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Estimating electrical conductivity of soil through ALOS satellite data using regression models

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Abstract

The Electrical Conductivity (EC) is the value of dielectric properties in soil normally used for significant indicator identifying normal soil and salt-affected soil. EC is influenced by many factors such as soil moisture, soil porosity, texture, and organic matter. EC estimation is the method able to classify soil salinity levels quickly and sufficiently accurate. To determine and monitor the spatial variations in saline soil from the field experience is very complicated and difficult as it often requires dependable models in applying to the specific arrangement and environmental limitations of the study to learn how it impacts on saline soil. ALOS is known as penetrated satellite data as it can detect character of land surface. They have been proved as a powerful tool to indicate the accuracy of salinity value in saline conditions. The main objective was to study the sufficiency of EC as derived from satellite data to predict EC values associated with soil salinity. A regression model was used to create an EC estimation model. EC values were related to scattering values extracted from ALOS satellite data which this research developed an estimation model that could explain the EC of saline soil. The results illustrated that a relationship between two different data sources, satellite data and ground data, the statistical model could be developed to accurately estimate the value of EC soil using ALOS satellite

Keywords: Electrical conductivity; soil salinity; ALOS; regression model.

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1. Introduction

Generally, the basic salt amount in soil depends on soil moisture content associated with dielectric properties. Electrical Conductivity (EC) is the ability of a material to conduct electrical current (Kitchen et al. 1996). The apparent EC of soil is influenced by many factors such as water content, soil porosity, texture, and organic matter (Rhoades et al., 1999). The availability of satellite microwave data (e.g. ERS1/2, JERS-1, Radarsat) facilitates the detection, assessment and mapping of wetlands, forests, and urban features, (Metternicht, 1999). The use of microwave data for an indirect measurement to detect salt-affected soils has been studied since 1996 (Taylor et al., 1996; Metternicht, 1998; Aly et al., 2004). Nevertheless, the arid and semi-arid regions researched in those studies were comparably simple to study since these were not affected by humidity limiting satellite image data application.

Apart from that, little research has been done on using ALOS data to study soil salinity. The developments in L-band microwave sensing have enabled new advanced techniques with predictive mapping capability (Sreenivas et al., 1995). The BC recorded in a synthetic aperture radar (SAR) image has a significant correlation to soil salinity based on laboratory measurements (Shao et al. 2003). Relatively few studies have investigated the possibility of matching SAR data to BC values from field research.

Most preceding studies have overlooked possibilities to investigate salinity, including the other parameters of the backscattering coefficient, or establishing BC using several backscattering models, the Small Perturbation Model, or the Physical Optic Model (Aly, 2004), for instance, which face constraints in their respective systems as they involve a huge amount of parameters. In order to diminish such complications through large numbers of parameters, the present model was designed to learn directly to enhance the relationship between BC value and soil salinity.

The hypothesis herein supposes that soil roughness of salt-affected areas has a relationship with their BC values obtained from ALOS. The purpose of this study was to estimate EC values of soil through the correlation between the EC values established during field research and BC values retrieved from ALOS. Microwave data was also applied in this study because signatures of saline deposits monitored on PALSAR data indicated an improved interpretation. The study purpose was to discover scattering properties of each salinity class.

Besides, the obtained correlations of different polarizations were processed by experiment. PALSAR images at HH, HV, VH and VV polarizations were compared to assess which polarization was the best for estimating the EC of soils.

2. Material and Methodology

The basic materials for this study were soil samples for laboratory measurement and BC values from ALOS imagery. This research should help to interpret EC variations under field conditions to improve the estimation model. The main methodology is given below in Figure 1.

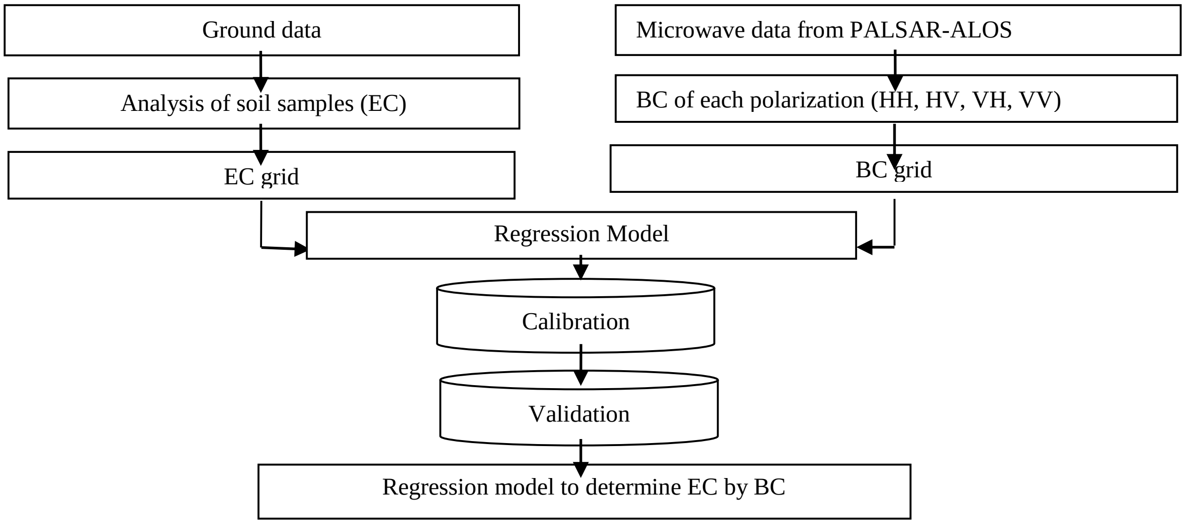

Figure 1. Processes of correlation analysis between BC and EC

2.1. Ground measurement data

250 soil samples were collected from bare land within the salinity affected areas. The soil sampling was scheduled at a date close to that of ALOS microwave data recording to best match EC values from soil samples with BC values from microwave data. The locations of the soil sampling points across all salinity levels were randomized. GPS was used to determine the exact coordinates of each point during field measurement. From each point, soil samples were gathered in 5-10 centimetre depth below the surface using 100 cm^3metal tubes. The soil samples were analysed for EC, pH, and soil texture.

2.2. Microwave data from PALSAR-ALOS

Regarding the input data for this study, BC was extracted from microwave imagery of ALOS-PALSAR. The selected scene was ALPSRP276800310-P1.5GUA with a resolution of 12.5 m. The centre of the image scene is between 15.943^o latitude and 103^{o}longitude. Image correction of the satellite image was necessary to allow geometric overlays of the image data and to remove effects of side looking geometry of SAR images because the ALOS image was geometrically terrain corrected. The relationship between DN and BC can be written as:

$$DN^2 = \text{const}\ (BC) \qquad (1)$$

Where DN is the pixel intensity value of the image, BC is the backscattering coefficient or sigma naught on image

The following equation is used in this research to obtain the backscattering coefficient in dB unit:

$$BC(dB) = 20 \log10\ BC = 20 \log10\ (DN) + K\ (dB) \qquad (2)$$

Where K is a constant of -83 dB (JAXA, 2008), determined as a constant compatible with ALOS image data

2.3. Stepwise multiple linear regression (SMLR)

An SMLR model was developed to estimate the EC of soil from the BC of PALSAR data. Estimate models were calculated based on four polarizations (HH, HV, VH, and VV) of BC variables. SPSS, statistical software, was used for developing the model. The equation of regression model represented the quantitative relationship between dependent variables and independent variables (Husch et al, 2003). The correlation analysis could interpret in causal terms the relation of BC and EC of saline soil. The regression was run with the entire dataset to find EC values to be included in a linear predicting model.

The square value of the correlation coefficient (R^2) can be interpreted as indicating the percentage of variation in one variable that is associated with another variable (Husch et al, 2003)

2.4. Model validation

After that, the regression model was built to estimate EC from BC. The remainder of the measured EC data from field survey was used to validate the model. The performances of predicting models were reported in terms of coefficient of determination (R^2) and root mean square error (RMSE) .The coefficient of determination (R^2) indicates the correlation of EC estimated from BC and EC measured in the field. The accuracy of predicting models was significantly improved using higher R^2 and lower RMSE.

3. Results and Discussion

3.1. Relationship between EC and BC by regression model

From the results of the examination of correlation coefficients between EC and BC from the three datasets, the BC of dataset1 was chosen for the regression model because its BC values produced a high correlation coefficient by Pearson. Table 1 shows the basic statistics of BC from ALOS data from two data sources: calibration data and validation data. The standard deviation (SD) values were found to be fairly equivalent to each other, which indicated that the data of each group showed no significant difference in their variations so they were all applicable as data samples for studying the relationship and comparing the results between the two seasons.

Table 1. Descriptive statistics of BC values for wet and dry season from ALOS

Season	Dataset	Sample	Min(dB)	Max(dB)	Mean(dB)	SD
Dry	Calibration	150	-31.94	-5.65	-17.29	1.64
	Validation	100	-29.72	-8.24	-19.22	1.13
Wet	Calibration	150	-28.24	-6.08	-15.83	1.35
	Validation	100	-29.11	-7.21	-13.29	1.25

The relationship of EC and BC as of the regression model estimates and in regression equation terms (Table2). The coefficient of determination (R^2) is presented as the result of the relationship between EC and BC values. The statistical significance level was a P-value of 0.01 (two-tailed test) at a 99 per cent confidence level.

Table 2. The coefficient of determination (R^2) of EC and BC and regression equations

	Polarized	Calibration (N=150)		Validation (N=100)		Regression equation
		R^2_c	$RMSE_1$	R^2_v	$RMSE_2$	
Dry season	BC-HH	0.743	1.04	0.641	1.41	EC = -0.435BCHH -1.597
	BC-HV	0.722	2.14	0.573	2.32	EC = -0. 369BCHV –0.111
	BC-VH	0.644	2.27	0.594	2.34	EC = -0. 033BCVH –0.364
	BC-VV	0.727	2.18	0.632	2.22	EC = -0.390BCVV –0.584
	Polarized	Calibration	(N=150)	Validation (N=100)		Regression equation
		R^2_c	$RMSE_1$	R^2_v	$RMSE_2$	
Wet season	BC-HH	0.707	3.38	0.584	2.25	EC = - 0.445BCHH -1.208
	BC-HV	0.643	3.23	0.521	3.04	EC = -0. 395BCHV –0.171
	BC-VH	0.593	4.06	0.556	2.68	EC = -0. 372BCVH - 0.309
	BC-VV	0.705	2.61	0.636	3.29	EC = -0.425BCVV –0.724

$RMSE_1$, $RMSE_2$: root mean square error of calibration and validation in unit of EC; R^2_c,R^2_v: coefficient of determination; high significance at a P-value of 0.01 for the fit between estimated and observed values.

It was noted that the correlation between EC and BC from co-polarization (HH and VV) was higher than that from cross polarization (VH or VV). The coefficient of determination (R^2) is a significant indicator of the relationship that proves the capability of the regression model used to predict EC from BC. The model would be efficient with an R^2 near 1.0. However, in this study, the highest R^2 was 0.743 for dry season and 0.707 for wet season. These results are consistent with those of previous studies (Aly, 2004) that looked into the BC-EC relationship in salt-affected areas from RADASAT image data using a C band frequency and found an R^2= 0.83, however, the relationship was learned through semi-empirical backscattering models which suffer from the constraint of requiring a huge amount of parameters. Concerning the results of predicting EC from BC by regression model, it was found that the data obtained during dry season generated a better prediction of EC values than those during wet season, as BC values were slightly influenced by humidity in wet season which conformed with the theory of the relationship between BC and soil moisture values (Ulaby et al. 1976, Ulaby et al. 1978, Wang et al. 1986, Dobson et al. 1986, Rombach et al. 1997, Shi et al. 1997,Jackson et al. 2012). Although the coefficient of determination was not quite high, it is acceptable as a guideline in developing a statistical model for satellite data. By the way, this is the most comfortable way to get EC values without wasting time and resources by traveling to the real site. This development will be an effective tool for the most accurate result in the future.

3.2. Model validation

The equation derived from the calibration model to estimate EC from BC for each polarization was subjected to validation by the residual data that had not been utilized in the model calibration. The values of the measured EC from field research and the estimated EC from the equation were compared, using coefficient of determination and root mean square error. The coefficient of determination (R^2) between estimated EC from BC and measured EC from field and the root mean square error (RMSE) are show, in Table 2. BCHH showed the highest R^2at all polarizations for both seasons with a lower RMSE of 1.41 for dry season and 2.25 for wet season. For dry season, the highest coefficient of determination was achieved by BCHH (R^2 = 0.64). For wet season, the highest coefficient of determination was from BCHH (R^2 = 0.58) again. The results conformed with preceding researches (Taylor, 1996 and Shao, 2003) finding that the HH backscattering gives a better result in relationship values than VV scattering, resolved by the scattering properties of soil surface in microwave imagery. However, EC values predicted from BC by linear regression mean could only produce an R^2 value of 0.64 which was not quite high. It was also found that with EC lower than 4 ds/m, R^2 was at0.71, which was in a higher range than that of EC values of more than 4sd/m, with an R^2 of 0.32 (Figure 2). Concerning surface roughness of the study area, in the EC range from 0 to 4, roughness characteristics appeared more distinctive than in areas with EC values above 4, whereby the EC range of 0 to 4 included the classes of normal soil (0-2 dS/m) and slightly saline soil (EC>2 dS/m) which have clearly different surface roughness characteristics. This conformed with the finding that the relationship of salinity and the reflection of BC was influenced by surface roughness (Ulaby et al., 1986, Engman et al., 1995, Santanello et al., 2007).

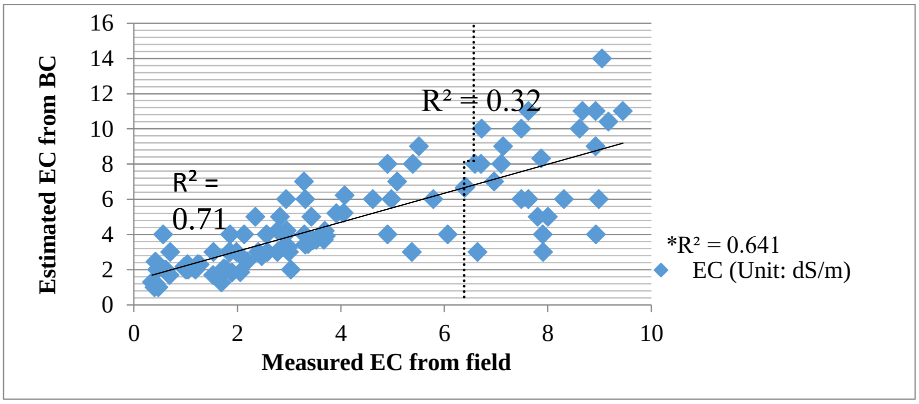

Figure 2. The R-square between estimated EC from BCHH and EC measured in the field. (*R^2: all EC data)

The accuracy of predicting models was significantly improved using higher R^2 and lower root mean square error (RMSE) values. RMSE was computed to check the reliability of the prediction. Date were divided into two datasets, a calibration dataset (N=150) and a validation dataset (N=100) for two seasons (wet and dry season. RSME values for predicting EC by regression model for the dry season were found to be lower than those for the wet season, yet they are only slightly unequal. R^2 and RMSE results are also only slightly different between the seasons, which indicate that the regression model equation with a single variable is well able to predict EC from BC for both seasons.

3.3. Relationship between EC and BC by polynomial model and logarithmic model

Normally, linear regression models are used to study the relationship of two variables. As a consequence of a low R-square value, the scatter plot does not improve by linear regression. This study used various model fittings to explore additional relationships in other dimensions such as logarithmic and 2ndto 6th order polynomial to investigate other aspects of the model. The R-Square value is also low compared to polynomial model techniques. Hence, using polynomial models in various orders yields a more satisfying result. The results of all model fittings are presented in Table 3. R-square values of polynomial models were higher than those of linear regression across all polarizations. In the higher orders from 2 to 6 of polynomial model fitting, R-square values were better. It can be concluded that predictions of non-linear models are more accurate.

3.4. Multiple regressions

Multiple regression analysis is a technique for predicting the relationships among variables. Here it was used to determine the relationship between EC and BC combining four polarizations (HH, HV, VH, and VV). Multiple regressions of data from dry season determined an R^2 of 0.889 with an estimated standard error of 1.09 while that of wet season data established an R^2 of 0.844 with an estimated standard error of 1.14.

The regression equations to predict EC from BC are: EC = -0.208(BCHH) - 0.145(BCHV) -0.026(BCVH) -0.109(BCVV) –2.194 for dry season, and EC = -0.218(BCHH) - 0.065(BCHV) -0.109(BCVH) -0.131(BCVV) – 2.279 for wet season. Combining all four variables of BC to determine their linear correlations with EC values increased the R^2 result, which indicates that employing BC to predict EC, all the four variables (BCHH, BCHV, BCVH, BCVV) should be included conjointly.

4. Conclusion

This study focused on the relationships between four BC polarizations and the EC of soil in saline areas. The main objective was to study the sufficiency of EC as derived from satellite data to predict EC values associated with soil salinity. A regression model was used to create an EC estimation model clarifying the variations of BC. EC measurement of soil surface samples (0-5 cm depth) is a common practice to define and assess soil salinity. BC from microwave data was also found to be a suitable indicator of soil salinity as this study revealed its significant relation with the observed EC. The highest coefficient of determination. R-square was 0.743 and root mean square error value was 1.04. The investigation via model fitting found that, with the polynomial exponent rising, R-square increases coherently in the polynomial model. The examination by multiple regressions produced an increased R-square value of 0.889.

In conclusion, by creating a relationship between two different data sources, satellite data and ground data, the statistical model could be developed to accurately estimate the value of EC soil salinity using BC from satellite. The advantage of this study was that the proposed evaluated statistic model can well give an accurate relationship between EC and BC, and it can be applied to estimate EC from other statistic models. In future studies, relational characteristics between these two data sources should be analysed by a non-linear model as this chapter of the study exposed that both sources of data inclined to have a more well-correlated relationship when applying a polynomial fitting model and the BC data should be considered in their combination, since multiple variables demonstrated more effective results than single variables.

Table 3. R-square models of logarithmic and polynomial orders 2 to 6

				Polynomial				
Fitting Model		Logarithmic	Linear	Order 2	Order 3	Order 4	Order 5	Order 6
Dry	BCHH	0.648	0.73	0.737	0.745	0.745	0.754	0.756
	BCHV	0.492	0.645	0.675	0.68	0.718	0.719	0.768
	BCVH	0.413	0.555	0.578	0.579	0.602	0.603	0.622
	BCVV	0.45	0.634	0.668	0.678	0.693	0.707	0.71
Wet	BCHH	0.477	0.614	0.618	0.629	0.629	0.637	0.642
	BCHV	0.352	0.506	0.525	0.539	0.554	0.555	0.594
	BCVH	0.311	0.457	0.500	0.501	0.543	0.544	0.593
	BCVV	0.431	0.591	0.608	0.634	0.658	0.675	0.675

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