Observation of soil moisture dynamic at a landslide affected Alpine hillside using electromagnetic induction (EMI) and Kmeans clustering

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Abstract

We investigate the soil moisture dynamic at a Alpine hillside as a function of electric conductivity values by a nine-month EMI monitoring under different weather conditions. The results show a zoning of test field as indication of soil moisture pattern. A two layer system could be indentified; one upper dynamic and a deeper, more inactive layer. For an assignment of zones with significant differences in dynamics, we use the standard deviation and the topography as input for a Kmeans clustering. The clusters reflect zones of different dynamics. A comparison of the cluster results with a hydrotope map shows significant similarities.

Key words: soils moisture pattern, EMI monitoring, cluster partitioning, landslide

Introduction

Soil moisture and its spatial and temporal dynamic play without dispute a major role at landslides and for its corresponding forecast (Bogaard & Van Asch 2002, Talebi et al. 2007). Although several direct methods of soil moisture measurements were established in the last decades, reliable information of spatial moisture dynamic from medium and large scale areas are still difficult to obtain. A possibility to filling that gap is the mapping of soil moisture by means of geophysical properties, e.g. from the electric conductivity measured by electromagnetic induction (EMI) due to the (dependent) relationship between hydraulic and electric soil conditions (Dietrich 1999). EMI has been an established tool for subsurface characterization for several decades. However, the recorded electric conductivity (EC) is a sum parameter affected by numerous soil properties, like clay and mineral content, porosity, bulk density and moisture content; hence, an allocation to one of these qualities, in this case soil moisture, is difficult. Regarding the relative temporal stability of soil properties within a year, seasonal changes in moisture dynamic predominate the relative changes of measured EC signal. Due to this assumption, comparison of different EMI maps is a potential opportunity to exploit changes in soil moisture and to identify more hydrologically active locations (Abdu et al. 2008). Despite the fact that several studies attest a positive correlation of measured EC with precipitation events, a simple determination of water content from EC before and after the rainfall at areas with higher precipitation is difficult because of the lack of a “dry reference day”, in particular if the monitoring distance is larger then the appearing rain events. In addition, the resident time of the water within inhomogeneous, cohesive soils is difficult to asses and do not imperatively fit to the precipitation events. Thus, we use EMI to investigate the soil moisture pattern in general without quantitative interpretations.
We monitored the EC at a very inhomogeneous, landslide effected Alpine soil during a nine-moth monitoring under different weather conditions. In comparison to other studies, we investigate the temporal, horizontal and vertical behavior of moisture distribution by a nine-month monitoring of four different investigation depths. For an assignment of zones with significant differences in dynamic, we use the standard deviation (SD) in combination with topographical data (TD) data as input for a Kmeans clustering. The cluster partitions reflex zones of more and lesser dynamic for further investigation and management approaches. A

comparison of the cluster results with a hydrotope map from the same area shows significant similarities.
Focus of this study is the development of a method for investigation of soil moisture from larger sites with challenging accessibility to delineate areas with significant differences in moisture dynamic. In addition, the method is address for the optimization of location of further measurement / instrumentations.

Materials and Methods

Test site
The test site belongs to the Heumoeser slope a wetness triggered land slide area located 10km east of the city Dornbirn/north-eastern Austria and is characterized by highly variable relief and small-scale features like bulging and plane areas that may be attributed to soil creep. Soil in this area is very cohesive and has stagnic properties that indicate low infiltration capacities (Lindenmaier et al. 2005). Randomly distributed soil probes of depth of 1m attest a very high clay and silt content (approx. 80%). The test field expands an area of approx. 7 500m² with an altitude from 1050m to 1100m NN. In generally the altitude falls from W to E and the slope increases partly up to 26°.

EMI survey and database
For the EMI monitoring we used the devices EM38DD and EM31 (Geonics Limited, Canada) in horizontal and vertical dipole coil configurations. Thereby we obtained the following integral values related to pseudo depths (PD) of 0.75 m - EM38 horizontal (EM38h), 1.5 m - EM38vertical mode (EM38v), 3 m - EM31vertical mode (EM31h) and 6 m - EM31vertical mode (EM31v). The PD means two-thirds of the response signal originates from the soil above – see details in McNeil 1980. Both EMI units were connected with a DGPS system and were used manually. The track distance was approx. 5m and the recording frequency was 5Hz for both instruments. The survey took place between March and October 2010.
To compare the different data ranges of the maps, we working with normalized relative data. Therefore, we first filtered the raw data with approx. 5 – 95 % from whole range in order to avoid an overweighting of values in the subsequently normalized data sets. Then we interpolated all data by means of variogram analyses and block Kriging to obtain a separate EC map for each measuring day and investigation depth. Subsequently, we normalize all EC values to a comparable data range with 0.00 as the smallest value to 1 as the biggest value. This maintained the relation in data range and allowed the visualization with identical scaling as well as further calculating.

Cluster analysis
A cluster analysis groups data according to their similarities and reduce the data to its significant characteristics. In this study we use the partitioning clustering of Kmeans (MacQueen, 1967): It partitions n observations into k clusters. We cluster with Euclidean distance as the common distance function capable for multi-dimensional data sets. In this study we use for the definition of suitable cluster numbers the elbow criterion (Dietrich & Tronicke 2009) and the software SYSTAT 12 (Systat Inc. 2007). As input variables we use the SD and the TD only.

Data analysis
For each of the four investigation depths we use the arithmetic mean from the (dimensionless) values to visualize the geological structure without the dynamic signal (fig 1). Then we subtract the mean EC from the day value to highlight the seasonal changes (SC) Furthermore, we calculate the standard deviation (SD) from each investigation depth.

Results and Discussion

EMI results

The mean values of EC in Fig 1 show clear patterns of areas with higher and lower conductivity. In general, the eastern area is more conductive in all maps, particularly in the upper and the CE decreases with depth. Regarding the structure of the EC distribution, a two-layer system could be detected with different orientations: one upper with E-W orientated pattern and one deeper with S-N oriented pattern represented by the uppermost signal (Em38h) and the lowest signal (Em31v). The different investigation depth reflects the contrast of the layers. By the assumption the structure of the mean values may reflect the geological situation, the higher conducted areas feature presumably regions with thicker local glacial till or clay layers. Comparing the EC data with the topographical information a relation of altitude and the uppermost map are obvious.

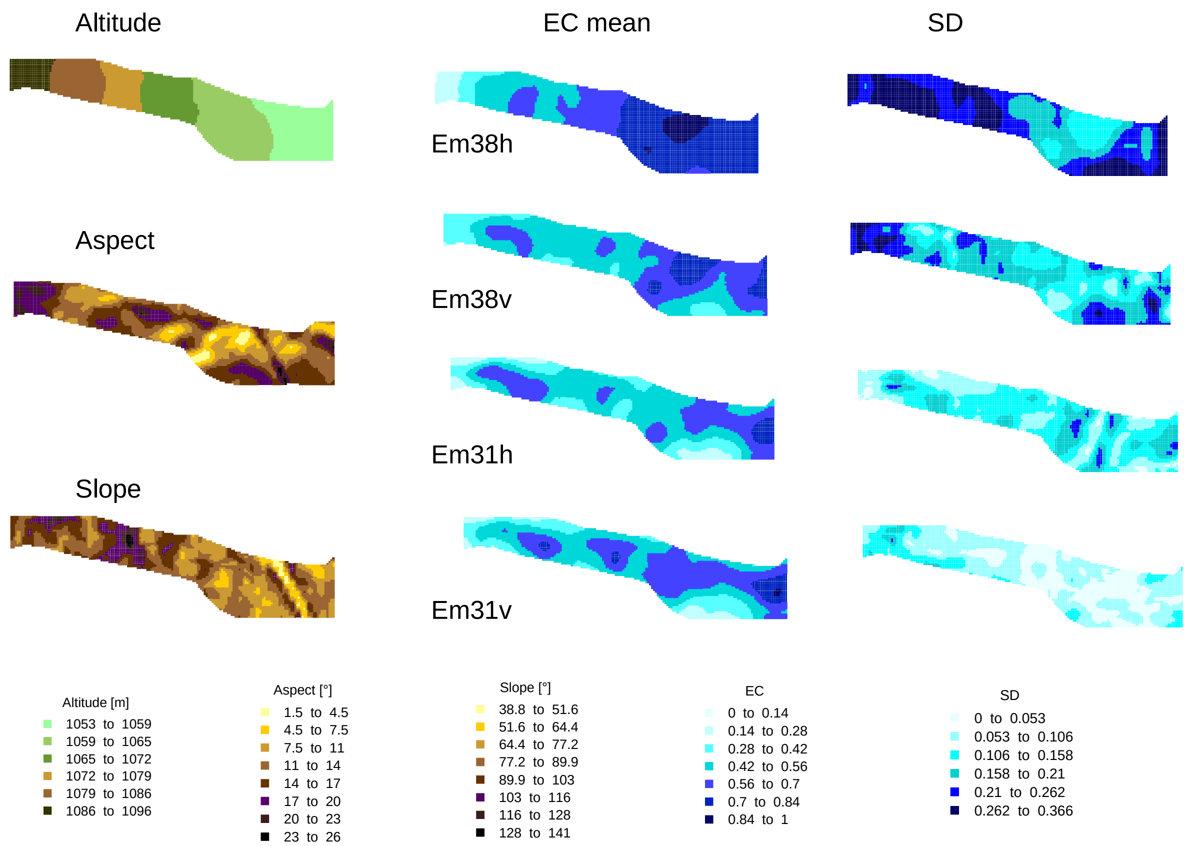
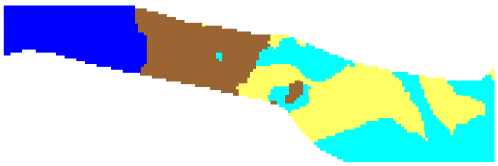


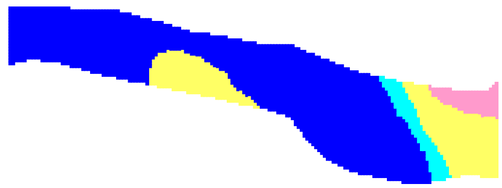
Figure 1 Topographical maps mean EMI results and standard deviations for the different pseudo depths

This gives reason to the assumption that the altitude controls the upper layer's moisture dynamic. To delineate dynamic areas, we use the standard deviation (SD) from all surveys over the complete monitoring period. The SD of maps is an appropriated indicator for moisture dynamic. Similar to the EC mean, the division in an upper and lower layer is identifiable with clear decreasing of dynamic with depth. Interesting is some higher dynamic areas in the upper layer corresponds with special lower areas in the lower maps, e.g. in the SE of the site.

Cluster results

The cluster result leads to four partitions, which reflects the significant characteristics of the input data SD and TD (figure 2 A). Although the test site is in generally subdivided by an E-W orientation, the eastern part also depicts the “line” (originates from an alley) as well as the dynamic zone in the SE. Despite distinct differences resemble the structure in the cluster map the hydrotope map in Fig.2 B. This map reflexes the hydrological conditions of the hill slope and was resulted from combining available vegetation, topography, slope, and geological data after Lindenmaier et al. 2005. Both maps are independent subdivided into four partitions with an E-W orientation, as well as a separate part in the middle. A possible reason for the differences can be the individual allocation of vegetation during the hydrotop mapping and the different investigation depths.





A **B**

Fig 2 Cluster result map (A) and hydrotope map (B), each color represents different cluster and different hydrotope respectively (four groups each)

Conclusion

We derived the soil moisture dynamic from temporal and spatial EC maps. The separation of the dynamic moisture signals from the geological stationary background by subtraction of the temporal values from the mean values leads to a delineation of relative changes from each investigation depth. A two-layer system could be identified, one upper more dynamic layer (PD 1,50m) and a deeper, more inactive layer (PD 6m) with a different structure.

The cluster partitions separate areas with significant differences in soil moisture dynamic. Regarding the cluster result map, the used methods seem adequate for delineation of areas with different hydrological properties at larger test sites with challenging accessibility.

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