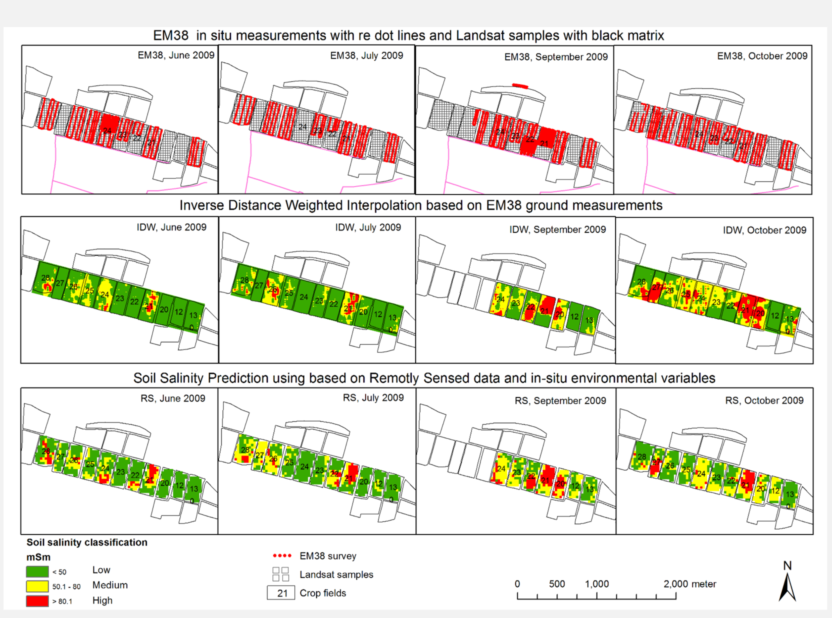
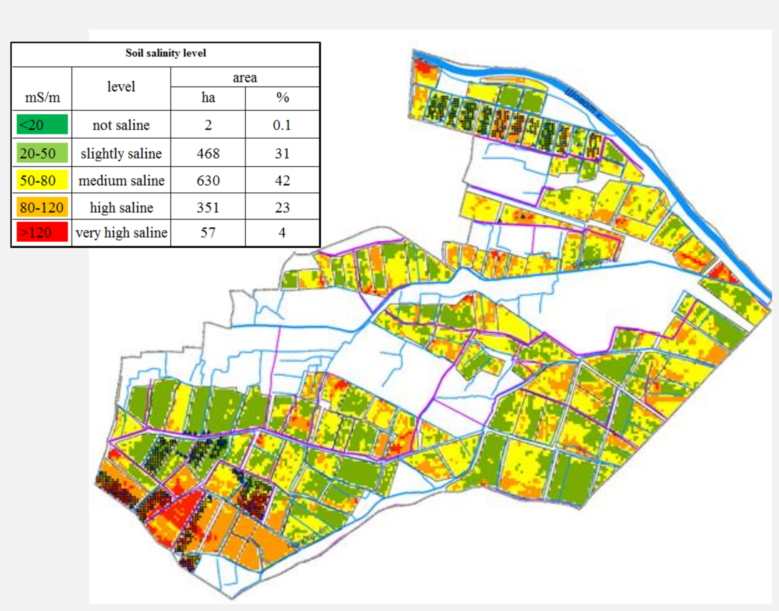


Figure 4: Soil salinity modelling and mapping in focus area CRS



Soil salinity level			
mS/m	level	area ha	area %
<20	not saline	2	0.1
20-50	slightly saline	468	31
50-80	medium saline	630	42
80-120	high saline	351	23
>120	very high saline	57	4

Figure 5: Soil salinity mapping in Paxtakor Water Consuming Association

The combined contribution of the remote sensing based indicators was assessed using both estimation methods (RF and LM) separately from the environmental and management factors during the study years (**Fig. 4**) and applied this model to the Paxtakor water consuming association (**Fig. 5**). Comparison shows that the relationship between both the remote sensing derived variables and the environmental and management factors estimated using the linear regression model was weak, ranging between 0.13 and 0.29. The strength of this relationship assessed using the RF model was much higher and ranged from 0.2 to 0.42. This result is clearly indicative of the fact that RF model is performing better than the linear modeling. However, the significant disadvantage of decision trees such as RF is in their inability to incorporate prior knowledge about the relationships between input attributes and the output classes, which may lead to over- or underestimate the extent and accuracy of salt-affected areas.

During the seasons, the predictions were better during 2009 and 2011 due likely to the years with varying water availability. The lower prediction coefficients in 2008 and 2010 could be indicative of the effects of water shortage, which likely depresses the normal plant growth and hence, causes lower reflectance in larger areas. Similarly, lower groundwater levels led to reduced capillarity and hence, lower soil moisture thus affecting crop development.

High correlation coefficients of the remote sensing-based indicators of plant health and environmental variables and their dynamics over the years clearly show that inclusion of both of these indicators is equally important for prediction of soil salinity and will likely enhance prediction capacity. It should also be noticed that inclusion of combined data obtained through remote sensing and environmental variables from a single year will likely lead to erroneous predictions of the soil salinity. Instead, multiyear analyses, possibly including dry, normal and high water availability years, should be used for predictions.

Discussion and Conclusions

Based on the results of both the linear regression and RF based predictions, the maps of soil salinity were produced for the four observation years (**Fig. 4**). The first is the soil salinity map produced from the detailed electromagnetic induction measurements (designated "EMI" in each of the maps), and the maps designated A and B are those assessed through RF and LM, respectively. Visual observation confirms that the soil salinity in the eastern part of CRS was well reflected in all four years in the RF-based maps, while overlooked in LM models. At the same time, a strong salinization of the western part of the study area was poorer represented by both models, although better represented by RF-based maps. Low saline areas were also much better predicted by RF models compared with LM models. The model, which included the composite indicators based on the Landsat time series datasets and the environmental and management factors, obtained using random forest regression, were reproduced soil salinity with higher degree of reliability. Therefore, this model can be considered operational for predicting salinity in the CRS. Further research is required to assess the applicability of utilizing the used indicators to assess soil salinization in the other irrigated areas of CA.

This research work was undertaken to improve salinity assessment over the large-scale irrigation schemes in Central Asia. The results indicated that the use of remote sensing techniques can reliably improve traditional direct sampling, while overcoming the problems of insufficient sampling, cost and labor intensity. A comparison between the random forest and linear regression method showed that the salinity distribution may not be linear in nature. At the same time, the use of additional indicators such as groundwater levels and capillary effects in areas of shallow groundwater, topographic features and distance to the irrigation and drainage infrastructure may greatly improve the prediction. The salinity maps produced based on the best performing model from the Landsat time series images with vegetation and water indices developed with the random forest regression, better mimicked the real salinity distribution compared with the linear models. Therefore, although further research on the application of this model is necessary, this model can be recommended for identification of the salinity-affected areas.

Literature

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