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Soil salinity modeling and mapping using remote sensing and GIS: The case of Wonji sugar cane irrigation farm, Ethiopia

Engdawork Asfaw^a, K.V. Suryabhagavan^{a,*}, Mekuria Argaw^b

^a School of Earth Sciences, Addis Ababa University, P.O. Box 1176, Addis Ababa, Ethiopia ^b School of Environmental Science, Addis Ababa University, P.O. Box 1176, Addis Ababa, Ethiopia

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KEYWORDS

Electrical conductivity; GIS; Prediction model; Salinity model; Salinity index **Abstract** Soil salinization is one of the most common land degradation processes, especially in arid and semi-arid regions, where precipitation exceeds evaporation. Under such climatic conditions, soluble salts are accumulated in the soil, influencing soil properties with ultimate decline in productivity. An integrated approach using remote sensing in addition to various statistical methods has shown success for developing soil salinity prediction models. The present study presents a model to map soil salinity using remote sensing and geographic information systems. Different spectral indices were calculated from original bands of landsat images. Statistical correlation between field measurements of electrical conductivity (EC_e) and remote sensing spectral indices showed that salinity index (SI) had the highest correlation with EC_e. Combining these remotely sensed and EC_e variables into one model yielded the best fit with $R^2 = 0.78$. The result obtained from SI was not only area-wise, but also with its intensity. Out of the total area, 18.8% and 23% were identified as moderately and slightly saline, respectively. This shows that remote sensing data can be effectively used to model and map spatial variations of soil salinity in irrigation areas. © 2016 The Authors. Production and hosting by Elsevier B.V. on behalf of King Saud University. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

Soil salinization is the process of enrichment of soil with soluble salts that result in the information of salt affected soil. Soil salin-

* Corresponding author. Tel.: +251 911998588.

E-mail address: drsuryabhagavan@gmail.com (K.V. Suryabhagavan).

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ity in irrigated areas is becoming a serious problem for agriculture. Saline soil conditions have resulted in reduction of the value and productivity of considerable areas of land throughout the world (Elhag, 2016). Salinity commonly occurs in irrigated soils due to the accumulations of soluble salts resulted from continuous use of irrigation waters containing high or medium quantity of dissolved salts (Jingwei et al., 2008; Allbed and Kumar, 2013). The main problems associated with arid and semi-arid regions are salinization and desertification. Soil salinization is a major form of land degradation in agricultural areas, where information on the extent and magnitude of soil salinity is needed for better planning and implementation of effective soil reclamation programs. Irrigation evaporation of

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moisture from the surface or shallow depths within the profile and the insufficient annual rainfall to leach down salts from the plant rooting zone favor excessive accumulation of soluble salts in soils of arid and semi-arid regions, rendering such lands with only marginal success (Abdelfattah et al., 2009; Gorji et al., 2015).

Excess salts in the root zone of soils in the arid and semi-arid climates are a worldwide phenomenon. However, the most serious salinity and sodicity problems are being faced in the irrigated arid and semi-arid regions of the world and it is in these regions that irrigation is essential to increase agricultural production to satisfy food requirements. Soil salinity is also a serious problem in areas where groundwater of high salt content is used for irrigation (Zewdu et al., 2015). On the other hand, irrigation is often costly, technically complex and requires skilled management. Failure to apply efficient principles of water management may result in wastage of water through seepage; over watering and inadequate drainage resulting in waterlogging and salinity/sodicity problems, which reduce the soil productivity, eventually leading to loss of cultivable land. Thus, developments of technology to control and mitigate salinity and sodicity are particularly important issues for modern agricultural management, especially for countries such as Ethiopia where arid and semi-arid climatic zones occupy over 60% of the total land area (OWWDSA, 2007).

Soil salinity has resulted in limiting agricultural land-use patterns. It is a severe environmental hazard that impacts the growth of many crops. Salt affected areas on average represent 20% of the world's irrigated lands whereas this figure in arid and semiarid countries increases to more than 30% (Newer et al., 2013). According to Tamirie (1994), salt affected surfaces have increased from 6% to 16% of the total land of

Ethiopia in recent years. About 9% of the population lives in the areas affected by salinity. The semi-arid and arid lowlands and valleys in Ethiopia have major problems of salinity and alkalinity. About 44 million ha in 36% of the country's total land is potentially susceptible to salinity problems. Out of the 44 million ha, 33 million ha has dominantly salinity problems, 8 million ha has combined salinity and alkalinity problems, and 3 million ha has dominantly alkalinity problems.

Salinization is a known phenomenon in irrigated agricultural. However, its intensity and effects vary from area to area and from region to region. With this basic understanding, the present investigation was planned to study the extent of salinity in Wonji sugar cane irrigation farm and to monitor changes of salinized soils, based on statistical regression models to predict and map spatial variation of soil salinity as impacts of human driving factors. Findings of this study are expected to have great significance in maintaining ecological stability and agricultural output, and to formulate better management strategies in irrigated areas.

2. Materials and method

2.1. Study area

Wonji irrigation farm established in 1954 is one of the largest commercial farms in Ethiopia, which irrigates about 8000 ha of land by diverting Awash River to the irrigation field. Wonji Sugar Estate lies downstream of the Koka Dam in the Central Rift Valley of Ethiopia in the Awash River Basin, 110 km southeast of Addis Ababa. Geographically, it is bounded by latitudes $8^{\circ}21'08''-8^{\circ}29'26''N$ and longitudes $39^{\circ}12'28''-39^{\circ}18'47''E$ (Fig. 1) with a total area of 6539 ha. The Wonji



Figure 1 Location map of the study area.

Irrigation Scheme is at an altitude of approximately 1500 m asl. The slope of the farm is very gentle and regular. It has a semi-arid climate and receives an average annual rainfall of 831.2 mm. The peak daily evapotranspiration of the area is 4.5 mm and mean annual maximum and minimum temperatures are 27.6 $^{\circ}$ C and 15.2 $^{\circ}$ C, respectively.

2.2. Soil

According to FAO soil classification major predominant soil types in the area of Wonji sugarcane plantation are described as Fluvisols, Andosols and Leptosols. Soils of Wonji are alluvial colluvial origin developed under hot, tropical conditions. In this region, diverse soil types are observed, which also vary in their production potential. In general, soils of Wonji can be described as a complex of gray cracking clays in the topographic depressions and semiarid brown soils. On the basis of texture, they are categorized into light (coarse textured) soils and heavy soils (clayey black types) (Ambachew and Girma, 2000).

2.3. Method

Different analyses, which involve Remote Sensing and GIS assisted spatial modeling, regression model and validation of the methods were used, to determine the feasibility of remote
 Table 1
 Formula used to analyze soil salinity and vegetation indices.

No	Index name	Formula	Reference
1	Salinity index (SI)	$\sqrt{\text{Band } 3 * \text{Band } 4}$	Dehni and Lounis (2012)
2	Brightness Index (BI)	$\sqrt{B3^2 + B4^2}$	Khan et al. (2005)
3	Normalized difference salinity index (NDSI)	[(Band 3 – Band 4)/ (Band 3 + Band 4)]	Khan et al. (2005)
4	Vegetation Soil Salinity Index (VSSI)	$2 \times \text{Band } 2 - 5 \times$ (Band 3 + Band 4)	Dehni and Lounis (2012)
5	Normalized differential vegetation index (NDVI)	[(Band 4 – Band 3)/ (Band 3 + Band 4)]	Khan et al. (2005)
6	Soil adjusted vegetation index (SAVI)	SAVI = $(1 + L)$ Band 4 - Band 3/L + Band 4 + Band 3	Alhammadi and Glenn (2008)

sensing and geographical information system to map soil salinity directly from the soil, and indirectly from vegetation.



Figure 2 Methodology flowchart.

2.3.1. Data acquisition and software

4

Landsat TM data of 2012, path 168 and row 054 were used for this study. A portion of the image covering 0839 C1 and C2 toposheet area was selected. The image has seven bands, having a pixel resolution of 30 m. Analysis of the image was carried out using ArcGIS 10.2, ERDAS Imagine® 11, ENVI 4.7 and JMP statistical software Version 11.

2.3.2. Modeling vegetation and salinity indices

Stressed vegetation could be an indirect sign for the presence of salt in the soils. Salt affected soils are usually characterized by poorly vegetated areas. Six selected remote sensing indices such as salinity index (SI), normalized difference salinity index (NDSI), Brightness Index (BI), normalized differential vegetation index (NDVI), Vegetation Soil Salinity Index (VSSI) and soil adjusted vegetation index (SAVI) were used to discriminate and map salt affected soils (Table 1). Salinity index was the ratio of red band to near infrared (NIR) band, while NDSI was the ratio of the difference of the red to NIR divided by the summation of the two. Salinity index, NDSI, BI, NDVI, VSSI and SAVI were computed as follows.

2.3.3. Model generation and selection

Initially, EC data were tested to establish whether it conformed to a normal distribution. Various spectral soil salinity indices were tested for assessing and enhancing the



Figure 3 Scatter plots of predicted vs measured EC using developed regression models.

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Model	Variable	Regression coefficient	Standard error	P-value
	Intercept	-0.705575	0.220087	< 0.0023*
1	SI	7.5189111	0.541522	<.0001*
	$R \ 0.9, \ R^2 \ 0.78$			
	Intercept	2.2375466	0.179712	<.0001*
2	SAVI	2.223279	0.399486	<.0001*
	R 1.04, R^2 0.37			
	Intercept	1.6082391	0.174729	<.0001*
3	NDVI	-4.045224	10.16913	0.6923
	R 1.6, R^2 0.002			
	Intercept	0.7626517	0.204428	0.0005^{*}
4	NDSI	2.793508	0.482298	<.0001*
	R 1.02, R^2 0.39			
	Intercept	-0.163753	0.21785	0.4556
5	BI	5.7966769	0.611587	<.0001*
	$R 0.79, R^2 0.63$			
	Intercept	1.4605214	0.175235	<.0001*
6	VSSI	0.6981626	0.236018	0.0046*
	R 1.2, R^2 0.14			

Table 2	Regression 1	models to predict	EC based c	on remotely	sensed data.
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variations in surface soil salinity. Out of all indices tested, the salinity index (SI), was used to create enhanced images for soil salinity in this study, due to its high significant correlation with EC (Goovaerts, 1999; Dehni and Lounis, 2012). Validation and comparison of the model derived from Soil ECe versus prediction model was done by plotting the EC_e value and raster value of salinity map from salinity index (SI) model and spatial overlay factor model on scattered diagram. Then correlation between EC value and raster value of each of the model was derived. The detailed methodology is presented in Fig. 2.

3. Results

The developed regression models are shown in Fig. 3 and their statistical results are summarized to show how well the spatial variation in soil salinity can be predicted by applying different developed regression models and their statistical results are summarized in Table 2. All the developed regression models were highly significant; however, soil salinity index (SI), Brightness Index (BI) and normalized difference salinity index (NDSI) models were best able to predict soil salinity spatial variation, as they met all the model selection criteria. Among this model, the model, which combines salinity index (SI) and EC_e, provided to be the best.

Stating which is the highest R^2 signified a strongly linear relationship between estimated and predicted EC_e and indicated that 78% of the variance in the ECe values could be explained by this model with relatively low standard errors for its variables at 0.54. Each of these variables had significant p-values, indicating a strong correlation with ECe (Fig. 3).

3.1. Salinity prediction model using salinity index

The model of EC_e vs SI offered coefficient of determination at 78% (Fig. 4). This model directly gives the salinity level at any point in the image. From the predicted salinity map, three



Figure 4 Regression analyses between EC and salinity index.

ranges of salinity level were generated (Fig. 5). The summary of salinity level, extent of the area in hectare and percentage are given in Table 3. The three salinity classes with varying degree of salinity were, moderately saline and slightly saline and non-saline, which covers 18.8%, 23.4% and 57.7% of the total area, respectively.

$$Salinity = -0.705575 + 7.5189111 \times X \tag{1}$$

3.2. Multivariate analysis

The spatial overly model of salinization in Wonji Sugarcane irrigation farm consists of ground water table, elevation, geology, soil texture and vegetation density (NDVI) with varying degree of influence. Salinity model was developed by overlaying factor layers, which have contribution to the occurrence of soil salinity directly or indirectly.

Probability of presence of salinity in an area

$$= 1/(1 + e - Z) \tag{2}$$

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Figure 5 Salinity map from prediction model.

Table 3	2 3 Area extent of soil salinity level derived from prediction model using salinity index.			
No	Salinity extent	ECe value	Area in (ha)	Area in (%)
1	Non-saline	< 2	3778	57.7
2	Slightly saline	2–4	1530.7	23.4
3	Moderately saline	4-8	1230.3	18.8
4	Total		6539	100



Figure 6 Salt affected area derived from multivariate analysis.

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Table 4 Extent of areas of various salinity levels derived from multivariate analysis.

Salinity extent	ECemScm	Area (ha)	Area (%)
Non saline	< 2	2362.5	36
Slightly saline	2–4	2209	33.7
Moderately saline	4-8	1967.4	30
Total		6539	100

where $Z = 117 + (\text{geology} \times 0.15) + (\text{elevation} \times 0.16) + (\text{soil texture} \times 0.22) + (\text{ground water table} \times 0.28) + (\text{vegetation density} \times 0.012).$

Based on the spatial overly salinity model result, three classes were identified with varying degree of salinity (Fig. 6). The extent of areas of each of the classes of the salinity is shown in Table 4. Moderate and slightly saline classes cover approximately 30% and 33.7% of the total area, respectively. None-saline class accounted for over 36% of the total area. From the results of multivariate analysis, one can clearly identify that moderately and slightly saline soils are in the areas underlaid by the lacustrine sediments and shallow ground water level. Moreover, the low-lying topography and less vegetation cover in the area have greatly enhanced the intensity of salinization in the farm.

3.3. Model validation and comparison of the models

The result of the validity of salinity model shows that the relation between measured EC_e value and salinity derived from the remote sensing index model has high correlation (63%) (Fig. 7). Validation for spatial overlay model was also made and the correlation between measured EC_e value and salinity derived from the spatial overlay was also correlated (23% of the total area). The coefficient values of correlation show that both models have predicted salinity of the area in different levels. However, the remote sensing induces from SI model has better validity compared to the spatial overlay factor model.

4. Discussion

Multi-class soil salinity maps are required for modern management of arid lands, and geospatial techniques are needed to efficiently develop such inventories. Our results indicate that use of landsat ETM + images of the study area identified bare areas that have a high reflectance due to their high salinity and/ or salt-efflorescence on the soil surface. This agrees with the views of Elnaggar and Noller (2010), who reported that saltaffected soils with salt encrustation at the surface are, generally, smoother than non-saline surfaces and cause high reflectance in the visible and near-infrared bands.

The efficiency of the selected regression model to predict and map the spatial variation in soil salinity is shown by the strong relationship ($R^2 = 0.78$) at the 95% probability level, and RMSE of 0.54 dS/m. This is partially due to the result of the selected remote sensing soil salinity indicators. The selected model in this study showed superiority in the prediction power of soil salinity over those reported by Shrestha (2006) ($R^2 = 0.23$). Moreover, the good performance of the selected model in this study was due to the enhanced image efficiency in highlighting information from soil salinity and suppressing other details. Several studies have shown that image enhancement techniques consisting of spectral indices (e.g., NDVI, SI, NDSI) have great potential in enhancing and delineating soil salinity details in an image (Noroozi et al., 2012). For example, Allbed et al. (2014) emphasized that identifying salt affected soils based on the image enhancement method, represented by the salinity index (SI) and IKONOS red band (band 3) had the highest correlation with EC, and yields better results than individual bands due to its ability to enhance the saline patches by suppressing the vegetation.

Further, the superiority of the visible red and NIR band over the other bands in retrieving soil salinity contributed to improving the regression model. This result is supported by those of Abdul-Qadir and Benni (2010), who found that the visible red band performs best among the Landsat ETM + bands at characterizing the pattern and features of soil salinity due to its high correlation with EC ground measurements. Soil salinity spectral reflectance is affected by physical and chemical properties of soil quality and mineralogy of salt, together with soil moisture, color and surface roughness. Salt influenced surface features are crusts without or with only a little evidence of salt, thick salt crusts and puffy structures.

Salt causes variations in the surface roughness, which induces variation in the soil spectral reflectance (Goldshleger et al., 2013). Most salt affected soils can be identified by a white salt crust that will form on the soil surface. These soils



Figure 7 Correlation between prediction model (A) and spatial overlay raster value (B).

tend to increase spectral reflectance (crusted soil), which affects soil and structure and reduces the soil infiltration rate, characterized with significant spectral changes due to the structural crust formation and color. Salt crust at its inception high infiltration rate presents low spectral reflectance, whereas in intense salt crust soil, the spectral reflectance will be significantly higher. Besides, smooth crust surfaces have higher spectral reflectance than rougher crust surfaces (Metternicht and Zinck, 2003).

Saline soils with a smooth and light salty crust surface showed high spectral reflectance in the red and NIR band, whereas saline soils characterized by coarse dark puffy surface crust exhibited a decrease in spectral reflectance. These findings are in agreement with Metternich and Zinck (1997), and confirm the fact that saline soil reflectance results from spectral properties such as the presence of salt crust, soil color and moisture content, which have a combined effect on the amount of reflectance. Thus, it is clear that a combination of spectral bands and image enhancement yields a better result than the actual band used for modeling and mapping soil salinity alone (Taigardan et al., 2007; Eldeiry and Garcia, 2008; Bouaziz et al., 2011; Noroozi et al., 2012; Zewdu et al., 2016). Thus, this method of combining spectral bands with enhanced images in a single model is a promising tool for soil salinity detection and mapping. That is to say, the combination is the key, giving better results than either spectral band alone or image enhancement alone.

5. Conclusion

This paper presents the first results of work dedicated to assess and validate salinity models in the study area. The sequence of the model from detection, site observations, correlation and verification, and model validation has proved to be applicable for mapping and modeling salinity using geospatial techniques. The use of remote sensing data, followed by site observations is a powerful tool in detecting salt affected areas. As nearly 80% of the saline areas could be delineated, it is a good indication for the validity of the model. Hence, this model can be used in similar areas that experience salinization problems. The great capacity of this combined model over the other developed models is attributed to the enhanced images and the band efficiency in highlighting information from soil salinity. The simplicity of this model and acceptable degree of accuracy make it a promising tool for use in soil salinity prediction.

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Soil salinity modeling and mapping

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