Uncertainty in the estimation of drought risk due to soil-climate interactions in Scotland

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Abstract— **The impact of climate change on ecosystems is a global issue. As a result of the interaction between decreasing precipitation during the growth period and soil properties, the water available for plants and crops may become a limitation factor for crops or certain forest species in some areas in Scotland. The aim of this study was to estimate the uncertainty of a model predicting drought risk in the Dee catchment in the North East of Scotland. The model focuses on the fundamental interactions between soil and climate, which are the critical drivers for determining the available water capacity. Soil available water capacity was calculated, using pedotransfer functions, with data derived from the Scottish Soil Survey Database at ca. 100 profiles. We used a variation of regression kriging to interpolate the data. The preliminary results showed that the uncertainty related to soil modelling is higher in areas with rougher morphology and complex hydrology. A Bayesian framework for uncertainty integration of soil and climate interactions is briefly presented. The evaluated overall uncertainty is useful to underpin informed policy decisions, via risk assessment.**

***Keywords:** Gaussian simulations, spatial uncertainty, geostatistics, stochastic modelling, General Additive Model*

I. INTRODUCTION

The impact of climate change on ecosystems is a global issue. Floods as a result of more extreme precipitation events, drought stress and extended drought periods are possible consequences. As a result of the interaction between decreasing precipitation during the growth period and soil properties, the water available for plants and crops may become a limitation factor for crops or certain forest species in some areas in Scotland.

The water content of soil has a major role in many environmental and hydrological processes (Western et al., 2004), such as infiltration and runoff (Bàrdossy and Lehmann, 1998; Herbst et al., 2006), soil erosion and flooding (Fitzjohn et al., 1998; Nunes et al., 2009; Wang et al., 2001). It plays an important part in pedogenic and geomorphological processes (Beven and Kirkby, 1993) and it has a considerable imapct on land capability and management of land uses (Gimona et al., 2009).

The spatial variability of the soil water content and of its available fraction is important for planning and risk mitigation purposes. AWC can be measured or derived from other soil properties at sampled sites. In order to obtain values at unsampled locations spatial models such as geostatistical techniques (Goovaerts, 1997) need to be used. To avoid misinterpretation, it is important to quantify the uncertainty of the predictions obtained with these techniques. Information on uncertainty should then be used in decision-making processes such as the identification of areas at risk of drought or erosion or flooding, which may need land management and conservation practices (Delbari et al., 2009).

The aims of this study were to i) devise a framework to integrate the uncertainty of soil-climate interactions and to ii) estimate the uncertainty of a model predicting drought risk in the Dee catchment in the North East of Scotland.

A. Test Area

The test area is the catchment of the River Dee (about 2100 km^2) in the North East of Scotland (Fig.1) with a wide range of different morphological features, soils and bioclimatic zones. The elevation ranges from see level to the mountain area with a maximum value of 1304 m.

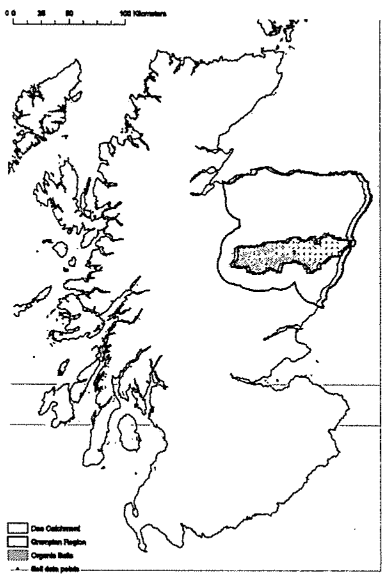

Figure 1. Test area.

II. AWC ESTIMATION

Soil available water capacity was calculated, using pedotransfer functions (Bibby et al., 1982), with data derived from the Scottish Soil Survey Database at about 100 profiles. A variation of regression kriging was used to interpolate the data. AWC values were first interpolated using a General Additive Model (GAM) with geomorphological features as covariates. Elevation, slope, flow accumulation and various landforms were used. The prediction matrix of the GAM model was used to obtain multiple realisations of the trend of the AWC surface. Multiple realisations of the residuals of each of the GAM-based realisation were obtained with:

1. Geostatistical Gaussian Simulations (GS; Goovaerts, 1997). They were used to obtain multiple (100) realisations of the surface residuals given each realisation of the trend. Further details on this procedure are provided in Poggio et al. (in review).

2. Bayesian kriging (BK; Diggle and Ribeiro, 2002). Bayesian analysis of geostatistical data allows the specifications of different levels of uncertainty in the model, i.e. variogram, parameters providing results on the posterior distributions for the model parameters.

Finally, for each realisation, trend and residuals were summed to obtain the AWC surface:

$$AWC_i = T_i + SR_i \qquad (1)$$

where T is the predicted value for the trend realisation, SR the Gaussian simulated residuals realisations and i in 1:100 is the number of the simulations (Gaussian or from Bayesian kriging) of the residuals.

The variability of the AWC (ΔAWC) was calculated as the difference between the 95 and the 5 percentiles.

A. *Results of AWC Interpolation*

Fig.2a and Fig.2b present respectively the median values for AWC and its variability (ΔAWC). The trend of median values follows the morphology of the area with higher values in the river valley and lower values in the hills where soils are thinner. The ΔAWC is very scattered and it is difficult to distinguish a trend.

Fig.2c presents the median values of AWC calculated using the BK method. The morphological trend is more evident with rather defined river valley. Fig.2d is similar to the ΔAWC calculated for GS (fig. 2b). The pixels values are slightly different, while the scattered spatial pattern is very similar.

In the conventional geostatistical approaches for interpolation, i.e. kriging, the covariance structure is estimated first, and then the estimated covariance is used for interpolation. The properties of the interpolants based on an estimated covariance structure are not well understood, and it is common practice to ignore the effect of the uncertainty in the covariance structure on subsequent predictions. The procedure proposed using GAM: 1. took into account the trend typical of geomorphic variables; 2. quantified the uncertainty of the trend; 3. considered continuous and categorical variables; 4. dealt with

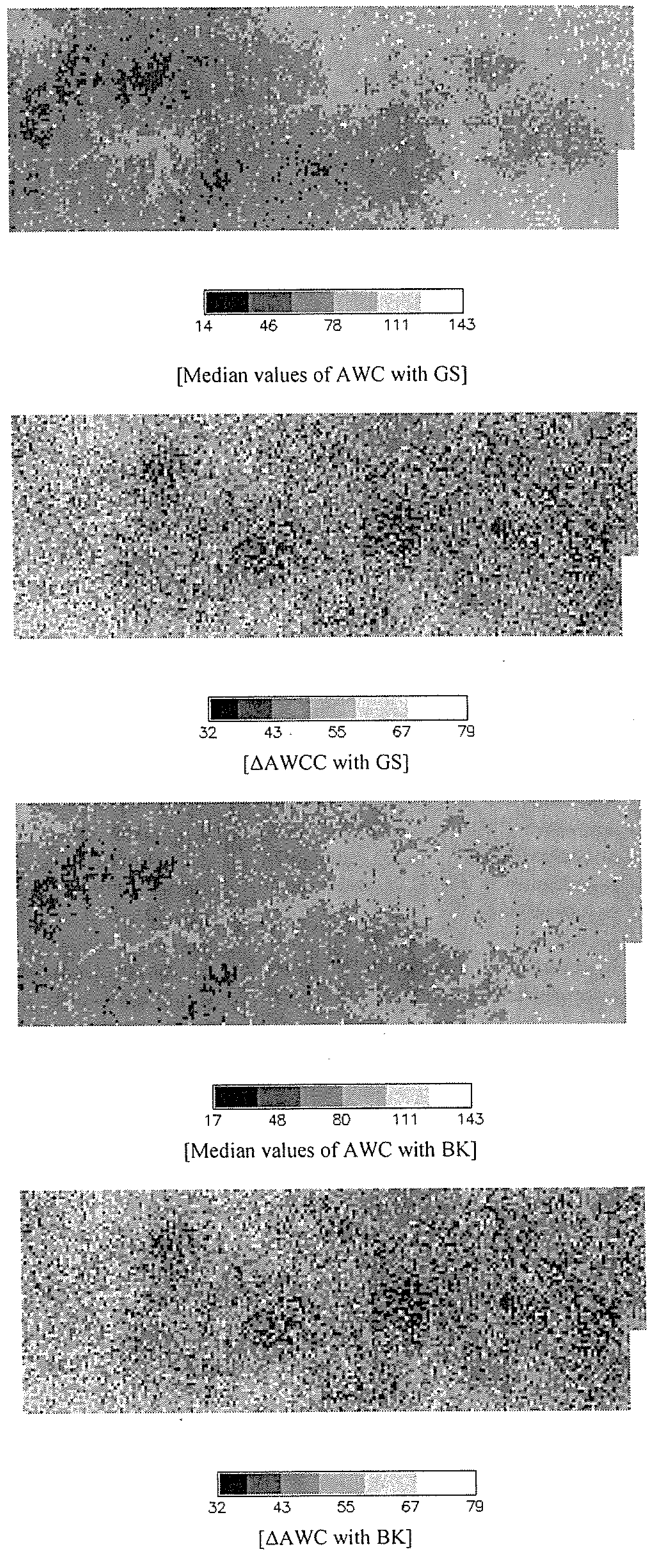

Figure 2. AWC and its variability in the Dee side (Scotland).

linear and non-linear relationships; 5. provided an assessment of the spatial uncertainty. A Bayesian approach to interpolation of spatial processes will provide also a general methodology for taking into account the uncertainty about parameters on subsequent predictions. The Bayesian approach leads to the same answers as the standard kriging predictor when the model parameters are known, but it also extends to the case where these parameters are unknown (Bivand et al., 2008).

III. Drought Risk

Agricultural drought risk can be quantified considering three factors: climate, soil water content and plant water requirements. Generally the methodology to define drought risk classes compares the available soil water reserves against the accumulated soil moisture deficit during the growing season, e.g. the method described in Thomasson (1979) and used operationally in the UK, Germany and Denmark. The drought risk assessment is repeated for a range of indicator crops, modified based upon growth period and rooting depth, influencing available soil water and loss of that water due to evapotranspiration.

A. Maximum Potential Soil Moisture Deficit estimation

The soil moisture deficit is based on potential evapotranspiration (PET) models and it can be estimated using both baseline (present) and predicted (future) climate data. The baseline period can be defined using variables (precipitation, PET, accumulated temperature) derived from a UK Met Office monthly climatology interpolated from station data onto a 5km grid (Perry and Hollis, 2005). Future changes in the same climate variables can be derived from the difference between the 2050s period (2046-2065) and the baseline (1981-2000) using data extracted from the HadRM3 climate mode (Murphy et al., 2004) on a 25km grid. The future change data can be downscaled onto the 5km observed climatology grid using the Δ change method, which projects then adds the 25km change factor onto the 5km grid. As the climate model provided data on open-water evaporation derived from the original Penman (1948) formula, other model parameters defined an adjustment factor to transform this into PET data based upon a reference surface of grass consistent with FAO convention (Allen et al., 1994) and standard LCA requirements. Derivation of evaporation data direct from the climate model rather than indirectly by a combination of other model outputs as has occurred previously has distinct potential advantages in terms of consistency and reliability, although comparisons of the two methods have shown similar results (Bell et al., 2006).

However, the uncertainty due to all the steps detailed remains to be fully estimated and used in further modeling. Fig.3 proposes a framework to take into account the uncertainty of both soil and climate compartments and its propagation in the assessment of drought risk. This approach is now being applied to data from the UK Climate Projections (UKCP09; Murphy et al., 2004) to evaluate future changes in drought risk compared to present, including spatial uncertainty.

IV. Preliminary Conclusions

The soil water content is an important factor to be considered in land use management. The interactions between soil water content and climate changes is a key issue to estimate the risk of soil drought and thus of desertification or changes in agricultural productivity. The assessment of the uncertainty associated to spatial distribution of environmental variables is a key issue in environmental modeling.

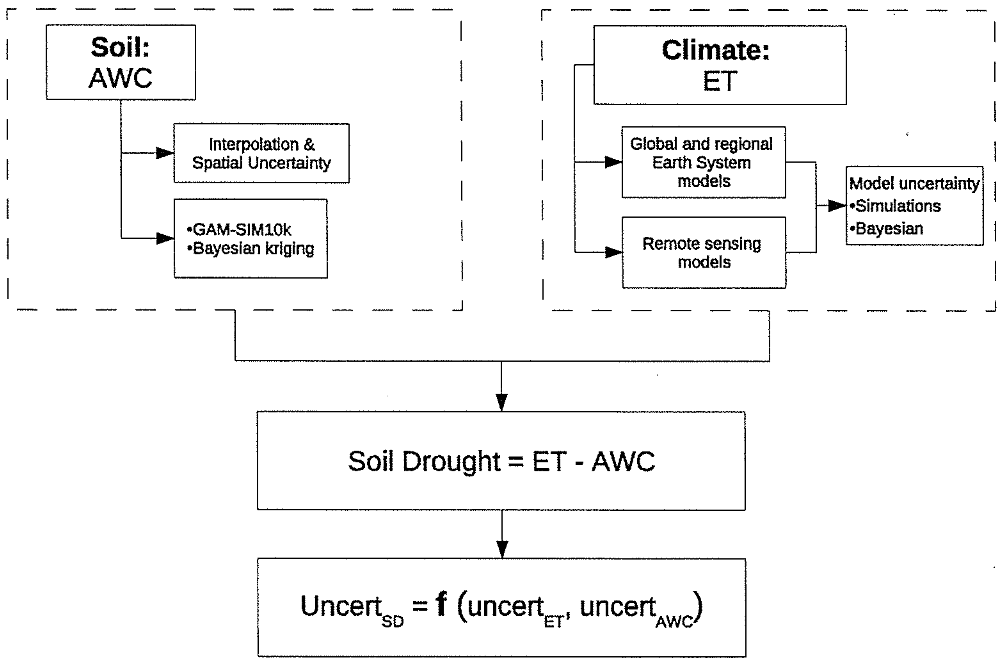

Figure 3. Toward the development of a Bayesian framework for uncertainty integration of soil & climate interactions.

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