(CR)² Center for Climate and Resilience Research	CEGA CENTRO DE EXCELENCIA EN GEOTERMIA DE LOS ANDES

"Using Exploratory Data Analysis and Machine Learning Methods to Improve Prediction of Regional-Scale Groundwater Flow Models"

Lugar:
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Fecha:
Jueves 04 de abril a las 17:00 hrs.

Expositor:
Albert J. Valocchi received his B.S. from Cornell University in 1975 and did his graduate studies at Stanford University in the Department of Civil Engineering, receiving his M.S. in 1976 and Ph.D. in 1981. He has been on the faculty of the Department of Civil and Environmental Engineering at the University of Illinois since 1981. His areas of research and teaching are groundwater modeling, contaminant transport and computational methods. He has approximately 90 publications in refereed journals. In 2009 he became a Fellow of the American Geophysical Union, and he was named an Abel Bliss Professor in the College of Engineering at the University of Illinois in 2011.

Resumen:
Ground water is an important resource since it provides base flow to rivers and serves as a supply for irrigation and municipal demands. Physically-based simulation models are powerful and commonly used tools for assessment and management of this resource. It is widely recognized that groundwater models suffer from uncertainty associated with errors in model structure, parameter values, input data and measurements. Similar difficulties are encountered in many other fields of envi-

ronmental simulation modeling, since it is impossible to capture the complexity of the natural environment and these models often depend upon many parameters that must be calibrated with observed data. Model predictions are often prone to large errors with both random and systematic components, and it can be very difficult to determine specific causes of the errors.

We have developed a framework to address systematic error in physically-based groundwater flow model applications that uses error-correcting data-driven models (DDMs) in a complementary fashion. The data-driven models are based on techniques from the field of machine learning. During the calibration phase, DDMs are separately developed and trained to capture patterns and trends in the errors of the physically-based model. During the prediction phase, the forecast of the physically-based model is augmented (i.e., "complemented") with the correction of the DDM. We demonstrate the performance of the complementary modeling framework for a regional-scale application based on the Republican River Basin groundwater flow model that was developed as part of the water sharing settlement reached among the states of Kansas, Nebraska, and Colorado. This semi-arid basin is heavily irrigated, and there is considerable uncertainty about input and parameter values. Promising results are obtained for this case study, which has a large amount of data available. Limitations and ongoing work will also be discussed.