Dynamic drift correction method for temperature-dependent measurement deviations in electromagnetic induction systems

Introduction

Electromagnetic induction (EMI) systems are commonly used to measure the bulk soil electrical conductivity (Rhoades and Corwin, 1981). This work is based on a frequency domain EMI system measuring the apparent electrical conductivity (ECa) of the soil by inducing a time-varying primary electromagnetic field into the ground using a transmitter. Since the subsurface is electrically conductive, the primary field produces eddy currents that lead to the generation of secondary electromagnetic fields. The superposition of the secondary and the primary electromagnetic fields is measured at a receiver, and the imaginary part of this superposed magnetic field is related to the ECa of the subsurface (McNeill, 1980).

In an agricultural context, the EMI method allows a fast non-contact measurement of the ECa of the soil, which is related to soil properties (Huang et al. 2016). EMI measurements have been used to characterize soil salinity, for instance Rhoades and Corwin (1984) found that a fast mapping of the soil could be done using EMI devices to investigate soil salinity profiles. In precision farming, Sudduth et al. (2001) used ECa measurements to determine the topsoil depth of soils using the EM38. Kachanoski et al. (1988) used the EM38 and EM31 devices to investigated the influence of soil water content on EMI data.

A limitation for using EMI systems in agricultural applications is that the accuracy is affected by time-varying external environmental factors, with temperature fluctuations being amongst the most dominant factors causing drift in EMI measurements. This makes it difficult to reproduce results and predict performances. A general procedure minimizing drifts in EMI systems is to perform a temperature drift calibration by heating the system up to particular temperatures in an enclosed environment. The ECa drifts at these given temperatures are recorded and used for static ECa drift correction. Here, a novel correction method is introduced that models the dynamic characteristics of drifts in EMI systems, using them for correction.

Theory and Method

This drift correction method is tested with a custom-made frequency domain EMI device (Mester et al. 2014), with an intercoil spacing of 1.2 m and equipped with ten temperature sensors simultaneously measuring the internal ambient temperature across the whole device. A simplified version of the measurement system is exemplary shown in Figure 1 for a one transmitter coil (Tx) and one receiver coil (Rx) arrangement. The Tx is energized with an alternating voltage U_0 from a generator (Gen). This produces an alternating excitation current I_E in the Tx, which is considered as a reference signal with initial phase difference zero. A current measurement circuit measures I_E by evaluating the voltage drop U_d across a shunt resistor serially connected to the Tx. I_E further generates a primary magnetic field H_1, which diffuses into the soil and induces eddy currents. These currents are generating a secondary magnetic field H_2, which is orthogonal in phase to H_1 at the location of the Rx. The measured magnetic field is a superposition of H_1 and H_2 and generates a voltage U_m, which is also measured at the Rx. U_m is amplified and together with U_d sent to the data acquisition unit (DAQ). Considering that H_1 is in phase with the reference signal I_E, the phase difference ΔPhi between H_1 and H_2 is computed at the output. The soil ECa can hence be described as (McNeill, 1980)

$$\mathrm{ECa} = \frac{4}{\omega \mu_0 s^2} * \Delta\mathrm{Phi} \quad (1)$$

where s is the intercoil spacing, ω is angular frequency and μ_0 is the conductivity of free space.

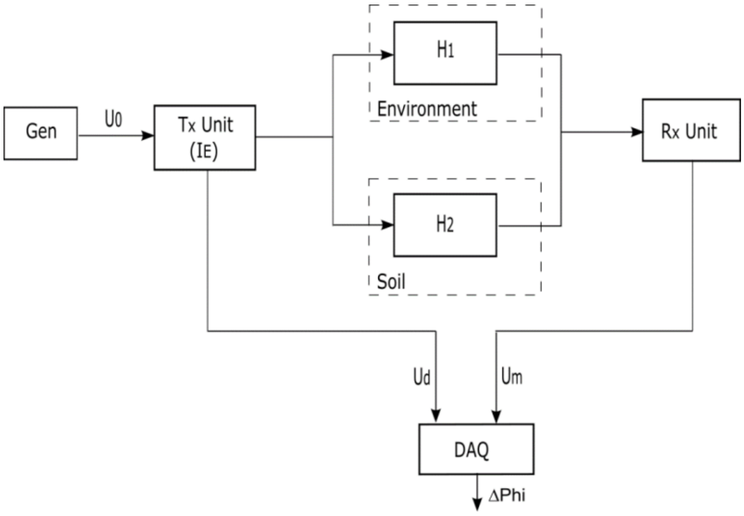

Figure 1 *Signal flow diagram for a custom-made EMI measurement system for a single Tx – Rx arrangement.*

The aim of this work is to develop a drift correction model that mitigates the effects of drifts in EMI data measured under uniform internal ambient temperature conditions. To determine typical ECa values in the range of 0 to 100 mS/m, very small phases must be measured. Despite optimization of the system hardware regarding low thermal drift, additional corrections are necessary for outdoor measurements with large temperature changes. In this approach, the temperature inside the system is measured and time-delayed by passing it through a drift model to match the reaction times of the internal electronic components. From the delayed temperature, the theoretical phase drift is calculated via a lookup table with spline interpolation and used to correct the measured phase. In this method, it is first assumed that a dominant source exists for the entire system drift and that the system as a whole heats up or cools down according to the ambient temperature. One challenge here is the selection of the appropriate temperature, which is measured with 10 sensors located at different locations. This requires investigating the various measured temperature data for uniform distribution and subsequently applying them to the model.

To minimize the effects of multi-collinearity in measured temperature data T_{meas}, principal component analysis (PCA) is applied. The calculation of the correlation coefficient is used as a filter to select the sensors that are similar to each other. Outlying sensors are excluded. Then the principal components are calculated to calibrate the measured data. The principal components obtained are orthogonal to each other, with the first component having the biggest correlation with the measured temperatures. The first principal component of temperature is thus evaluated and passed through the drift model.

Results

Data were acquired by performing outdoor calibration measurements, during which a broad range of ambient temperatures were recorded, with the device held at a height of 0.7 m above ground. First, let's take a closer look at the measured temperatures inside the system. The correlation between the ten temperature sensors is depicted in Figure 2. There is a strong correlation better than 0.997 between the respective sensors in groups 1, 3, 5, 7, 9 and 2, 6, 8. Both sensor groups are distributed over the entire length of the measurement system. This clearly indicates a uniform temperature distribution in the measurement device. In contrast, sensor 10 shows a poor correlation with the other sensors. This sensor is mounted on the ADC module and shows a different time series of temperatures due to its own heating. The PCA is used to calculate the first principal component from these sensor groups and applying it as input to the phase model.

The effect of ambient temperature on EMI systems is exemplary shown in Figure 3 where one PCA-calculated temperature signal of the second group (2, 6, 8) is compared to the measured phase signal.

This measured phase signal is caused by the system's ambient temperature drifts and the static phase offset of the system. It can be seen that the temperature signal reacts faster to ambient temperature changes than the measured phase of the measurement system components. It is therefore necessary to model this delayed reaction of the measurement system to ambient temperature variation using a low pass filter (LPF) to get an effective correction.

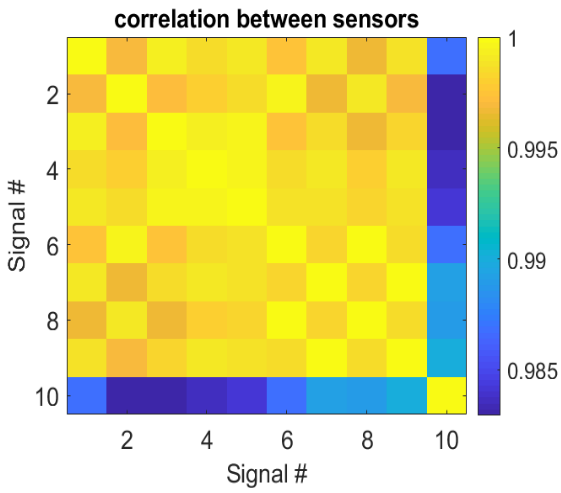

Figure 2 *Correlation between temperature sensors signals (columns and lines 1-10)*

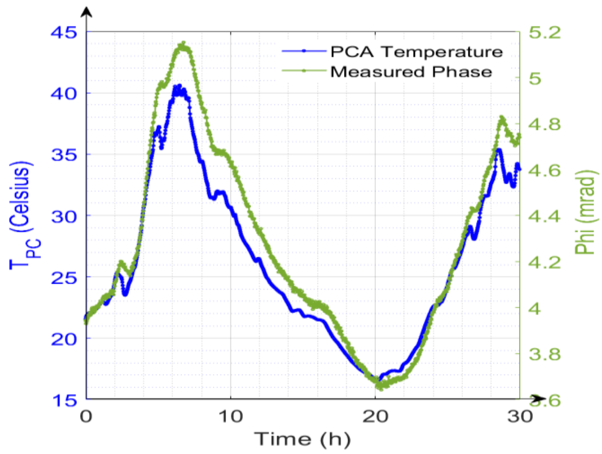

Figure 3 *Comparison of temperature signal with measured phase drift.*

Next the performance of data calibration using the full dynamic drift correction model is investigated as shown in Figure 4. In comparison to a perfect case (1:1 regression line), the synthetic ECa generated with the model matches the measured ECa to a very high degree. The time-delayed drift response of the system to the outdoor temperature changes is hence well modeled by the presented new approach.

It is possible to improve the accuracy of the drift correction by modeling the dynamic thermal characteristics by a factor of four compared to purely static correction methods. Without the additional model-based phase correction, an average temperature-dependent and phase drift of 0.064 mradK^{-1} and a translated ECa drift of about 2.26 mSm^{-1}K^{-1} would become effective for a temperature range of about 27 K. For comparison of the correction effect, the time series of the uncorrected and corrected ECa values is shown in Figure 5 with the arithmetic mean removed. For further evaluation, the correction method is currently being tested for measurements in the field at various locations.

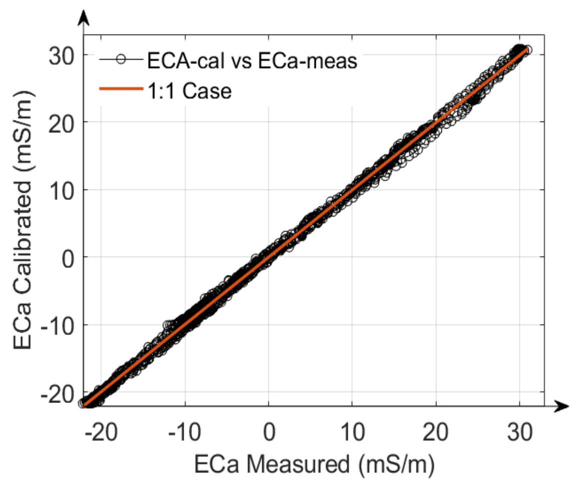

Figure 4 *Comparison of measured and modeled phase drift. The arithmetic mean has been removed from the diagram.*

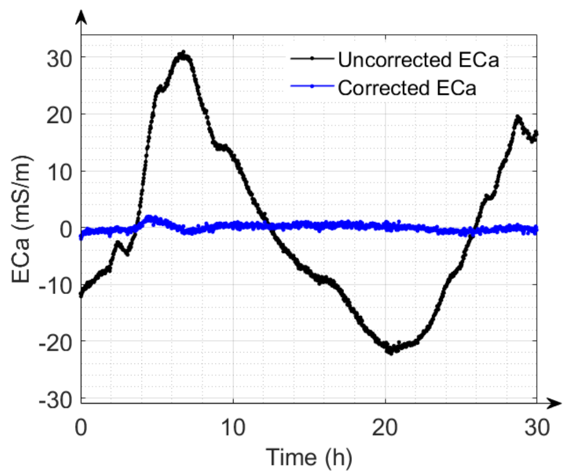

Figure 5 *Uncorrected and corrected ECa signals. The arithmetic mean has been removed from the diagram.*

Conclusions

These results show that our novel correction method based on the modeling of the dynamic thermal characteristics of electromagnetic induction (EMI) systems using multiple temperature sensors in combination with principal component analysis (PCA) and a low pass filter (LPF) is adequate and effective for the improvement of drift correction.

References

Badewa, E. et al. (2018) ‘Soil moisture mapping using multi-frequency and multi-coil electromagnetic induction sensors on managed podzols’, Agronomy, 8(10), pp. 1–16. doi: 10.3390/agronomy8100224.
Huang, J. et al. (2016) ‘Temperature-dependent hysteresis effects on EM induction instruments: An example of single-frequency multi-coil array instruments’, Elsevier Science B.V. Elsevier B.V., 132, pp. 76–85. doi: 10.1016/j.compag.2016.11.013.
Kachanoski, R. G., Gregorichi, E. G. and Wesenbeecki, I. J. (1988) ‘Estimating spatial variations of soil water content using noncontacting electromagnetic inductive methods’, Canadian Journal of Soil Science, 68, pp. 715–722.
McNeill, J. D. (1980) Electromagnetic terrain conductivity measurement at low induction numbers Technical Note TN-6. Ontario.
Mester, A. et al. (2014) ‘Development and drift-analysis of a modular electromagnetic induction system for shallow ground conductivity measurements’, Measurement Science and Technology, 25(5). doi: 10.1088/0957-0233/25/5/055801.
Rhoades, J. D. and Corwin, D. L. (1981) ‘Determining Soil Electrical Conductivity-Depth Relations Using an Inductive Electromagnetic Soil Conductivity Meter1’, Soil Science Society of America Journal, 45(2), p. 255. doi: 10.2136/sssaj1981.03615995004500020006x.