Iran Agricultural Research, Vol. 27, No. 1-2, 2008 and Vol. 28 No. 1, 2009
Printed in the Islamic Republic of Iran
Shiraz University

Review and Classification of Modeling Approaches of Soil Hydrology Processes***

K. DAVARY[1*], B. GHAHRAMAN[1] AND M. SADEGHI[1*]**

[1]Department of Water Engineering, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, I.R. Iran

ABSTRACT-To use soil hydrology processes (SHP) models, which have increasingly extended during the last years, comprehensive knowledge about these models and their modeling approaches seems to be necessary. The modeling approaches can be categorized as either classical or non-classical. Classical approaches mainly model the SHP through solving the general unsaturated flow (Richards) equation, numerically or analytically. Due to some shortcomings of classical approaches, a trend toward the application of non-classical models has been initiated in recent years. Artificial neural networks and fuzzy logic systems are two main categories of non-classical approaches. In this study, existing modeling approaches of SHP are examined and compared, with an emphasis on recent trends. Also, modeling approaches of soil hydraulic functions are reviewed briefly as a main part of SHP models. Finally, different perspectives on classifications for SHP models are presented.

Keywords: Artificial neural networks, Classical, Fuzzy logic, Modeling approaches, Soil hydrology processes

Classification of SHP Models

Before going through the classification of the models, a few points must be clarified. Firstly, models may be classified as either single or multi-process. SHP computer simulation models are mostly multi-process models. Such models include different components or processes which can be technically modeled in different ways. Accordingly, classifying multi-process models is often impossible. Alternatively, single-process models or any sub-model can be categorized in one certain class. Secondly, models may be classified from different perspectives. In fact, different classification systems have been suggested and introduced most of which being complementary rather than contradictory to each other. Thirdly, to consider any model as belonging to a certain class, minimum information is required, and to compare models to each other even more information, especially on model performance, is needed. Unfortunately, most model reports do not provide this information, but rather present supportive information on their pros. It seems that a model report guideline would be very beneficial if followed by authors of papers on

* Assistant Professor, Associate Professor, and Former Graduate Student, respectively
** Corresponding Author
*** Due to space limitation of the journal, this article is divided into two sections. Part1, which covers the first two topics, is presented in the last issue (Vol. 25, No. 2 and Vol. 26, No.1-2 - Pages.37-60) The remainder is presented here.

newly developed or enhanced models. The information offered in such papers should, for instance, include facts on the algorithm employed and the platform used. In the following sections, a model classification is proposed.

From the Modeling Approach Viewpoint

From modeling approach perspective, models may be generally classified as *physical*, including *analog* and *replica* models, versus *non-physical* models. *Replica* models are those physical models constructed with real materials but *analog* models are simulated with unreal materials. For instance, Hillels electrical model (6) is an *analog* model proposing that using electricity flow simulates water flow.

In *physical* models, the modeled relationship may be presented via different means such as equations, graphs, databases or tables, rules, and linguistic knowledge-bases. Regarding different viewpoints, *non-physical* computer simulation models may be categorized in different ways. From the first viewpoint, *non-physical* models may be categorized in sub-classes as *mathematical* versus *non-mathematical*. The fact that computer technology is based on a binary digit system has led the modelers to deal with the continuous processes in a discrete manner. Moreover, soft data or qualitative variables have to be expressed as hard data or quantitatively (i.e., translated into numbers). It is not easy for model users to adopt these artificial views. Being no exception, SHP computer simulation models, too, have been based on *mathematical* expressions that only accept numbers as input. In many cases, these models have also been based on *numerically* expressed models that discretize the model domain (space/time) to solve the governing equations step by step. Along with the innovations in computer technology (such as fuzzy logic, expert systems, parallel computing, and fuzzy based processors) new computer simulation models based on *non-mathematical* expressions are emerging gradually. On the other hand, *mathematical* models have evolved to become capable of handling the real world uncertainty through the utilization of different tools such as the Monte-Carlo simulation, Bayesian estimation, and fuzzy mathematics. These breakthrough tools have bestowed upon computer simulation models the ability to somewhat handle soft data as input and/or output. Sub-classes of *mathematical* models are *analytical* and *numerical* models.

From the second viewpoint, *non-physical* models may be grouped into *deterministic* and *non-deterministic* models. *Deterministic* models are founded on the premise that an almost accurate anticipation of a SHP response, due to any certain excitation, is achievable. The conflict between the *deterministic* approach and soil heterogeneity has mostly restricted the application of *deterministic* models to very small-scale problems. To overcome the scale barrier, deterministic models have evolved by adopting the effective parameter concept which refers to the estimation of lumped parameters from a heterogeneous domain in such a way as to assure proper model output, possibly using inverse methods. However, as the domain gets larger and/or more heterogeneous and as the share of *deterministic* sources decreases in the domain heterogeneity, model input becomes more uncertain which leads to a more *non-deterministic* model. Hence, due to scale dependency, categorizing the models is somewhat confusing for the two classes mentioned. The traditional *non-deterministic* modeling approach, *stochastic* modeling, which has been in practice during the last three decades, resolves the scale barrier statistically. Alternatively, a novel *non-deterministic* approach employs fuzzy variables as input to the model.

The classification of SHP models from the modeling approach standpoint is presented in Fig. 1, schematically.

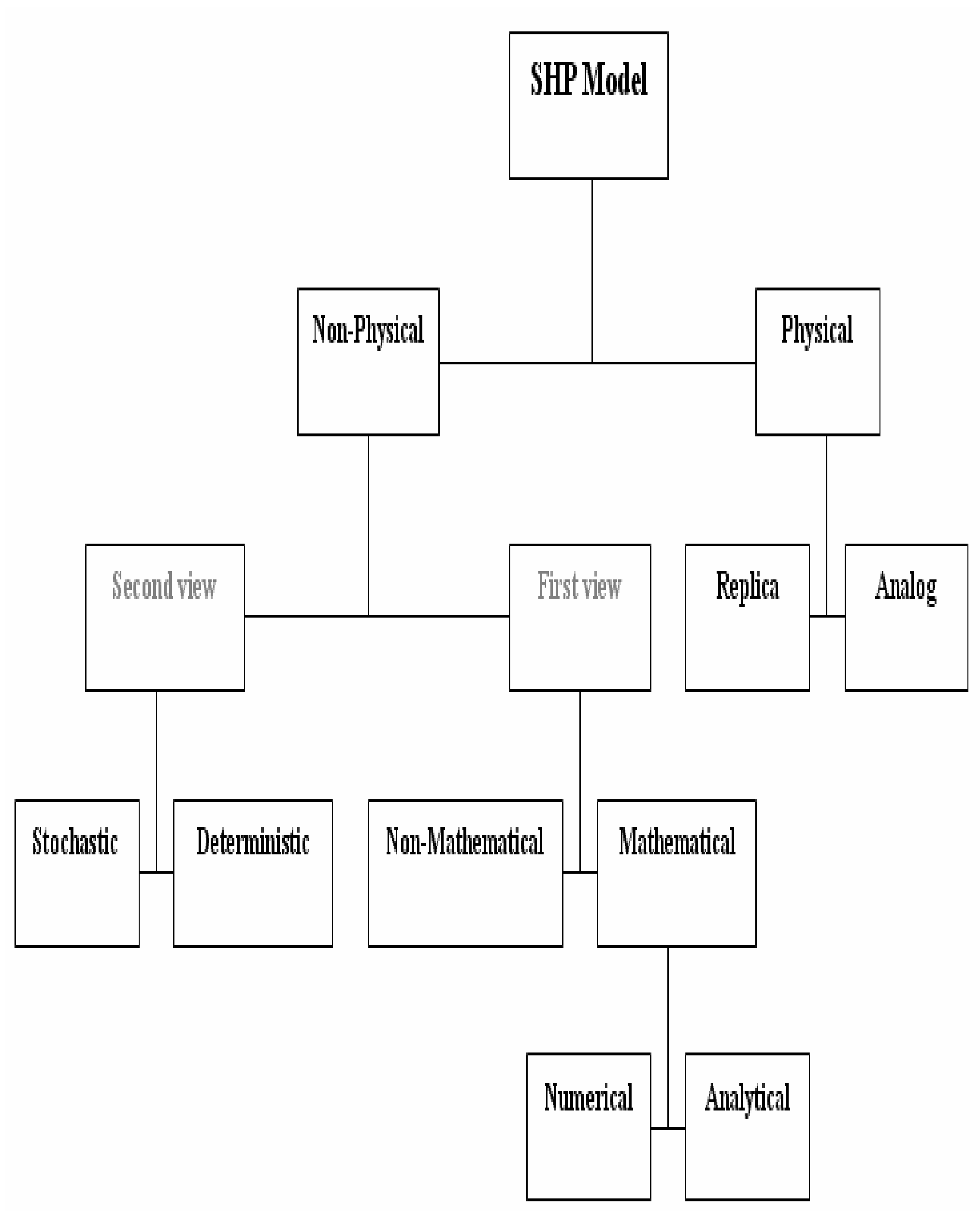

Fig. 1. Classification of SHP models from the viewpoint of modeling approach

From the Model-box Viewpoint

Model-box is a virtual space that takes the input and converts it to the output through a number of processes. SHP models from the model-box viewpoint are classified as *white-box* versus *black-box*. Models originated from phenomenal explanations are accepted as *white-box*. On the other hand, *black-box* models simulate the relationship between input and output blindly (i.e. the model does not explain the real physical link between input and output) and are not informative as regards to the internal processes of the prototype. Between the two white and black extremities, there may be *gray-box* models which are not purely white or black.

Most classical models may be classified as *white-box* or *gray-box*. Regression and ANN techniques have been mostly employed to define *black-box* models. A model is a pure *black-box* model if neither model formulation nor its parameters are known beforehand and are expected to be determined from data afterwards. Rules or linguistic knowledge-bases may also be used to define a *black-box* model.

Another view which is very similar to the above mentioned classification, categorizes SHP models into *empirical* and *mechanistic* sub-classes. Crudest *empirical* models are pure *black-box* models. Other *empirical* models consider some physical aspects of the prototype to define the model formulation, at least partially. These models are still dependent on the data mostly for the determination of the models' parameters. Inasmuch as the *empirical* models owe to the data for their existence they are also called *data driven* models. The more a model considers the physics of the process modeled, the more independent of the data and more *mechanistic* it becomes. At the other extreme of a pure *black-box* model, is a fully *mechanistic* or pure *white-box* model which breaks down the main process, reducing it repeatedly to sub-processes. Eventually, the most basic components of the system are revealed and the modeling task is executed, followed by an integration of the results in order to get back to the main process level. Some of the classification aspects, discussed here, are explained graphically in Fig. 2. It is obvious that no distinctive partition exists between *empirical* and *mechanistic* models.

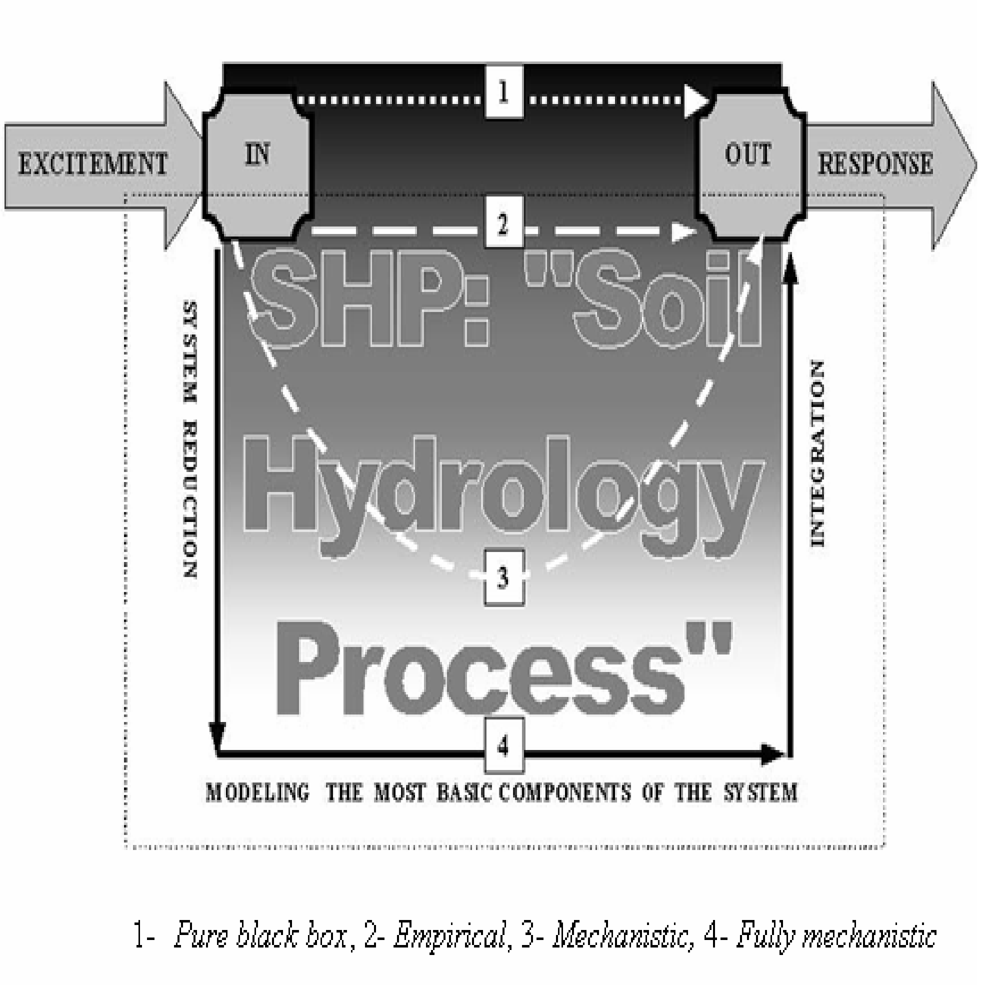

Fig. 2. Graphical explanation of different model-boxes

The above mentioned models otherwise known as *conceptual,* are models that realize the relationship between input and output but require calibration for any system. For instance the Green-Ampt infiltration model is conceptual. *Conceptual* models are *gray-box*.

Any single process model can be classified according to all the views mentioned above simultaneously. For example DRAINMOD developed by Skaggs (9) is an original *conceptual* model that employs water balance analytical equation in a soil profile confined between the soil surface and a shallow water table. The model executes quite quickly on a PC but has its limitations: it does not provide soil moisture content data through the soil profile and its concept has been developed only for a 1D vertical flow. DRAINMOD, then, is classified as a *white-box*, *deterministic*, and *analytical-mathematical* model. At the same time, it may be considered as *mechanistic* as well.

Models may also be categorized by other classifying methods. For instance, *discrete* versus *continuous* models (regarding the events' duration and sequence), *steady* versus *unsteady* (considering dynamics of the model), *one-, two-* or *three-dimensional* (with respect to the model's spatial extent), and *research-* versus *practice-oriented* (due to the model utilization mode). Regarding the categories mentioned above, an historic classification of some models is presented in Table (1).

Table 1. Classifying some historic models

		From viewpoint of modeling approach							From viewpoint of kind of model-box		
		Physical		Non-Physical							
		Re[†]	Ag	Ma		NMa	De	St	WB	GB	BB
Author(s)	**Year**			Nu	An						
Hanks and Bowers (5)	**1962**			*			*			*	
Skaggs (9)	**1981**				*		*		*		
Chung and Austin (3)	**1987**			*				*		*	
Philip (7)	**1991**				*		*			*	
Hillel (6)	**1991**		*								
Altendorf et al. (1)	**1992**					*	*				*
Bardossy and Disse (2)	**1993**					*					*
Van den Brook et al. (10)	**1994**			*			*			*	
Ewen (4)	**1996**							*		*	
Simunek et al. (8)	**2005**			*			*			*	

[†] **Re: replica, Ag: analog, Ma: mathematical, NMa: non-mathematical, Nu: numerical, An: analytical, De: deterministic, St: stochastic, WB: white-box, GB: gray-box, BB: black-box**

CONCLUSIONS

Periodical comprehensive technical reviews and summaries on soil hydrology processes (SHP) models are very useful and necessary for modelers and model users. In the absence of such review papers, this article has tried to offer a brief review.

The models reviewed in this paper show that existing SHP models can mostly be classified as *deterministic, mathematical* (*numerical*), and *mechanistic*. However, in recent years, non-classical models have gradually become a visible trend in SHP modeling. Along this trend, the number of *non-deterministic* and *non-numerical* SHP models has been growing due to the new opportunities provided. For example, the use of fuzzy variables in SHP modeling has paved the way towards employing linguistic variables. Also, the use of artificial neural networks (ANN) has facilitated the modeling of highly complex and non-linear relationships with reasonable error, even when data is uncertain/noisy.

ANN models are data driven models. As such, in order to obtain the best match between measured and simulated data sets, model parameters (weights) have to be adjusted while minimizing the error. ANN models are particularly useful when data is vague. These specifications are pivotal to the modeling of SHP, especially to the complex problem of variably saturated soil moisture (VSSM) flow, with uncertain and noisy data. On the other hand, fuzzy logic systems bring up the possibility of accepting soft data as input as well as providing a simple method to deal with the non-determinism of VSSM flow parameters.

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مرور و طبقه‌بندی نگرش‌های مدل‌سازی فرآیندهای هیدرولوژی خاک

کامران داوری [۱]*، بیژن قهرمان [۱] و مرتضی صادقی [۱]***

[۱]بخش مهندسی آب، دانشکده کشاورزی، دانشگاه فردوسی مشهد، مشهد، جمهوری اسلامی ایران

چکیده- برای استفاده از فرآیندهای هیدرولوژی خاک (SHP)، که در سال‌های اخیر شدیداً گسترش یافته‌اند، درک جامعی از این مدل‌ها و نگرش‌های مدل‌سازی آنها ضروری به‌نظر می‌رسد. این نگرش‌ها را می‌توان به دو دسته‌ی کلی کلاسیک و غیر کلاسیک تقسیم‌بندی کرد. روش‌های کلاسیک عمدتاً SHP را از طریق حل عددی و یا تحلیلی معادله‌ی عمومی جریان غیراشباع (معادله‌ی ریچاردز) مدل می‌کنند. به‌دلیل محدودیت‌های روش‌های کلاسیک، در سال‌های اخیر تمایلی به استفاده از روش‌های غیر کلاسیک شکل گرفته است. شبکه‌های عصبی مصنوعی و سیستم‌های منطق فازی دو دسته‌ی عمده از روش‌های غیر کلاسیک به شمار می‌آیند. در این مقاله روش‌های رایج مدل‌سازی SHP با تاکیدی بر کارهای فعلی مرور و مقایسه شده‌اند. هم‌چنین روش‌های مدل‌سازی توابع هیدرولیکی خاک به عنوان یک بخش عمده از مدل‌های SHP به‌طور مختصر مرور شده‌اند. در نهایت تقسیم‌بندی‌هایی برای مدل‌های SHP از دیدگاه‌های مختلف ارائه شده است.

واژه های کلیدی: روش‌های مدل‌سازی، سیستم‌های منطق فازی، شبکه های عصبی مصنوعی، فرآیندهای هیدرولوژی خاک، کلاسیک

* به ترتیب، استادیار، دانشیار و دانشجوی پیشین کارشناسی ارشد

** مکاتبه کننده