Combining remote sensing and modeling approaches to assess soil salinity in irrigated areas of the Aral Sea Basin

Mirzakhayot Ibrakhimov\textsuperscript{a*}, Usman Khalid Awan\textsuperscript{b}, Murodjon Sultanov\textsuperscript{a}, Akmal Akrakhanov\textsuperscript{b}, Kakhramon Djamboev\textsuperscript{c}, Christopher Conrad\textsuperscript{d,e}, John Lamers\textsuperscript{f}.

\textsuperscript{a} Khorezm Rural Advisory Support Service (KRASS), Urgench, Khorezm, Uzbekistan
\textsuperscript{b} International Center for Agricultural Research in Dry Areas (ICARDA), Tashkent, Uzbekistan
\textsuperscript{c} International Water Management Institute (IWMI), Central Asia Regional Office, Tashkent, Uzbekistan
\textsuperscript{d} University of Würzburg Institute of Geography and Geology, Department of Remote Sensing, Würzburg, Germany
\textsuperscript{e} University of Halle, Institute of Geosciences and Geography, Halle, Germany
\textsuperscript{f} Center for Development Research (ZEF), Department of Ecology and Resource Management, University of Bonn, Germany

\* Corresponding author
Email: hayot-i@yahoo.com

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Abstract

Accurate assessment of the soil salinization is an important step for mitigation of agricultural land degradation. Remote sensing (RS) is widely used for salinity assessment, but knowledge on prediction precision is lacking. A RS-based salinity assessment in Khorezm allows for modest reliable prediction with weak ($R^2=0.15–0.29$) relationship of the salinity maps produced with RS and interpolation of electromagnetic EM38 during growth periods and more reliable ($R^2=0.35–0.56$) beyond irrigation periods. Modeling with HYDRUS-1D at slightly, moderately and highly saline sites at various depths showed that irrigation forces salts to move to deeper layers: salts reappear in the upper profile during dry periods. Beyond irrigation events, salts gradually accumulated in the upper soil layers without fluctuations. Coupling RS techniques with numerical modeling provided better insight into salinity dynamics than any of these approaches alone. This should be of interest to farmers and policy makers since the combination of methods will allow for better planning and management.

Keywords: HYDRUS-1D, salt transport modeling, Aral Sea, irrigation, land salinization

1. Introduction

Irrigated agriculture is practiced only on approx. 20% of agricultural areas worldwide, but accounts for at least 40% of the global food production (FAO 2003). Irrigation practices such as common in Central Asia, increase natural land productivity manifold (www.cawater-info.net). However, unfavorable natural conditions and land and water resources mismanagement in many arid and semiarid agricultural areas had led to wide-spread land
degradation. The same is true for the agricultural areas in the Central Asian countries, where soil salinization and waterlogging has become truly severe. Soil salinization estimates range from ca. 11.5% of all areas in Kyrgyzstan to 50% in Uzbekistan and as much as 95.9% in Turkmenistan (Bucknall et al. 2003). In the areas close to the Aral Sea Basin such as in the Khorezm and Karakalpakstan regions, virtually all agricultural areas have become saline (FAO 2000). Soil salinization not only results in environmental degradation, but also causes decline of land productivity and economic losses.

Current soil salinization assessments typically rely on soil sampling to determine solute concentrations or measuring electrical conductivities (EC). Such assessments are accurate but time-consuming, necessitate repetitions and often demand many soil samples to process. Moreover, registering results manually and preparing paper maps are not conducive for rapid analyses of the salinity causes and consequences, and hence delays the spread of information. In addition, an overlay with other key explanatory variables (e.g. groundwater table and salinity), are rarely possible. In consequence, these techniques are insufficient when aiming at a detailed mapping over large-scale irrigation areas and over single agricultural seasons. In contrast, remote sensing (RS)-based techniques offer much faster assessments of large areas including for the assessment of soil salinity (Dwivedi & Rao 1992, Metternicht & Zinck 2003; Farifteh et al. 2005; Mulder et al. 2011). Since the 1970s, spectral features of the soil surface have e.g. been investigated in detail (Hunt et al. 1972, Metternicht 1998, Furby et al. 2010) but these studies illustrated mainly the existence of a correlation between soil and vegetation indices with soil salinity, whereby the latter could be predicted over the cropped areas but to a certain extend only. Despite well-known advantages of RS techniques for a rapid and wide coverage of soil salinity identification, shortcomings of the method exist as well. These flaws are associated with irrigation, which frequently obscure salinity development, and cause salinity relocation over the soil profile. Metternicht and Zink (2003), Rao et al. (1995), and others showed that in the irrigated areas spectral reflectance of topsoil is insensitive to slight levels of salinity. In addition, RS-based measurements are per definition limited to aboveground monitoring only, whereas in irrigated areas, salinization processes are complex and dynamic, and may concentrate in the subsoil without being exposed on a surface (Akramkhanov 2011). Hence, under vegetation cover, only indirect measurements, e.g. via crop stress that is visible in the spectral information permit the assessment of soil salinity through RS. On the other hand, insufficient capacities exist to separate the stressor soil salinity on crop growth from other stressors such as e.g. moisture or nutrient stress.

The uncertainty of soil salinity assessments with RS–based approaches thus still remains but the accuracy and precision of salinity assessments can be improved using numerical modeling as a complement. The modeling of soil salinity dynamics permits detailed temporal salinity assessments over required depths and can be setup in as many points as needed (Šimunek et al. 2008) once being able to handle several shortcomings of modeling such as input requirements (Oster & Rhoades 1990). Various existing salinity models address components of solute transport (e.g., Srinivasulu et al. 2004; Vanderborght et al. 2005; Vrugt & Bouten
2002), but only few combine the assessment of salinity variation in space and depth without the need for extensive data. Thus, the integration of RS information on soil salinity with water and solute transport models for finally predicting soil salinity dynamics may be a valuable option to close this research gap. The objective therefore was to support a more precise identification and mapping of soil salinity in irrigated areas by combining RS techniques and deterministic modeling of the salt dynamics. The specific objectives included: 1) a verification of the uncertainty and precision of salinization assessment from RS by a solute transport model and 2) extending the assessment of salinity to the depth of the soil root zone.

2. Materials and methods

2.1. Study area

The case study was conducted in the large-scale irrigated area of the inner Aral Sea basin, in the Khorezm province of Uzbekistan located between 41°- 42°N and 60°- 61°E. The region, bordered by the Karakum and Kizilkum deserts in the south, southwest and west, has an extremely arid continental climate, which creates the need for irrigation of crops. From the total of 560,000 ha, about 270,000 ha are annually irrigated (Akramkhanov et al. 2012). Average annual precipitation is 92 mm, while the average annual evapotranspiration rates are 1,400 mm and more (Awan et al. 2011; Conrad et al. 2012). Khorezm is a flat region with elevation points between 112–138 m a.s.l. The topographic flatness combined with low hydraulic conductivities of the soil causes extremely slow lateral, and mostly vertical, groundwater (GW) flows (Khodjibaev 1979). Soils in the region are mainly alluvial, mostly silty loamy (occupying 55%), loamy (13%) and sandy loamy (12%) (Akramkhanov et al. 2012). Shallow saline GW is among the major contributors to soil salinity in the province (Ibrakhimov 2007; Forkutsa et al. 2009). In spring period, the irrigation water contains 1.2 dSm\(^{-1}\) of dissolved salts, and drops to 0.8-1.0 dSm\(^{-1}\) in summer season.

Detailed fieldwork was conducted at the Cotton Research Station (CRS) of the Pakhtakor Water Consumers Association (Figure 1). The total agricultural study was 145 ha; the sub-area encompassing the current case study covered the central part occupying 62.8 ha. Cotton was constantly cultivated on all fields monitored. The soil and climatic conditions of the research area are typical for large parts of the Khorezm province.
2.2. Data collection

Empirical data on soil salinity were collected through measuring electrical conductivity (EC) and electromagnetic induction measurements using EM38 (Geonics Ltd) and hence describe soil salinity (Figure 1). The EC of the soil and water salinity was measured with a portable EC-meter (soil EC diluted in 1:1 proportion with distilled water) at 0-30 cm, 30-90 cm and below 100 cm. The measurements were conducted immediately before, and after leaching events as well as during the vegetation period or in total eight times between March to October 2008 and 2009. In 2008, salinity data were collected over some fields, while the most complete dataset of salinity was collected in 2009. The apparent electrical conductivity (EC_p of the soil paste) was converted into internationally comparable saturated soil extract of EC_e (Rhoades et al. 1999) according to the equation EC_e = 3.5 EC_p, which was derived earlier for the study region (Forkutsa et al. 2009). In some fields, divers for automated readings of the groundwater depth and salinity were also installed.

The EM38 estimates soil salinity to a depth of 75 and 150 cm, but the readings should be calibrated against direct measurements of salinity. Therefore, twenty EC samples were collected at randomly selected areas covered by the EM38 measurement locations. The
resulting points were interpolated using the Inverse Distance Weighted (IDW) method to create salinity maps for the dates of measurements. An effort was made to conduct the EM38 readings during the acquisition dates of the RS images.

2.3. Remote sensing imagery for estimation of soil salinity
Ten Landsat 5TM satellite images from March until October for the period of 2008 – 2009 were used for estimating vegetation indices and generating salinity maps in the CRS (Path 160, Row 31). The selected imagery was atmospherically corrected through the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS, Masek et al. 2013). A comparison between two considered indices, Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) showed a higher relationship between the soil salinity maps obtained by interpolating of the EM38 measurements and SAVI and hence, this index was used for further analyses. The main purpose of selecting a single index is to improve salinity prediction accuracy through modeling.

2.4. Modeling soil salinity
The HYDRUS-1D model (Šimunek et al. 2008) was used for the simulation of the water and solute transport based on its proven calibration and validation for the region (e.g. Forkutsa 2009; Awan 2009). To assess the prediction accuracy of the RS approach, the HYDRUS model was set up for three locations known as slightly, moderately or highly saline areas. These locations were next selected from both the findings of the RS and EM38 salinity maps. The modeling period included 2008–2009. The water dynamics in the soil profile are simulated through the Richards’ equation:

\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left[ K(h) \frac{\partial h}{\partial z} + K(h) \right] - S(h) \tag{1}
\]

where \( \theta \) is the volumetric soil water content \([\text{cm}^3\text{cm}^{-3}]\); \( t \) = time \([\text{d}]\); \( h \) = soil water pressure head \([\text{cm}]\); \( z \) = gravitational head as well as the vertical coordinate \([\text{cm}]\) (upwards is positive); \( K(h) \) = unsaturated hydraulic conductivity \([\text{cm} \text{d}^{-1}]\); and \( S \) = soil water extraction rate by plant roots \([\text{cm}^3 \text{cm}^{-3} \text{d}^{-1}]\). To parameterize the Richards’ equation, a modified Mualem-van Genuchten model was used to describe soil water retention and hydraulic conductivity (Vogel and Císlarová. 1988). Key input data for HYDRUS such as evaporation, transpiration and groundwater data (Šimunek et al. 2008) were used for modeling daily time steps. The top boundary conditions for the model were defined by irrigation and precipitation. The volumes of applied irrigation water were estimated in the three locations with the different salinity classes. It was assumed that similar irrigation rates occurred in all fields, which is justified because of the same cropping pattern (cotton), topographic slopes and water supply rates (pump for the entire CRS) for all fields. The bottom boundary conditions were fully governed by the GW table dynamics.
Solute transport in HYDRUS-1D is driven by convection and dispersion processes, and by diffusion in the gaseous state in the soil profile. The salt flux density in the irrigated fields can be described as a sum of convective and dispersive fluxes, while the gaseous diffusion can be ignored (Singh et al. 2003):

\[ J = J_{\text{con}} + J_{\text{dis}} \]  

(2)

where \( J \) = total salt flux density [g/(cm\(^2\) day)], \( J_{\text{con}} \) = convection flux density [g/(cm\(^2\) day)], and \( J_{\text{dis}} \) = dispersion flux density [g/(cm\(^2\) day)]. This equation is solved numerically for specified initial and boundary conditions (Šimunek et al. 2008).

Calculations of solute transport were conducted to a soil depth of 300 cm, which is the approximate depth of the deepest GW level measured during the study period. Soil texture and bulk density over the soil profile were determined by sampling the soil with 30 cm increment in depth till 120 cm. For the numerical modeling, the soil profile at all three sites was assumed to be divided in three layers (0–30 cm, 30–90 cm and 90–300 cm) necessary for the balance calculations.

The soil hydraulic properties were inversely modeled to predict the van Genuchten water retention parameters \( \theta_r \), \( \alpha \), \( n \), and saturated hydraulic conductivity \( K_s \) from soil texture and bulk density. The differences between the observed and simulated data were minimized by the Levenberg-Marquardt nonlinear minimization method (Marquardt, 1963).

The necessary climatic data for the scenario analyses (e.g. air temperature, wind speed, relative humidity, precipitation, solar radiation) were measured daily and provided by a local climatic station installed on the premises of CRS. Evapotranspiration was estimated according to the Penman-Monteith equation (Allen et al. 1998) separately taking into account evaporation and transpiration of cotton.

\[ ET_c = (K_{cb} + K_e) \times ET_0 \]  

(3)

For assessing the accuracy of the simulation results, the Root Mean Square Error (RMSE) was estimated as:

\[ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left[ M(t_i) - S(t_i, b) \right]^2}{n}} \]  

(4)

where \( M(t_i) \) = measured value at time \( t_i \), \( S(t_i, b) \) = predicted value at time \( t_i \); \( n \) = total number of observations.

The conversion from soil electrical conductivity (EC, dSm\(^{-1}\)) measured at selected locations in the CRS fields to units of milligrams of salts per cm\(^3\) was completed according to relationships developed by Forkutsa et al (2009) for the Khorezm region:

\[ \text{TDS}_{\text{soil}} = 0.6546 \times EC_e \]  

(5)
where TDS refers to the total dissolved solids (milligrams cm\(^{-3}\)), and \(EC_e\) to the electrical conductivity of the saturation extract (dSm\(^{-1}\)). The concentration of salts in the solution was calculated from the estimated TDS, soil bulk density at specified depths and soil water contents (\(\theta\), cm\(^{-3}\) of water per cm\(^{-3}\) of soil).

3. Results

3.1. Assessment of soil salinity by electromagnetic conductivity measurements and remote sensing

Based on the interpolation of the EM38 measurements for 2008 and 2009, soil salinity maps of the cotton fields in the CRS were completed and revealed heterogeneous, within-field salinity patterns, with patches of slight, moderate and high salinity (Figure 2 and 3). The salinity levels correspond to the EM38 ranges between 0 – 50 (slight), 50 – 80 (moderate) and 80 – 160 (high) mSm cm\(^{-1}\). The largest highly saline areas appeared in the western and eastern parts of the CRS (fields 20-22 and 25-27).

Furthermore, while the high salinity of the fields 20-22 (east of the center) remained relatively unchanged during the entire observation period, in the western part the salinity disappeared and reappeared during June to October 2009. Overall, the fields 20 through 26 were partly moderately saline, while the rest of the fields could be characterized as slightly saline. In October, the slight, moderate and highly saline areas constituted 52%, 31% and 17%, respectively of the total. Hence, cropping patterns and management activities provoked an increase in moderately and strongly saline areas at the expense of the slightly saline areas.

Overall soil salinity levels as well as within field-soil salinity of individual fields predicted by the RS approach ranged from slightly to highly, with salinity patches occurring in some of fields as well. The fields 20 through 22 were largely high saline areas, while the class moderate salinity prevailed in the western part of the CRS. The salinity areas estimated with the RS approach in October revealed about 82% of slight, 10% moderate and 8% of high saline soils.
**Figure 2.** Soil salinity maps based on the interpolation of EM38 measurements and RS techniques in 2008. Green color indicates slight salinity, yellow moderate salinity and red high salinity levels.
Figure 3. Soil salinity maps based on the interpolation of EM38 measurements and RS techniques in 2009. Green color indicates slight salinity, yellow moderate salinity and red high salinity levels.

Visual comparison of the maps showed a similarity of the spatial distribution of soil salinity within the study area. For example, predominantly slightly saline areas occurred in the east, center and far west of the CRS, whereas the high saline patches appeared in the western parts and to the east of the center. However, a further comparison of the salinity maps suggested that with the exception of the salinity distribution in September and October 2009, the RS maps in both study years deviated from the EM38 measurements. Especially during the peak cotton growing periods, the RS-based classification in 2008 underestimated the moderately saline areas by more than 30% and the high saline areas by more than 50% whereas the slightly saline soils were overestimated by more than 20% (Table 1). The correlation coefficient of the maps prepared by both methods for the periods June and July 2009 ranged between 0.15–0.29 (P>0.05). At the same time, the correlation of the maps beyond the intensive irrigation events (September and October 2009) rose to 0.35–0.56 (P>0.05), respectively.
Table I. Areas (ha) under slight, moderate and high soil salinity in the study area of 62.8 ha measured by electromagnetic conductivity meter (designated EM38) and by RS in 2008 and 2009. The correlation between the EM measurements and RS-based classification is shown for 2009 only.

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3.2. Calibration and modeling soil salinity with HYDRUS-1D

Three locations with slightly (field 23), moderately (field 26) and highly (field 28) saline fields were selected for modeling soil salinity dynamics with HYDRUS model. The decision to select the fields for modeling was made by visual examination and accounting for the completeness of the data collection. In these fields, detailed soil profile description, number of EC and EM38 readings and diver datasets allowed better modeling analyses. The simulation (Figure 4) accurately reproduced the salinity dynamics for the depths of 0 – 30 cm and > 100 cm as evidenced by an RMSE of the simulations ranging between 0.59 and 0.89 dSm\(^{-1}\). In contrast, the RMSE for the depths of 30 – 100 ranged between 0.96 – 1.16 dSm\(^{-1}\), implying that the changes in salinity were predominated by the dynamics of downward irrigation and upward groundwater contribution. Overall, the model reflected the salinity levels sufficiently well.
Figure 4. Observed (squares) versus simulated (lines) soil salinity (dSm$^{-1}$) at a soil depth of 0–30 cm (a), 30–100 cm (b) and > 100 cm (c) at the highly saline site of the CRS in 2009.

A leaching of the highly saline location reduced the soil salinity dynamics of the upper layer (0-30 cm) to around 7 – 10 dSm$^{-1}$, and hence they fluctuated between moderate and high levels throughout the cropping period. At the 30–100 cm depths, the soil salinity level dropped after leaching as anticipated, but remained with 8–12 dSm$^{-1}$ still at critical (highly saline) levels. As was observed for the other soil layers, overall, the salinity dropped immediately following irrigation events, but rose otherwise. The salts moved in general below...
100 cm, in turn changing this deep horizon from low-moderate level to moderate-high salinity level as evidenced by the range of 5 to 9 dSm$^{-1}$.

4. Discussion

Soil salinity was successfully identified and mapped in irrigated agriculture using RS techniques, but as noticed before, the accuracy of such estimations remains critical (Metternicht & Zinck 2003). Also, even though substantial amounts of salts can be accumulated in the soil profile, RS-based methods inherently cannot detect such key information (Farifteh et al. 2005). The findings here showed that this particular drawback from the RS approach can be successfully eased when combining an indirect RS assessment with water and solute transport modeling. It thereby was assumed that for the case study area a single plant-stress factor (soil salinization) occurred and while considering only cotton, a crop that is considered also as a good indicator plant for salinity studies (Golovina et al. 1992; Metternicht & Zink 2008). The assumption of cotton cultivation facing only soil salinization as stress was however justified given not only the overall good soil moisture holding capacity at the CRS, but also owing to the same land and water management implemented on the different fields monitored. In addition, a similar water accessibility, the absence of water supply problems (ensured to a common pump at the large irrigation channel), and the relative topographic flatness of all study fields justified this assumption.

The findings showed consequently that RS approaches in combination with modeling of the solute transport within the soil profile can successfully map and predict soil salinity dynamics much better than each of the methods alone. Furthermore, a visual comparison of the salinity maps created by EM38 measurements and those predicted by the RS-approach for the cotton fields suggested a clear relationship between the results of both approaches. Hence, the current findings together with those of Abbas et al. (2013) and Lhissou et al. (2014) for irrigated areas in similar environmental settings, e.g. in Morocco and Pakistan, confirmed the benefits of a delineation of similar spatial patterns of soil salinity detected by both approaches. Moreover, the relationship between the EM38 readings and RS-based assessments was lower ($R^2=0.15–0.29$) during the irrigation periods (June, July) but increased ($R^2=0.35–0.56$, Table 1) outside water application periods (September, October). These lower-level relationships during the vegetation period were likely due to a series of intensive irrigation events, which in turn reduced salinity concentrations and moved salts to deeper horizons. Therefore, information on key factors such as soil moisture, texture and management conditions are often reported as limiting the accuracy and hence usefulness of RS-based assessment soil salinity mapping (Metternicht & Zink 2003).

The RS-based methods allowed for salinity assessments at fixed point in time only, namely during the time of the image acquisition. However, various factors, which may modify the vegetation status and certainly over time may render the use of the RS assessment methods
less effective (Metternicht & Zink 2003; Farifteh et al. 2005). This includes e.g. the amount and effect of salinity due to differences in field water applications or dry periods, but also due to changes of GW tables and salinity, that all may accelerate green biomass development of stronger plants, etc. At the same time, modeling allows simulating not only the status, but also dynamics of salinity at various depths, while taking into account the above-mentioned factors. Figure 4 shows e.g. the rapid changes of soil salinity during irrigation periods, which move gradually upward till just outside the last irrigation events (since the end of August). While the RS image may be obtained at a period of rapid salinity change, the modeling approach permits by far a more accurate prediction of salinity at that point in time.

These findings indicate that soil salinity dynamics can be well captured through a modeling in space and time. The simulated salt dynamics showed that the solute transport model predicted well a reduction in soil salinity during September and October due to irrigation water applications (Figure 4) in the study year. Hence, not only a dilution of the soil salinity during watering events was mimicked, but also the removal of salts during such events. This showed that the approach was able not only to capture the temporally changes in soil salinity concentrations and amounts, but concurrently showed the effects of cotton coping better with soil salinity. These dual effects are less pronounced just outside irrigation period.

The HYDRUS-1D model simulated soil salinity over the vertical profile while separating for the three layers: top 30 cm, 30 – 100 cm and below 100 cm up to groundwater. The low RMSE, ranging between 0.59–0.89 dSm$^{-1}$ at the topsoil and beyond 100 cm, but somewhat higher (0.96–1.16 dSm$^{-1}$) for the 30–100 cm layer of (Figure 3) evidenced a successful application of the model to mimic temporal salinity dynamics over the agricultural season under cotton cultivation. This confirms earlier findings (e.g. Forkutsa et al. 2009) for the case study region, which however were with 1.4 and 3.2 dSm$^{-1}$ higher.

The simulation analysis revealed similar temporal salinity dynamics: the salinity was reduced by pre-season leaching in March from the topsoil down to the soil horizons below 100 cm. Outside the leaching period, simulations showed that salts partially moved upwards, while another part was moved out of the system through drainage. These salinity dynamics are to be expected given the amounts and low salinity of the applied water: they used to suffice to trigger the downward movements of salts from the upper layers and a consequent proper functioning of the drainage system in CRS to remove access salts from the system. These are thus the anticipated effects of leaching and drainage, nevertheless hardly achieved in the study region (Forkutsa et al. 2009). Most previous studies pointed as culprit for the growing soil salinity in the region the dysfunctional drainage system and an ill-management of the irrigation resources and networks. Also, the current simulations at CRS considered a 3 m profile, as opposed to the 2 m profile simulated by Forkutsa et al. (2009) for sandy loam locations in the south of Khorezm province, where salts were not removed from the system, but rather shifted to deeper layers only during the growing season.
Similarly, model simulations indicated a reduction in soil salinity levels following irrigation events, which gradually increased in the periods between such events. The model simulations revealed even the fluctuations of salinity classes from high to moderate and in some cases even to slight saline levels. However, the processes that drive mostly salinity buildup and fluctuations were and cannot be captured through RS techniques. Hence, the relatively low correlation of the salinity classification during June and July is indicative of the quick changes in soil salinity due to irrigation events combined with effects of groundwater movements. This explains hence why immediately outside the irrigation periods (from mid-August onwards) the relationship between RS estimations and modeling results grow stronger.

Modeling salt dynamics over the soil profile is thus a supporting technique to complement the RS method and ease a present major drawback of the RS approach, which is the accuracy of the mapping of various soil salinity levels at any time and soil depth. Moisture and solute modeling requires single (i.e. soil texture) or continuous (irrigation dates and amounts, groundwater depths, EC_s and EC_w, etc) measurements and as such is input- and computation-demanding. Modeling analyses demand also expert knowledge, huge initial efforts for proper calibration for specific locations, which in some way restricts a wide-practical implementation (Bastiaanssen et al. 2007). On the other hand, the potential of RS to accurately map various salinity levels remains restricted as substantiated by the low correlation between several RS indices such as Salinity Index and Normalized Difference Salinity Index (Metternicht & Zink 2003; Bannari et al. 2008; Lhissou et al. 2014). But under specific site conditions, the disadvantages of both can be eased by the other to a mutual benefit of the land user and planner alike. Hence, the resulting integrative methodology becomes capable for assessing soil salinity in irrigated fields accurately and over a wide area, which is highly desired by planners and land users aiming at improving planning and assessing the impact of mitigating and corrective measures.

5. Conclusion

The findings of this study showed that RS techniques can be reliably used to classify and map soil salinity in the cotton growing irrigated areas of the Aral Sea basin. This was evidenced by the results from the case study region Khorezm for which all necessary data sets were available. However, a comparison of the RS approach with direct salinity measurements using an EM38 with RS-incorporated precision showed a strong relationship towards the end of vegetation season only whilst during the intensive irrigation period (June-August 2009) this correlation was much lower. Moreover, with the use of the RS-approach, no information about the vertical distribution of salinity within the soil profile was provided although this is of crucial importance before deciding on in-season corrective measures. Yet, once the spatial salinity assessment was combined with solute-based modeling, valuable insights emerged about the causes of seasonal salinity development. The simulation results of the salinity levels at the highly saline site confirmed the empirical results and assured thus a provision of
quantitative information and dynamics of salinity. Hence, coupling the RS techniques with numerical modeling provided valuable insight into soil salinity dynamics, which in turn would allow for better management strategy planning. The use of RS for salinity identification and mapping may be limited as other seasonal or long-term plant stress factors (soil moisture shortage, changed groundwater effects, etc.) may affect accuracy. In such cases the modeling will be of even higher value, not only for assessing, but also for predicting soil salinity. This should be of interest to the cotton producers in all Central Asia countries because of their similar agro-ecological conditions.

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7. References


