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Effects of measurement uncertainties of meteorological data on estimates of site water balance components

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SUMMARY

Numerical water balance models are widely used in ecological and hydro sciences. However, their application is related to specific problems and uncertainties. The reliability of model prediction depends on (i) model concept, (ii) parameters, (iii) uncertainty of input data, and (iv) uncertainty of reference data. How model concept (i) and parameters (ii) effect the model's performance is an often treated problem. However, the effects of (iii) and (iv) are typically ignored or only barely treated in context of regionalisation and generalisation. In this study, the actual measurement uncertainties of input and reference data are the main focus. Furthermore, the evaluation of model results is analysed with regard to uncertainties of reference data. A special feature is the use of evapotranspiration (measured via the eddy covariance) instead of runoff for evaluation of simulation results. It is shown that seemingly small uncertainties of measurements can create significant uncertainties in simulation results depending on the temporal scale of investigation. As an example, the uncertainty of measurements of daily global radiation sum up to an uncertainty of 250 MJ (equivalent to 100 mm) on an annual scale, which causes an uncertainty of 40 mm in simulated grass-reverence evapotranspiration. Summarised and generalised, the measurement uncertainties of all input data create an uncertainty on average of around 5% in the simulated annual evapotranspiration and of around 10% in the simulated annual seepage. However, the effects can be significantly higher in years with extreme events and can reach up to 15%. It is demonstrated that uncertainties of individual variables are not simply superposed but interact in a complex way. Thereby, it has become apparent that the effects of measurement uncertainties on model results are similar for complex and for simple models.

1. Introduction

The quantification of the water balance and its individual components is a necessary precondition for successful and sustainable water resources management, farming and forestry (Wisser et al., 2010; Xu and Singh, 2004; Peel and Blöschl, 2011). Typically, the water balance or individual components of water balance are estimated using numerical models (Xiong and Guo, 1999; Boughton, 2005; Schwärzel et al., 2009a). The models are very different in terms of concept, structure and complexity as various reviews have shown (e.g., Dooge, 1986; Beven, 1989; Xu and Singh, 1998; Xiong and Guo, 1999; Xu and Singh, 2004; Boughton, 2005; Liu and Gupta, 2007). Very complex models address all relevant processes (e.g., interception, transpiration, snowmelt and soil water movement) by physically based approaches. But there are also much simpler models which are driven by conceptual approaches or empirically derived relations.

All models are abstractions, simplifications and interpretations of reality (Refsgaard et al., 2006). Therefore derivations are inevitable between observations and simulations (Gupta et al., 2006; Wagener and Gupta, 2005; Kuczera et al., 2010). Following Renard et al. (2010), Butts et al. (2004) and Oudin et al. (2006), four sources for discrepancies and hence for inherent uncertainties of simulated water balance components can be identified.

1.1. Model uncertainty

Depending on scientific question and spatial and temporal scale of study, specific simplifications of model structure are absolutely essential. However, the algorithms and internal structures must be able to describe all relevant processes (and so the system) suffi-

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ciently (Wagener et al., 2001; Beven, 2006; Refsgaard et al., 2006; Kavetski et al., 2011). Thus a model never reflects or accounts all hydrological processes (Butts et al., 2004; Kuczera et al., 2010; Andréassian et al., 2010). This uncertainty is called model uncertainty.

1.2. Parameter uncertainty

Parameters are necessary numerical information to adapt a model to a specific application (Yang, 2011). The 'parameter uncertainty' reflects our limitation to specify exact values for these parameters (Renard et al., 2010). The main reasons are due to temporal dynamics of parameter values and limitations of parameter estimation (Yang et al., 2007; Reusser et al., 2011). The last point is correlated with the fact that a lot of parameters can't be measured objectively and must be determined inversely by calibration (Gupta et al., 2006; Kavetski et al., 2006; Pappenberger et al., 2006; Wagener and Wheater, 2006). But even measurable parameters are not certain as their accuracy and representativeness is limited due to scale dependence and measurement uncertainties (Bergström and Graham, 1998; Blöschl, 2001; Beven, 2006). It is necessary to know how much information is needed to get reliable simulation results (Wagener et al., 2001; Sieber and Uhlenbrook, 2005). This question includes also which information is important and which is dispensable. Thus the analysis of parameter uncertainty is closely connected with analysis of parameter sensitivity (Reusser et al., 2011; Nossent et al., 2011).

1.3. Input uncertainty

Every measurement is related to specific tolerances. So any measured value deviates somewhat from the actual value (Taylor, 1997). The questions arise, how do uncertainties of meteorological input data (model drivers), e.g. precipitation P, affect the simulation results and do the individual uncertainties amplify or compensate each other? The term 'input uncertainty' includes both 'actual measurement uncertainties' (sampling errors) as well as uncertainties regarding to regionalisation and generalisation of measured values to derive at area or catchment estimates (Renard et al., 2010).

1.4. Reference uncertainty

This point is directly related to the former point. If input data are uncertain, the data being used for verification of simulation results - the reference data as observed streamflow or (as in this study) measured evapotranspiration - include similar uncertainties. Here it is important to know how uncertainties of these data influence the evaluation of simulation results. Reference uncertainties are caused (similar to input uncertainties) by (a) limitations of measurability and (b) limitations of representativeness. A classical example for (b) is the representativeness of measured streamflow in catchments where the groundwater flow is significant share of total runoff.

Andréassian et al. (2001), Stisen et al. (2011) and Yang (2011) emphasise effects of moderate input uncertainties are often compensated by model calibration. The same can be assumed for reference uncertainties. In that way, uncertainties due to (iii) and (iv) do not only affect the prediction accuracy but also the parameter identification (Andréassian et al., 2001; Refsgaard et al., 2006; Vrugt et al., 2008; Kuczera et al., 2010; Looper et al., 2012). This should be considered if models and parameters are to be improved (Kavetski et al., 2006; Oudin et al., 2006; Stisen et al., 2011). All methods of parameter optimisation or all structural improvements of model concept are non-effective if the background noise due to input and reference uncertainties are unknown. This point is particular important for the practical application of models. So ignoring background noise due to measurement uncertainties can lead to serious misinterpretations and bad resource management if the simulation results form the basis of decision making processes (Saisana et al., 2005; Kavetski et al., 2006).

Uncertainty analysis and uncertainty assessment are important issues in hydrological research (Wagener and Gupta, 2005). Details of model uncertainties can be found in Butts et al. (2004), Refsgaard et al. (2006), Clark et al. (2008), Renard et al. (2010). Problems of parameter uncertainties are discussed in Duan et al. (1992), Bárdossy (2007), Bárdossy and Singh (2008), Nossent et al. (2011), Krauße and Cullmann (2012). Effects of input uncertainties on modelling results have been studied since the late sixties (Andréassian et al., 2001). In particular, effects of sampling errors in precipitation data (e.g., Wood et al., 2000; Adam and Lettenmaier, 2003; Molini et al., 2005; Stisen et al., 2012) and shortcomings in context of up-scaling and interpolation of precipitation point measurements to areal (catchment) precipitation data (e.g., Moulin et al., 2009; Shao et al., 2012; Renard et al., 2011; Looper et al., 2012) are analysed.

Comprehensive studies about the complex interactions between input and reference uncertainties as well as about their effects on parameter identification and model structure optimisation have been published recently; see Renard et al. (2007), Bárdossy and Das (2008), Vrugt et al. (2008), Salamon and Feyen (2009), Thyer et al. (2009), Renard et al. (2010), Kavetski et al. (2011), McMillan et al. (2011) and references therein. Predominately, the focus was on catchment scale. Thus the majority of these studies deal with shortcomings of conceptual modelling and uncertainties of areal precipitation data. However, sampling errors, uncertainties in other input variables (e.g., global radiation R_G, temperature T, vapour pressure e, wind speed u) as well as uncertainties of the reference were seldom tackled. These uncertainties can also have significant influence on model performance as demonstrated by Andréassian et al. (2004), Oudin et al. (2006) and McMillan et al. (2010).

As already noted, effects of moderate input uncertainties and reference uncertainties are damped or compensated by model calibration. Therefore, their impact on the reliability of model results is blurred on catchment scale. This study analyse effects of input and reference uncertainties on site scale. In contrast to previous studies, the measured evapotranspiration is used as reference instead streamflow. Furthermore, the uncertainty assessment is related to the typical range of effects rather than on potential effects (worst cases).

On site scale, input data and model parameters are hardly affected by regionalisation and generalisation; necessary simplifications of model concept and model structure are also reduced; but 'actual measurement errors' emerge (Blöschl and Sivapalan, 1995; Bergström and Graham, 1998; Sivapalan, 2006). Thus, the site scale is optimal to analyse direct effects of measurement uncertainties in meteorological variables but also in physical site parameters. The knowledge about effects of measurement uncertainties on simulated site water budget is very important as exact quantifications of water balance components and correct process understanding on site scale are fundamental for system understanding and system description on catchment scale (Bergström and Graham, 1998; Vázquez et al., 2002; Blöschl, 2006; Sposito, 2008; Martina et al., 2011).

2. Material and methods

2.1. Methodology

The four key questions, (i) model uncertainty, (ii) parameter uncertainty, (iii) input uncertainty and (iv) reference uncertainty,