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The spatial distribution of soil salinity: Detection and prediction

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ABSTRACT

Inefficient irrigation and the excessive use of water on agricultural lands in the Aral Sea Basin over several decades have led to highly saline soils. Salinity appraisal in the Aral Sea Basin however, is still dependent upon traditional soil surveys with subsequent laboratory analyses for the total dissolved solids (TDS). This thesis has three specific objectives, namely, to identify techniques that enable rapid estimation of salinity, to characterize the spatial distribution of soil salinity and to estimate the spatial distribution of soil salinity based on readily or cheaply obtainable environmental parameters.

Soil salinity was measured by four electrical conductivity (EC) devices (2XP, 2P, 4P, and CM-138) on a regular grid covering an area of approximately 3 km by 4 km. Six nested samplings within selected grids were conducted to account for small-scale variation. The farm-scale (~15 km^2) results were used to upscale soil salinity to a district area (~400 km^2). Apart from widely used terrain indices and those acquired from remote sensing, distance to drains and long-term groundwater observation data were used to account for local parameters possibly influencing soil salinity. Standard statistical procedures were applied for data description, correlation between variables, analysis of variance, and regression. Characterization of the spatial distribution of soil salinity and interpolation of point data were carried out using geostatistics. Soil salinity estimation based on environmental attributes was carried out using a neural network model, as this offers enhanced generalization compared to other models. Analyses were integrated into a GIS for visualization and presentation of the results.

Techniques for rapid determination of soil salinity based on electrical conductivity were assessed and proved to be satisfactory in all cases. Measurement based on soil paste (EC_p) was highly accurate ($R^2=0.76$), whereas EC_a measurements at point scale in the field were of low accuracy ($R^2<0.5$). However, field assessment of soil salinity was considerably enhanced by the use of CM-138, because large areas can be quickly assessed, which in spite of lower accuracy, is desirable.

Topsoil (30 cm) salinity was highly variable even at short distances (40 m) compared to average soil salinity at 0.75 m and 1.5 m depth measured by the CM-138. Overall distribution of soil salinity was influenced by soil texture and topography, while at the local scale terrain attributes such as curvature, plan and profile curvatures, and solar radiation were the most influential factors. Factors obtained by remote sensing had significant correlation coefficients ($r=0.2$) with both the salinity of topsoil and salinity measured by the CM-138. Distance to drains is an important factor, especially for the bulk soil salinity (measured by the CM-138) of the profile. Correlation between distance to drains and salinity of the topsoil was low, which might be due to higher spatial variation of the topsoil salinity. Groundwater table depth and salinity had marked correlations with soil salinity; however, the direction of the influence could not be explained. The inclusion of these controlling variables in modeling is fundamental, and efforts must be directed towards obtaining reliable and accurate databases in order to derive them.

With an environmental correlation model that was built for the farm scale, soil salinity was estimated using environmental parameters in a neural network approach and shows a high correlation coefficient between estimated and measured soil salinity of 0.83. The accuracy of the prediction of soil salinity was satisfactory taking into account

that the measurement scales of soil salinity and environmental data derived from different estimations with unknown but certainly varying accuracy.

The use of environmental attributes and soil salinity relationships to upscale the spatial distribution of soil salinity from farm to district scale resulted in the estimation of essentially similar mean soil salinity values (0.94 dS m^{-1} vs. 1.04 dS m^{-1}). However, visual comparison of the maps suggests that the estimated map had soil salinity that was overly uniform in distribution, which is thought to be caused by inaccuracy of environmental data (including scale problems) or overgeneralization by the neural network model.

The upscaling proved to be satisfactory, but further research is needed before the model can be applied. Considering that the neural network model is an empirical model, further training of the model is required at locations where conditions are different to those on the farm where the model was generated. Furthermore, the model depends on the strength of the relationship between environmental variables and soil salinity. Therefore, the environmental variables must be either available for the study area in high spatial resolution or easily measurable.

Die räumliche Verbreitung des Bodensalzgehaltes: Erkennung und Vorhersage

KURZFASSUNG

Schon seit mehreren Jahrzehnten kommt auf den landwirtschaftlich genutzten Flächen des Aralseebeckens mangelhafte Bewässerungstechnik bei gleichzeitig übermäßigen Wassereinsatz zum Einsatz. Die Umweltkonsequenzen dieser Entwicklung sind durch hohe Salzgehalte verseuchte Böden. Eine Abschätzung des Salzgehalts im Aralseebecken erfolgt jedoch immer noch mit Hilfe von traditionellen Bodenuntersuchungen mit darauf folgenden Laboranalysen zur Bestimmung der Gesamtmenge gelöster Feststoffe (total dissolved solids; TDS). Diese Doktorarbeit hat drei spezifische Ziele: (i) Identifizierung der Methoden, die eine schnelle Abschätzung des Salzgehalts im Boden erlauben, (ii) Charakterisierung der räumlichen Verteilung des Salzgehalts im Boden und (iii) Abschätzung der räumlichen Verteilung des Salzgehalts im Boden mit Hilfe von vorhandenen oder leicht erhältlichen Umweltparametern.

Der Bodensalzgehalt wurde mit vier Geräten (2XP, 2P, 4P und CM-138), welche die elektrische Leitfähigkeit (EC) messen, in einem regelmäßigen Gitter, das ein Gebiet von 3 km x 4 km umfasst, bestimmt. Es wurden sechs verschachtelte Probenahmen (nested samples) innerhalb ausgewählter Gitter vorgenommen, um Abweichungen auf kleinem Raum zu berücksichtigen. Die auf Farmebene (~15 km^2) erzielten Ergebnisse wurden verwendet, um den Bodensalzgehalt auf eine Bezirksebene hochzurechnen (~400 km^2). Abgesehen von weit verbreiteten Bodenindizes und Fernerkundungsdaten wurden die Entfernungen der Messpunkte zu Drainagekanälen und Langzeit-Grundwasserdaten verwendet, um Parameter zu berücksichtigen, die möglicherweise einen lokalen Einfluss haben. Für die Datenbeschreibung, die Korrelation zwischen Variablen, die Varianzanalyse und die Regression wurden statistische Standardmethoden verwendet. Die Charakterisierung der räumlichen Verbreitung von Bodensalzgehalt und die Interpolierung von Punktdaten wurden mit Hilfe der Geostatistik vorgenommen. Die Schätzung des Bodensalzgehalts basierend auf Umweltparametern wurde mit Hilfe eines Neuralen Netzwerk-Modells durchgeführt, weil es im Vergleich zu anderen Modellen eine bessere Generalisierung erlaubt. Die Analysen wurden zur Visualisierung und Ergebnispräsentation in einem GIS integriert.

Schnelle Bodensalzgehalt-Bestimmungsmethoden auf der Grundlage elektrischer Leitfähigkeit wurden in allem Fällen zufrieden stellend bewertet. Die Salinitätsmessung in wässriger Bodenpaste (EC_p) war sehr präzise ($R^2=0.76$), doch EC_a Punktmessungen im Feld waren von geringer Genauigkeit ($R^2<0.5$). Allerdings war die Abschätzung des Bodensalzgehalts auf dem Feld beträchtlich verbessert, wenn das CM-138 verwendet wurde, weil große Flächen schnell geschätzt werden können, was trotz schlechter Genauigkeit wünschenswert ist.

Der Salzgehalt des Oberbodens (bis 30 cm) variierte sehr (sogar bei kurzen Entfernungen (40 m)) im Gegensatz zum mit dem CM-138 gemessenen durchschnittlichen Bodensalzgehalt in 0.75 m and 1.5 m Tiefe. Die Verteilung des Gesamtbodensalzgehalts wurde von Bodenbeschaffenheit und Topographie beeinflusst,

während auf der lokalen Ebene Terraineigenschaften wie *curvature*, *plan* und *profile curvatures* und Sonnenstrahlung die einflussreichsten Faktoren waren. Auf Fernerkundung basierende Faktoren korrelierten signifikant sowohl mit dem Salzgehalt des Oberbodens als auch mit dem Salzgehalt, der mit dem CM-138 gemessen wurde. Ebenso ist der Abstand zu Drainagekanälen ein wichtiger Faktor, insbesondere für den Gesamt-Bodensalzgehalt im Profil (bei Messungen mit dem CM-138). Der Salzgehalt war im Oberboden geringer, eventuell aufgrund der größeren räumlichen Verteilung des Oberbodensalzgehalts. Die Tiefe des Grundwasserspiegels und der Salzgehalt zeigten starke Korrelationen mit dem Bodensalzgehalt, doch die Ursache der Beeinflussung konnte nicht erklärt werden. Die Miteinbeziehung dieser Variablen, die einen starken Einfluss auf den Bodensalzgehalt haben, ist sehr wichtig und es deshalb sollten zuverlässige und präzise Datenbanken aufgebaut werden, damit diese Variablen erworben werden können.

Mit einem Umwelt-Korrelationsmodell, das für die Farmebene gemacht wurde, wurde der Bodensalzgehalt unter Verwendung von Umweltparametern mit Hilfe eines neuralen Netzwerks abschätzt; der Korrelationskoeffizient zwischen geschätztem und gemessenem Bodensalzgehalt war mit 0.83 hoch. Die Vorhersage des Salzgehalts mit diesem Modell war zufrieden stellend, insbesondere wenn man berücksichtigt, dass die Übereinstimmung in den Messskalen der Bodensalzgehalte und der Umweltfaktoren aufgrund der unterschiedlichen Erfassungsmethoden und unbekannter, aber sicherlich variierender Erfassungsgenauigkeiten stark variierte.

Die Verwendung von Relationen zwischen Umweltparametern und Bodensalzgehalt, um die räumliche Verteilung des Bodensalzgehalts von Farmebene auf Bezirkebene hochzurechnen, ergab im Wesentlichen übereinstimmende Abschätzungen der durchschnittlichen Bodensalzgehaltwerte (0.94 dS m^{-1} vs. 1.04 dS m^{-1}). Doch deutet ein visueller Vergleich der Landkarten darauf hin, dass der Bodensalzgehalt in der geschätzten Landkarte in seiner Verteilung zu einheitlich war. Dieses Problem wurde vermutlich durch Ungenauigkeiten in der Verteilung (einschl. Probleme bei der Skalierung) oder durch eine zu weit gehende Verallgemeinerung durch das Neuralnetzwerk-Modell verursacht.

Das Hochrechnen der Bodensalinität aus Umweltparametern hat sich als akzeptabel erwiesen, aber weitere Forschungen sind nötig, bevor das Modell praktisch angewendet werden kann. Unter Berücksichtigung, dass das neurale Netzwerk ein empirisches Modell ist, ist weiteres Training des Modells an anderen Standorten und unter anderen (sich von denen der ersten Farm unterscheidenden) Bedingungen notwendig. Das Modell hängt von der Stärke der Beziehung zwischen Umweltvariablen und Bodensalzgehalt ab. Deshalb müssen die Umweltvariablen für das Forschungsgebiet in sehr guter räumlicher Auflösung verfügbar oder einfach zu messen sein.

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1 GENERAL INTRODUCTION

1.1 Introduction

Inefficient irrigation and the excessive use of water on agricultural lands in the Aral Sea Basin over several decades have led to highly saline soils. The history of agriculture shows that irrigated agriculture cannot survive indefinitely without adequate salt balance and drainage (Tanji, 1990). An often quoted example of excessive irrigation and resulting salinization dating back to Ancient Mesopotamia is briefly explained by Hillel (2000). Similar problems are currently faced in all Central Asia, where extensive land development for irrigated agriculture with the subsequent recession of the Aral Sea is blamed for the current widespread salinization and ecological deterioration. This problem affects roughly 75% of the irrigated land in the Aral Sea basin (van Dijk et al., 1999).

Despite the ample and repeated criticism of the wasteful irrigation practices (Micklin, 1988) there has been little progress in reversing the trend of soil degradation. Detailed overviews of the environmental problems and recommendations for overcoming these problems are extensively documented in numerous reports of international organizations such as UNESCO, GEF, UNEP, as well as in individual studies. For example, Micklin (1988) attributes the causes of reduced inflow into the Aral Sea since 1960 to both climatic and anthropogenic factors. Aladin (1998) stresses that isolation from other large water basins and highly arid continental climatic conditions are the most important features distinguishing similar areas with that of the Aral Sea. However, anthropogenic factors have had particularly disastrous effects, especially the drastically high water use rates of 10,000-12,000 m^3 ha^{-1} of irrigated land and 2,500 m^3 $capita^{-1}$, compared to 5,500 m^3 ha^{-1} in Israel and 1,700 m^3 $capita^{-1}$ as the world average (Saifulin et al., 1998). The current understanding is not to refill the sea per se, but at least to stabilize the worsening environmental and social conditions of the most strongly affected adjacent territories and populations.

Since the two major rivers feeding the Aral Sea, Amu Darya and Sir Darya, pass through several countries, the affected environment covers a much wider area than that of the Aral Sea that is at the tail end of these rivers. One of the adversely affected areas in the Amudarya delta is the Khorezm region (Uzbekistan), which has received

little attention since the onset of the Aral Sea disaster. It is one of the oldest agricultural areas in the world.

Currently, the region heavily depends on river water for mainly cotton cultivation, while rice and wheat used to be the dominant crops in the past. The Khorezm region covers 455,000 ha of which 260,000 ha are irrigated (map of Ministry of Agriculture and Water Resources, 2000).

During three years of drought, from 1999 to 2001, the consequences of inefficient irrigation were hard felt by the local population in Khorezm. Furthermore, water supply problems have been revived through recent geopolitical developments in the Central Asian region with Afghanistan possibly wanting to lay claims to its share of the Amu Darya river water (Glantz, 2002). Therefore, a lack of water in the future should be anticipated and the 1999-2001 drought not just be viewed as a single event.

Located in the low deltaic plains, Khorezm is subject to high loads of salt particles in the river water (Abdullaev, 2002). Reports estimate that saline soils in the Khorezm region constitute more than 80% of the irrigated soils, which range from slightly to highly saline. According to Kust (1997), salinity change and profile distribution in this area is mainly governed by fluctuation of the groundwater table, duration of dry season, and location of the soils within the lower mesorelief elements within the river deltas. The general trend as described in soil surveys by Zhollybekov (1995) indicates that soil salinity has risen in the river delta due to the receding sea level.

It is a well known fact that high soil salinity impedes crop growth. Depending on the salinity level, crop yields are suppressed by 10-20% even by weakly saline soils (Kaurichev, 1989). For example, the maximum tolerance of cotton and wheat is to a chloride content of 0.03 g $100g^{-1}$ (ibidem). Various monitoring programs have been set up by governments to prevent and manage affected areas. These traditional soil salinity estimates are based on laboratory analysis of soil samples. However, this method requires considerable time, expense and effort. Therefore there is a need for new and more practical methods and tools to determine and predict soil salinity (i.e., quick, cheaper, on-the-spot determination, and GIS application) to improve decision making processes. Methods should target primary benefactors such as the Ministry of

Agriculture and the branches directly involved in land-use planning and water allocation.

With the need for monitoring in combination with the technological progress of salinity assessment based on electrical conductivity, more practical assessment methods have evolved. Specifically, a model by Rhoades et al. (1989) received great attention in this regard (Corwin and Lesch, 2003; Hall et al., submitted; Rhoades et al., 1999). It requires two additional parameters, clay and water content, which could be easily estimated in the field.

In part, facilitated by the availability of the quick appraisal methods, the intricate processes of soil salinity occurrence in irrigated arid regions are well understood but difficult to measure. As in other similarly difficult to measure processes, especially in soil formation, they are measured by their response. However, it can be argued that while soil processes to manifest may take thousands of years to come to equilibrium, soil salinity, being a mobile and dynamic attribute in the soil, reaches a state of equilibrium at a much faster pace (e.g., Park and Vlek, 2002). Soil salinity surveys at the landscape level in the developing world still remain the major source of information on salinity distribution, although these have many limitations, for example, conventional soil maps neither delineate all of the field's inherent variability nor represent specific soil attribute variations (Moore et al., 1993). The recent development of quantitative methods based on geostatistics and incorporation of environmental variables partly stem from practical constraints of conventional soil survey methods, which can be criticized as being too qualitative and too focused on soil management and land-use planning (McBratney et al., 2000).

1.2 Research objectives

Based on the understanding of the processes of soil salinity development and the technological progress, an intensive investigation of various aspects of the soil salinity in the setting of irrigated land has been designed. The overall research objective of the study was to develop a spatially distributed model to estimate soil salinity distribution at the farm and district level with an emphasis on readily available and cheaply obtainable measurements, so that real-time decision making can be supported both on-farm (by farmers) and off-farm (by policy makers) in Khorezm, Uzbekistan.

To achieve the overall objective, the following specific objectives were set:

i) Identify a technique for quick determination of soil salinity based on electrical conductivity devices, and comparatively assess suitability and sensitivity of the different methods;

ii) Characterize the spatial variability of soil salinity at both farm and district levels in the study region;

iii) Develop a soil salinity prediction model taking into account environmental factors (a method that would allow predicting soil salinity without actually measuring it);

iv) Predict the spatial distribution of soil salinity in Khorezm by combining remote sensing with the available soil database.

1.3 Scope of the study

Soil salinity is one of the major side effects in the agro-environment of former large-scale irrigation projects that lacked adequate water and currently threatens agriculture in the Khorezm region. The long-term German-Uzbek multidisciplinary research program on sustainable land and water use, of which the present study forms a part, was launched in 2002 with the main aim of understanding the structure of the agro-ecosystems and developing cost-effective landscape management options in this type of constrained environment. When discussing landscape management options, the use of maps is indispensable; however available maps are often obsolete. Moreover, the utility of existing conventionally surveyed maps is challenged by the development of modern mapping techniques (the shortcomings of the traditional soil survey methods are described elsewhere; (McKenzie et al., 2000; Moore et al., 1993; Tomer and James, 2004; Zhu et al., 2001). Therefore, the mapping of natural resources was a fundamental building block for the program, and hence, the present study engages not only in identifying adequate methods for field salinity measurement and assessment, but also in modeling of soil salinity, based on environmental predictors, for upscaling data from intensive field surveys onto a larger area.

1.4 Limitations of the study

Similar to many other successful attempts (i.e. Leij et al., 2004; i.e. McKenzie and Ryan, 1999; Moore et al., 1993; Tomer and James, 2004) to develop analogues of conventional surveys by terrain attributes, this study builds on readily available or easily obtainable data to account for the spatial variation of soil salinity. Therefore, the number of parameters is restricted by data availability. The accuracy of these datasets can be questioned, as they have not been specifically developed for this study, and all have intrinsic strengths and flaws (such as number of observations, representativity, layout of sampling locations, etc.), but they are regarded to be representative of the landscape and contain information valuable for salinity analysis and management. The focus here was whether it would be possible to develop models using the readily available existing data sets with their intrinsic flaws. If so, it would help decision making under the conditions encountered by farmers or decision makers. In order to achieve this, an artificial neural network (ANN) model was used. Historically, much of the inspiration in the field of ANNs came from the desire to produce artificial systems capable of sophisticated, perhaps "intelligent", computations similar to those that the human brain routinely performs. ANNs "learn" from examples, as children learn to distinguish dogs from cats based on examples of dogs and cats. If trained carefully, ANNs may exhibit some capability for generalization beyond the training data, i.e., to produce approximately correct results for new cases that were not used for training (Sarle, 1997).

1.5 Overall research procedures and thesis outline

Figure 1.1 shows the overall research procedures followed in this study. The thesis consists of 5 chapters, each with a brief introduction into the topic to be dealt with and the discussion of the results. This general introduction (Chapter 1) is followed by the comparison of electrical conductivity devices (Chapter 2) for a quick appraisal of the soil salinity. Chapter 3 characterizes the variation of soil salinity and other attributes and explores the influencing environmental factors at the farm scale. The farm scale results were then used to build a neural network model in Chapter 4. The same environmental attributes which were considered at farm level were obtained at the district scale and fed into the neural network model to estimate soil salinity at the