Wind energy forecast ensembles using a fully-coupled groundwater to atmosphere model

JOHN L. WILLIAMS, III[1] & REED M. MAXWELL[1,2]
1 Colorado School of Mines, Department of Geology and Geological Engineering,
Hydrologic Science and Engineering Program, 1500 Illinois St, Golden, Colorado 80401, USA
johwilli@mines.edu
2 Integrated Groundwater Modeling Center, 1500 Illinois St, Golden, Colorado 80401, USA

Abstract As wind energy becomes an increasingly important component in the renewable energy portfolio, accurate wind forecasts become critical. We apply the PF.WRF model, a fully-coupled groundwater-to-atmosphere model incorporating the parallel three-dimensional variably-saturated hydrologic model ParFlow and the Weather Research and Forecasting (WRF) atmospheric model to simulate the components of the hydrologic cycle from bedrock to the top of the atmosphere. Model components are coupled via moisture and energy fluxes in the Noah Land Surface Model. The fully-coupled model dynamically simulates important meteorological effects of interactions between the land surface and the atmosphere, controlled in part by soil moisture distribution and land surface energy flux partitioning. In this study, we complete ensemble simulations for three wind ramping events at a wind energy production site on the west coast of North America using varying stochastic random fields of subsurface hydraulic conductivity and forced with meteorological data from the North American Regional Reanalysis dataset for a series of wind ramp events. We attribute error between the modelled and observed data to uncertainty in the statistical representation of subsurface heterogeneity and errors in boundary condition forcing data.

Key words land–surface atmosphere feedbacks; uncertainty; heterogeneity; wind; wind energy; weather forecasting

INTRODUCTION

Because of the intermittent nature of wind as an energy source, incorporating wind energy into power grids as part of a renewable energy portfolio is challenging. In the absence of viable storage options, accurate and reliable forecasting systems are critical for load balancing. In this study, we use a fully-coupled subsurface–land-surface–atmospheric model to generate a wind energy forecast ensemble based on uncertainty in characterization of subsurface hydraulic conductivity. It has been shown that uncertainty in the subsurface propagates into variables that are measurable in the atmosphere (Williams & Maxwell, 2011). The connection between the land surface and the atmosphere is established through moisture and energy fluxes, which are controlled in part by soil moisture distribution (Betts *et al*., 1996; Dirmeyer *et al*., 2000; Betts, 2004).

Soil moisture has been shown to have a significant effect on local and mesoscale atmospheric processes, manifested in temperature, precipitation and wind (e.g. Chen & Avissar, 1994). It has also been shown in work by Betts *et al*. (1996), Beljaars *et al*. (1996), Seuffert *et al*. (2002) and Holt *et al*. (2006), for example, that more advanced land surface formulations and soil moisture initialization in models generate more skilful forecasts. Traditionally, land surface and subsurface have been treated as simplified parameterizations in atmospheric forecast models (Golaz *et al*., 2001; Kumar *et al*., 2006). The forecasting system presented here replaces this parameterization with a three-dimensional (3D) and dynamic physical subsurface to generate more realistic soil moisture conditions. Soil moisture is spatially heterogeneous over a wide range of scales (Famiglietti *et al*., 2008), temporally variable (Wendroth *et al*., 1999; Western *et al*., 2004), and dependent, in part, on hydraulic conductivity. Hydraulic conductivity is spatially heterogeneous and can vary across several orders of magnitude over short distances; however, it has been shown to be spatially correlated, allowing hydraulic conductivity to be represented statistically as a correlated random field (Rubin, 2003). We run an ensemble forecast simulation based on different, but statistically equivalent, realizations of subsurface hydraulic conductivity stochastic fields. Using the results of these ensembles, we can evaluate the circumstances under which hub-height wind speeds are affected by land-surface to atmosphere feedbacks, and when wind speeds are dominated by boundary forcing.

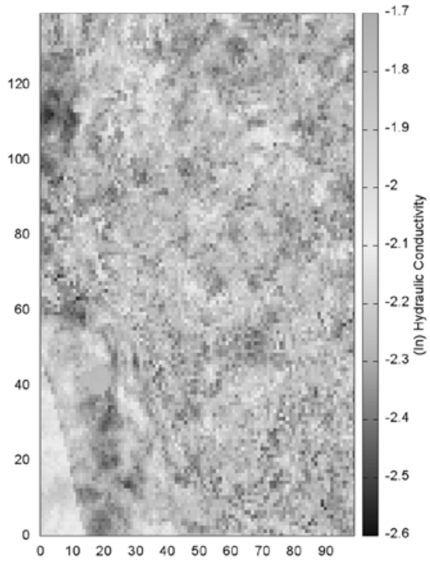

Fig. 1 Plan view of ensemble averaged stochastic field of (ln) hydraulic conductivity at the surface.

METHODS

We ran high-resolution wind forecast ensembles using the ParFlow-WRF (PF.WRF) model (Maxwell *et al.*, 2011), a fully-coupled modelling system that incorporates the ParFlow hydrologic model (Ashby & Falgout, 1996; Jones & Woodward, 2001; Kollet & Maxwell, 2006) into the Weather Research and Forecasting–Advanced Research WRF (WRF-ARW) model (Skamarock & Klemp, 2008). Briefly, the models are coupled by replacing the simplified hydrology that it built into the WRF model with ParFlow, a variably-saturated surface and subsurface hydrologic model that solves Richards equation in three spatial dimensions for flow in the subsurface with integrated surface flow routing using the kinematic wave approximation. Mass and energy fluxes across the land surface are calculated using the Noah Land Surface Model (Chen & Dudhia, 2001), which is a component in the WRF model. The natural log transform of subsurface hydraulic conductivity is represented in this model as a correlated random field with specified mean, variance and correlation lengths. Hydraulic conductivity fields are generated using the Turning Bands random field algorithm (Tompson *et al.*, 1989) following a correlation structure defined by the covariance

$$C(r) = \sigma^2_{lnK} \exp\left(\frac{-r}{\lambda}\right)$$

where σ^2 is the variance, r is the separation distance, and l is the correlation length. A separate stochastic hydraulic conductivity field was generated for each forecast ensemble member. An example of a stochastic hydraulic conductivity field is shown in Fig. 1.

Soil moisture initialization

The spinup phase, a critical component in the use of a forecast model, was completed to generate realistic soil moisture conditions with which to initialize the subsurface portion of the fully-coupled PF.WRF model. We used ParFlow coupled to the Common Land Model (CLM, Dai *et al.*, 2003) to simulate hourly soil moisture fields over a two year period from 1 September 2006 to 31 August 2007 for each ensemble member. The simulation continued through 31 August 2008 to enable model initialization at any hour during the period from 1 September 2007 until 31 August 2008. Meteorological reanalysis data from the North American Land Data Assimilation System (NLDAS, Mitchell *et al.*, 2004) was used for atmospheric forcing for the spinup and initialization runs. While the time period employed in this spinup may not be sufficient for deep groundwater to reach an equilibrium state from its initial condition with the water table near the bottom of the domain, it is expected that soil moisture at and near the surface equilibrates and perched water-bearing zones begin to form within one rainy season in this location. Since the forecast model system used in this study focuses on land–surface to atmosphere feedbacks and their effects on wind speeds, moisture at and near the surface are considered critical.

Forecast ensembles

We completed forecast ensemble simulations for a wind ramping event from 12 to 14 February 2008. We examine a 40-h time period encompassing the wind ramp. The ensemble was allowed to run for 24 h (simulated time) to spin up before the beginning of the observation periods. The forecast model ensemble comprises 11 ensemble members. Atmospheric initial conditions and boundary forcing are identical for each ensemble member. The ensemble members differ only in their hydraulic conductivity fields and their soil moisture initializations, which are directly correlated to hydraulic conductivity in the moisture limited scenario present in this ensemble. When the system is moisture limited, areas of low hydraulic conductivity tend to retain moisture for a longer duration compared with areas of high hydraulic conductivity (Atchley, 2011). The hydraulic conductivity fields used for the forecast ensemble runs are the same fields used in the corresponding spinup simulations, described above.

RESULTS AND DISCUSSION

The 40-h study period includes both low wind speeds prior to the ramp and the ramp itself in order to explore the capabilities of the fully-coupled hydrologic and atmospheric model before and during a wind ramp event. Our analysis of the model results is based on 2D time slices taken at peak wind speed during the ramping event, time series of domain averaged variables, and time series of variables at points with available wind speed observations. We observe variables as they relate serially from the subsurface into the atmosphere beginning with saturation (soil moisture divided by porosity, ranging from 0 to 1), which is a function of hydraulic conductivity among other variables. Latent heat flux represents evapotranspiration (ET) expressed in terms of energy, which embodies the interaction between the land surface and the atmosphere. We evaluate the effects of these land surface to atmosphere feedbacks on wind speed magnitude at hub-height (80 m above ground level). In addition to analysing the magnitudes of these variables, we also examine the relationships between their variances in order to evaluate the impact of the land surface on wind speed observations *versus* prevailing winds provided by the model boundary forcing data.

The peak observed wind speed during the ramping event occurred at approximately 20:00 UTC (12:00 PST) on 13 February 2008, 26 h into the observed period. The peak simulated wind speed occurred at 18:00 UTC, 24 h into the observed period. Because the saturation in the southwest portion of the domain is high (Fig. 2(a)), ET and latent heat flux are energy limited. The remainder of the domain is water limited. The small scale spatial variability in saturation is reproduced in the latent heat flux field, shown in Fig 2(b). Latent heat flux also displays a larger scale spatial pattern that resembles the pattern of variability seen in hub-height wind speed (Fig. 2(c)), providing a bridge between variability in the atmosphere and on the land surface.

Saturation at the surface does not change substantially through the observed time period. Latent heat flux shows a typical diurnal cycle in time series (Fig. 3). The ensemble variance in latent heat flux also follows this diurnal cycle. When latent heat flux shuts off during the night-time hours, it does so for all ensemble members, and the variance drops to near zero.

The important relationship is between the variances of latent heat flux and hub-height wind speed, shown in Fig. 4. The simulated wind speeds increase at each location starting at hour 20 (16:00 UTC, 13 February), and recover after hour 30. During this time, the variance in hub-height air temperature and hub-height wind speed drops to nearly zero, indicating that each ensemble member is reaching the same solution for the wind and temperature fields. This is an indication that the elevated wind speeds of the ramping event are decoupled from local land–atmosphere

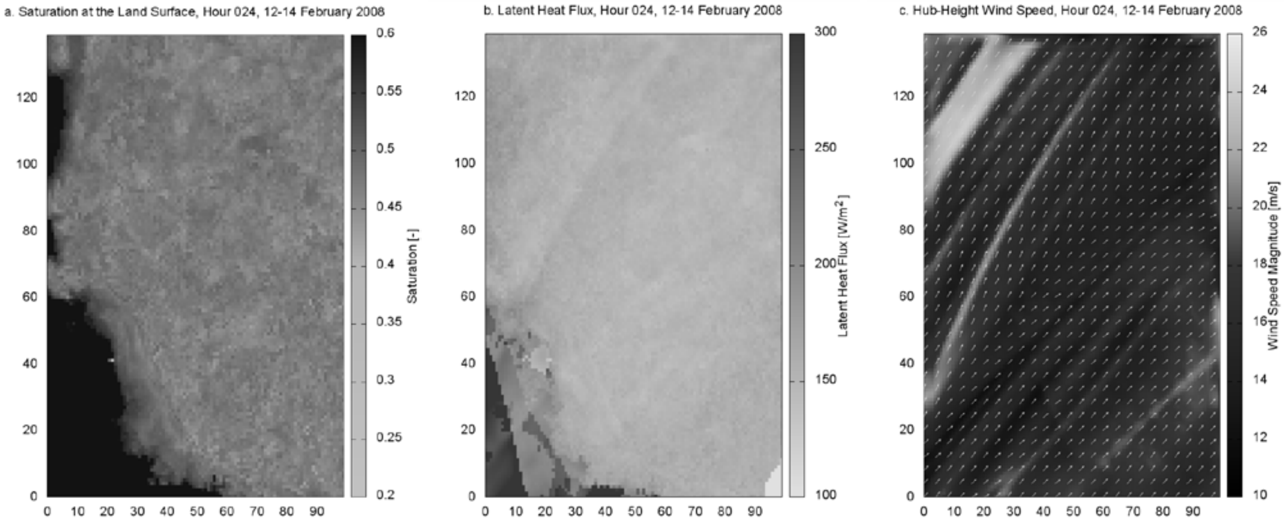

Fig. 2 Ensemble average timeslices at peak wind speed for the FEB08 ramping event: (a) saturation at the land surface; (b) latent heat flux; (c) hub-height wind speed.

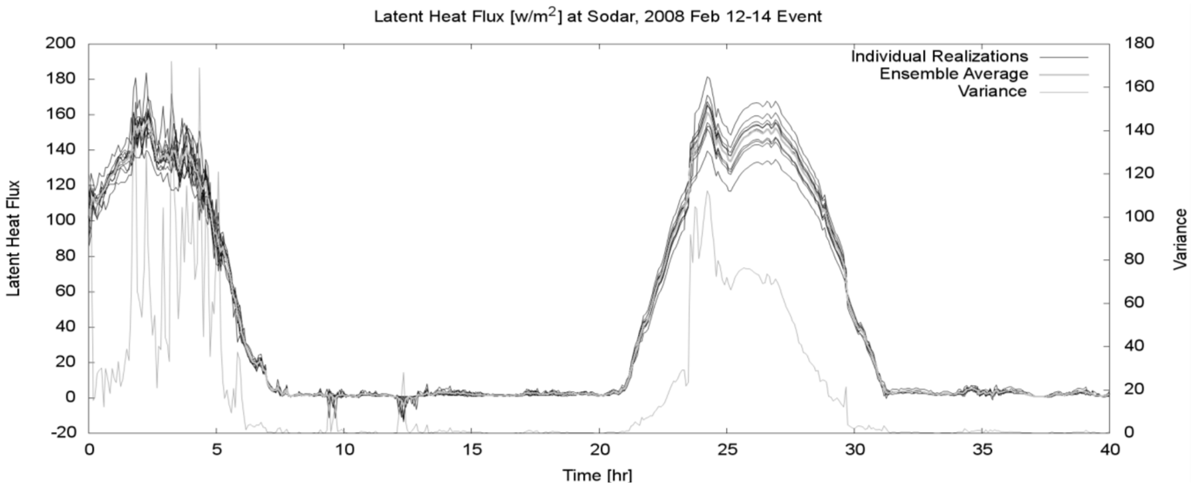

Fig. 3 Time series of latent heat flux at the sodar observation location for the FEB08 ramping event.

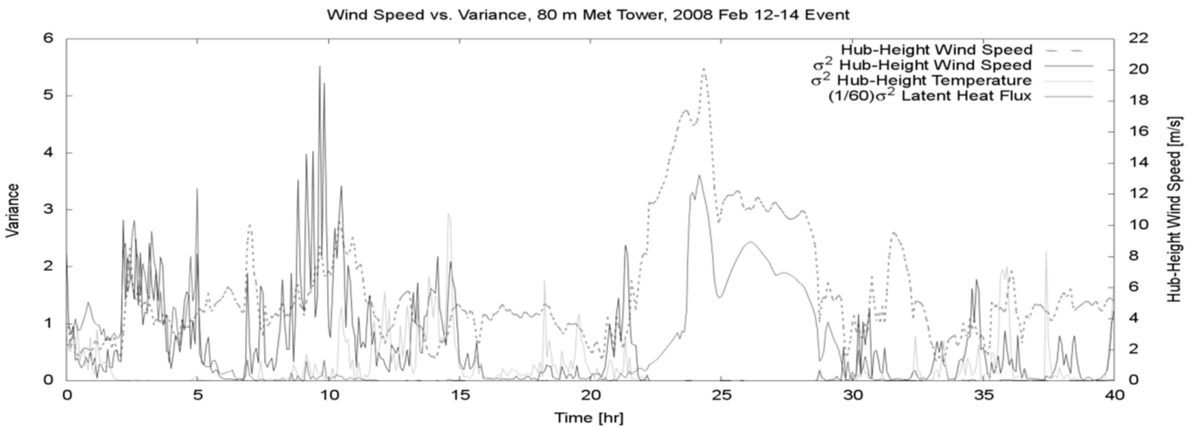

Fig. 4 Comparison of variances of latent heat flux, hub-height air temperature and hub-height wind speed for the FEB08 ramping event at: (a) the 80-m meteorological observation tower, (b) the 50-m observation tower and (c) the sodar.

interactions, and instead are dominated by boundary forcing. The variance in latent heat flux follows a diurnal pattern independent of the wind speed; however, in the domain averaged time series, the daytime ensemble variance is dampened during the ramping event as compared to the variance during the previous day. The higher variances in hub-height temperature and wind speed when the wind speed is lower indicate that the effects of land surface feedbacks with the atmosphere may be more localized during calm wind periods.

CONCLUSIONS

Based on the results of this study, we make the following conclusions regarding the wind forecast model ensembles we completed using PF.WRF. Wind ramps at this scale and at this location are strongly influenced by external forcing. The influence of land-surface to atmosphere feedbacks are mostly observed in the model at low wind speeds, but boundary forcing appears to control the higher wind speeds. This forecast model appears to capture the magnitude of the wind speeds associated with the ramping events with reasonable accuracy. The timing of the wind ramping events appears to be controlled by the forcing data. Errors in timing in the forcing data are likely carried into the model output. As shown by Williams & Maxwell (2011), assimilating observed hydraulic conductivity data could also improve the forecast by reducing uncertainty in subsurface characterization and in variables that depend directly or indirectly on hydraulic conductivity. We believe the spatial and temporal accuracy of this forecasting system could be further improved by expanding the domain to capture the non-localized effects of soil moisture heterogeneity.

REFERENCES

Ashby, F. S. & Falgout, R. D. (1996) A parallel multigrid preconditioned conjugate gradient algorithm for groundwater flow simulations. *Nuclear Science and Engineering* 124(1) 145–159.

Atchley, A. L. & Maxwell, R. M. (2011) Influences of subsurface heterogeneity and vegetation cover on soil moisture, surface temperature and evapotranspiration at hillslope scales. *Hydrogeology J.* 19, 289–305.

Beljaars, A. C. M., Viterbo, P., Miller, M. J. & Betts, A. K. (1996) The anomalous rainfall over the United States during July 1993: sensitivity to land surface parameterization and soil moisture anomalies. *Mon. Weath. Rev*. 124, 362–383.

Betts, A. K. (2004) Understanding hydrometeorology using global models. *Bull. Amer. Meteor. Soc*. 85(11), 1673–1688.

Betts, A. K., Ball, J. H., Beljaars, A. C. M., Miller, M. J. & Viterbo, P. A. (1996) The land surface–atmosphere interaction: A review based on observational and global modeling perspectives. *J. Geophys. Res*. 101(D3) 7209–7225.

Chen, F. & Dudhia, J. (2001) Coupling an advanced land surface–hydrology model with the Penn State–NCAR MM5 Modeling System. Part I: Model implementation and sensitivity. *Mon. Weath. Rev.* 129(4) 569–585.

Chen, F. & Avissar, R. (1994) Impact of land–surface moisture variability on local shallow convective cumulus and precipitation in large-scale models. *J. Appl. Meteorol*. 33, 1382–1401.

Dai, Y., Zeng, X., Dickinson, R. E., Baker, I., Bonan, G. B., Bosilovich, M. G., Denning, A. S., Dirmeyer, P. A., Houser, P. R., Niu, G., Oleson, K. W., Schlosser, C. A. & Yang, Z. (2003) The Common Land Model. *Bull. Amer. Meteor. Soc*. 84(8), 1013–1023.

Dirmeyer, P. A., Zeng, F. J. Ducharne, A. Morrill J. C. & Koster R. D. (2000) The sensitivity of surface fluxes to soil water content in three land surface schemes. *J. Hydrometeor.* 1(2), 121–134.

Famiglietti, J. S., Ryu, D., Berg, A. A., Rodell, M. & Jackson, T. J. (2008) Field observations of soil moisture variability across scales. *Water Resour. Res*. 44(1) W01423.

Golaz, J., Jiang, H. & Cotton, W. R. (2001) A large-eddy simulation study of cumulus clouds over land and sensitivity to soil moisture. *Atmos. Res.* 59–60, 373–392.

Holt, T. R., Niyogi, D., Chen, F., Manning, K., LeMone, M. A. & Qureshi, A. (2006) Effect of land–atmosphere interactions on the IHOP 24–25 May 2002 Convection Case. *Mon. Weath. Rev*. 134(1) 113–133.

Jones, J. E. & Woodward, C. S. (2001) Newton-Krylov-multigrid solvers for large-scale, highly heterogeneous, variably saturated flow problems. *Adv. Water Resour*. 24(7), 763–774.

Kollet, S. J. & Maxwell, R. M. (2006) Integrated surface–groundwater flow modeling: a free-surface overland flow boundary condition in a parallel groundwater flow model. *Adv. Water Resour*. 29(7), 945–958.

Kumar, V., Kleissl, J., Meneveau, C. & Parlange, M. B. (2006) Large-eddy simulation of a diurnal cycle of the atmospheric boundary layer: atmospheric stability and scaling issues. *Water Resour. Res*. 42(6), W06D09.

Maxwell, R. M., Lundquist, J. K., Mirocha, J. D., Smith, S. G., Woodward, C. S. & Tompson, A. F. B. (2011) Development of a coupled groundwater–atmosphere model. *Mon. Weath. Rev*. 139(1), 96–116.

Mitchell, K. E., Lohmann, D., Houser, P. R., Wood, E. F., Schaake, J. C., Robock, A., Cosgrove, B. A., Sheffield, J., Duan, Q., Luo, L., Higgins, R. W., Pinker, R. T., Tarpley, J. D., Lettenmaier, D. P., Marshall, C. H., Entin, J. K., Pan, M., Shi, W., Koren, V., Meng, J., Ramsay, B. H. & Bailey, A. A. (2004) The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system. *J. Geophys. Res*. 109(D7) D07S90.

Rubin, Y. (2003) *Applied Stochastic Hydrogeology*. Oxford University Press, Oxford; New York, 391 pp.

Seuffert, G., Gross, P., Simmer, C. & Wood, E. F. (2002) The influence of hydrologic modeling on the predicted local weather: two-way coupling of a mesoscale weather prediction model and a land surface hydrologic model. *J. Hydrometeor.* 3(5), 505–523.

Skamarock, W. C. & Klemp, J. B. (2008) A time-split nonhydrostatic atmospheric model for weather research and forecasting applications. *J. Computational Physics* 227(7) 3465–3485.

Tompson, A. F. B., Ababou R. & Gelhar, L.W. (1989) Implementation of the three-dimensional turning bands random field generator. *Water Resour. Res*. 25(10), 2227–2243.

Wendroth, O., Pohl, W., Koszinski, S., Rogasik, H., Ritsema, C. J. & Nielsen, D. R. (1999) Spatio-temporal patterns and covariance structures of soil water status in two Northeast-German field sites. *J. Hydrol.* 215(1–4), 38–58.

Western, A. W., Zhou, S., Grayson, R. B., McMahon, T. A., Bloschl, G. & Wilson, D. J. (2004) Spatial correlation of soil moisture in small catchments and its relationship to dominant spatial hydrological processes. *J. Hydrol*. 286, 113–134.

Williams, J. L. & Maxwell, R. M. (2011) Propagating subsurface uncertainty to the atmosphere using fully coupled stochastic simulations. *J. Hydrometeor*. 12(4) 690–701.