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Estimating the spatial distribution of soil moisture based on Bayesian maximum entropy method with auxiliary data from remote sensing

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ABSTRACT

Soil moisture (SM) plays a fundamental role in the land–atmosphere exchange process. Spatial estimation based on multi in situ (network) data is a critical way to understand the spatial structure and variation of land surface soil moisture. Theoretically, integrating densely sampled auxiliary data spatially correlated with soil moisture into the procedure of spatial estimation can improve its accuracy. In this study, we present a novel approach to estimate the spatial pattern of soil moisture by using the BME method based on wireless sensor network data and auxiliary information from ASTER (Terra) land surface temperature measurements. For comparison, three traditional geostatistic methods were also applied: ordinary kriging (OK), which used the wireless sensor network data only, regression kriging (RK) and ordinary co-kriging (Co-OK) which both integrated the ASTER land surface temperature as a covariate. In Co-OK, LST was linearly contained in the estimator, in RK, estimator is expressed as the sum of the regression estimate and the kriged estimate of the spatially correlated residual, but in BME, the ASTER land surface temperature was first retrieved as soil moisture based on the linear regression, then, the t-distributed prediction interval (PI) of soil moisture was estimated and used as soft data in probability form. The results indicate that all three methods provide reasonable estimations. Co-OK, RK and BME can provide a more accurate spatial estimation by integrating the auxiliary information Compared to OK. RK and BME shows more obvious improvement compared to Co-OK, and even BME can perform slightly better than RK. The inherent issue of spatial estimation (overestimation in the range of low values and underestimation in the range of high values) can also be further improved in both RK and BME. We can conclude that integrating auxiliary data into spatial estimation can indeed improve the accuracy, BME and RK take better advantage of the auxiliary information compared to Co-OK, and BME outperforms RK by integrating the auxiliary data in a probability form.

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Introduction

Soil moisture (SM) plays a fundamental role in the land–atmosphere exchange process because it controls both evaporation from bare soil and transpiration from vegetated areas. Many scientific studies and applications require global, continental or regional soil moisture data to represent the initial state for the soil moisture variables, just like forecasts of weather variations, models of plant growth and carbon flux and models of land surface hydrological processes etc. A number of studies have been conducted to obtain soil moisture estimates from various observations and models (Vereecken et al., 2008; Wang and Qu, 2009; Guswa et al., 2002), but more often, the large spatial–temporal variation results in very uncertain estimation. Obtaining accurate soil wetness information by remote sensing techniques has great potential and is the focus of ongoing research, especially after the operation of the Soil Moisture and Ocean Salinity (SMOS) (Kerr et al., 2010), Aquarius (Le Vine et al., 2010), and the launch of Soil Moisture Active Passive (SMAP) in future (Entekhabi et al., 2010). Monitoring land surface soil moisture by ground-based techniques can also be valuable, for drought monitoring, precision agriculture, and especially for the validation of remote sensing soil moisture

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products (Jackson et al., 2009, 2011). With the development of wireless communication techniques, the wireless sensor network (WSN) has been increasingly used in eco-hydrological monitoring (Akyildiz et al., 2002; Ruiz-Garcia et al., 2009). This technology makes it possible to take simultaneous measurements of regional soil moisture, unlike conventional ground-based methods (Bogena et al., 2010).

Soil moisture information from WSN can be regarded as a multi-point simultaneous survey. To understand the spatial distribution and variation of soil moisture or to compare it to remote sensing products, we need to estimate the soil moisture distribution map or up-scale to a certain scale. Traditional geostatistics, such as kriging, is a powerful interpolation tool that quantifies and reduces the uncertainties of estimation and minimizes investigation costs, and has been used to provide linear unbiased predictions at unsampled locations for over four decades (Burgess and Webster, 1980; Cressie, 1990). The estimation accuracy of the kriging method is usually limited by the density and distribution of sample sites. Theoretically, if additional covariates which are spatially correlated with soil moisture and more easily or intensively sampled are integrated into the estimator, the estimation accuracy may be improved. Spatial estimation methods (such as co-kriging, regression kriging, and universal kriging, et al.) that account for covariates could play an important role here. These methods could conceivably result in a considerable reduction of costs while achieving a comparable degree of accuracy by using fewer relatively expensive variables and more relatively inexpensive covariates (Stein et al., 1988; Stein and Corsten, 1991; Zhang et al., 1992, 1997; Wu et al., 2003), especially in the under-sampled cases (Yates and Warrick, 1987). Universal kriging and regression kriging differ in the computational steps, however, the resulting predictions and prediction variances are the same. Co-kriging (Co-OK) is mainly developed for situations in which the auxiliary information is not spatially exhaustive (Knotters et al., 1995), in cases where the covariates are available as maps, regression kriging (RK) will generally be preferred over Co-OK, although Co-OK may in some circumstances give superior results (Asli and Marcotte, 1995; Goovaerts, 1999; Rivero et al., 2007; Moral, 2010; Hernández-Stefanoni et al., 2011). Studies have also demonstrated that Co-OK is only minimally superior to ordinary kriging when the auxiliary variables are not highly correlated with object variables (Asli and Marcotte, 1995; Triantafilis et al., 2001; Wu et al., 2009), and in some cases, the covariates were of little significance for prediction due to underweighting (the weights of covariates sum to zero and are often of small magnitude) (Goovaerts, 1998). Thus, different methods that may fit certain situations better. New methods are needed in spatial estimation of soil moisture which can incorporate auxiliary data of different origin and reliability in a systematic and rigorous way.

Bayesian maximum entropy (BME) (Christakos, 1990a, 1990b, 1991, 2000), which belongs to the field of modern spatiotemporal geostatistics, provides a systematic and rigorous approach for integrating physical knowledge into spatiotemporal analysis, including statistical moments of any order, physical laws, scientific theories, empirical relationships, and uncertain observations (Christakos and Serre, 2000; Christakos et al., 2001). As a significant generalization of commonly used geostatistical techniques, it does not make the Gaussian distribution hypothesis, and it can estimate variables by non-linear prediction (Christakos, 1990a; Christakos and Li, 1998). In the two decades since its initial proposal, BME has been successfully used in many research fields. In the field of environment and public health, the PM10 distribution in the state of North Carolina was studied by using the Bayesian maximum entropy (BME) mapping method (Christakos and Serre, 2000). Another study focused on the spatiotemporal distribution of ozone (Yu et al., 2009; Bogaert et al., 2009). BME can readily consider uncertain yet valuable information at the estimation points. Additionally, in the framework of BME, good estimates of childhood asthma prevalence at fine spatial resolution were obtained by nonlinear integration of prevalence data aggregated over large areas and the data obtained at the fine scale of interest (Lee, 2005; Lee et al., 2009). In the field of soil science, D'Or et al. (2001) and D'Or (2003) investigated the use of BME for estimating soil textural fractions in space by integrating a small hard data set with a larger soft data set. The results show that BME is more accurate than simple kriging estimates, thus offing a better picture of the soil reality. Similarly, in Bogaert and D'Or (2002), the thematic maps and the data from laboratory analysis were incorporated into BME to obtain a more accurate estimation map of soil texture. BME illustrates the advantages of using soft information on a sound theoretical basis. Additionally, as one of the spatiotemporal knowledge synthesis and mapping methods, BME has been successfully applied in the data fusing field for the fusing of observations and model predictions (Christakos et al., 2004; Nazelle et al., 2010) or multi-sensors data (Li et al., 2012, 2013a,b). Only a fraction of the possible applications are listed above, but this list still shows that BME performs wonderfully in the field of spatial (or spatiotemporal) estimation, especially for the fusing of uncertain auxiliary information. BME has also been shown to be more accurate and physically meaningful than classical geostatistics (e.g., Christakos and Li, 1998; Serre and Christakos, 1999; Douaik et al., 2004; Pang et al., 2010). In this study, we attempt to introduce BME as a spatial estimator of soil moisture.

In the ground ecosystem, both land surface soil moisture and land surface temperature (LST) vary spatially due to soil type, land cover, and land use, and they vary temporally with the time of day and the season of the year. Studies show that the LST maximum during moist conditions occurs later in the day than during dry conditions, and land surface soil moisture and LST have been found to be negatively correlated (Lakshmi et al., 2000; Sun and Pinker, 2004), which indicates that valuable information about the spatial distribution of soil moisture can be obtained from the LST. The purpose of this study is to present a novel approach to estimate the spatial pattern of soil moisture by using BME method based on wireless sensor network data and the auxiliary information from ASTER (Terra) LST. For comparison, traditional geostatistic methods were also applied: ordinary kriging (OK), co-kriging (Co-OK) and regression kriging (RK).

Materials and methods

Study area and soil moisture wireless sensor network

The experimental area involved in this study (Fig. 1) was located in the Zhangye artificial oasis in the middle reaches of the Heihe River Basin (HRB) in northwestern China (38.871° N, 100.359° E). As a typical inland river basin characterized by distinct cold and arid landscapes distributed upstream to downstream, the HRB has long served as a test bed for integrated watershed studies and hydrological experiments (Cheng, 2009). Comprehensive experiments such as HEIFE (Hu et al., 1994) and WATER (Li et al., 2009) have taken place in the HRB, and HiWATER (Li et al., 2013a,b) is still in progress. The soil moisture wireless sensor network (WATERNET) shown in Fig. 1 was part of the first thematic experiment of HiWATER, which is referred to as Multi-Scale Observation Experiment on Evapotranspiration over heterogeneous land surfaces 2012 (MUSOEXE-12). The experiment included two nested matrixes: one large experimental area (composed of oasis and desert) covering an area of 30 km × 30 km and one kernel experimental area (completely in the oasis) covering 5.5 km × 5.5 km. WATERNET was located in the kernel experimental area, and the observations lasted from May 2012 to September 2012. The

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