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Review

A review of coupled hydrologic and crop growth models

Si Mokrane Siad[a,b,c,*], Vito Iacobellis[b], Pandi Zdruli[e], Andrea Gioia[b], Ilan Stavi[d], Gerrit Hoogenboom[c]

[a] Institute for Electromagnetic Sensing of the Environment (IREA), Italian National Research Council (CNR),Via Amendola, 122/D - 70126 Bari, Italy
[b] Polytechnic University of Bari, Via Orabona 4, Bari, 70125, Italy
[c] Institute for Sustainable Food Systems, University of Florida, Gainesville, Florida 32611-0570, USA
[d] Dead Sea and Arava Science Center, Ketura 88840, Israel
[e] International Centre for Advanced Mediterranean Agronomic Studies (CIHEAM) Mediterranean Agronomic Institute of Bari, Via Ceglie 9, Valenzano (BA) 70010, Italy

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ABSTRACT

Coupling hydrologic and crop models is becoming an increasingly important approach in the development of agro-hydrologic theme. Scientists and decision makers working to address issues in the areas of resource conservation and agricultural productivity are interested in the complementary processing of the two coupled systems. The objective of the present work is to review relevant studies related to hydrologic and crop models coupling, and to analyze the domain applicability, limitations, and other considerations.

1. Introduction

Hydrologic and crop growth numerical modeling has progressed over the last decades, and the scientific modeling community has recognized the complementary nature of various aspects of hydrologic and crop systems. Debates and issues on food security, environmental degradations and climate change have raised the need for integrated simulation models to cope with issues of sustainable agriculture production tandem with resources scarcity and climate stresses. A proper answer to the question of how water can be efficiently used to maximize crop yields is therefore needed (White et al., 2011a). Furthermore, agricultural pricing and policies have a high impacts on farmers' incentives, with a consequent high control of their cropping systems (Siad et al., 2017). Being a major user of water, agriculture is a potential adequate field to study water use efficiency (Jia et al., 2011).

Agricultural water use for crops relies on several factors, such as: climatic conditions, topography, lithology, soil, management practices, type of crop, etc. Knowledge of these parameters allows estimating crop-water requirement and establishing cropping management procedures. Water requirements by agricultural crops can be determined locally at the field. Nevertheless, being all these processes observed at small spatial scales, they are mainly conditioned by rainfall and its distribution and redistribution at the basin scale. To date, hydrological practices have been developed to their greatest advancement in the study of large catchments for water resources purposes and yet, have a limited implication in agriculture (Jia et al., 2011). With an increasing importance of improving low agricultural productivity in marginal lands, where capital investments are not beneficial (subsistence activity), water harvesting is the determinant of agricultural production. Thus, Given the importance of water in agriculture, an enhanced understanding of hydrological conditions is essential to efficiently exploit soil moisture opportunities (Antonelli et al., 2015).

This paper presents a review of studies on crop growth and hydrologic models. We begin with an introduction to the general concepts related to hydrologic, crop growth and coupling models, and coupling computer models. Then, we synthesize literature sources which coupled hydrologic and crop growth models applied for various purposes. Finally we provided some considerations and implications.

2. Concepts and notions

The concept of environmental modeling deals with the relations among water, climate, soil, and plants (Iacobellis et al., 2002; White et al., 2011b), and includes temporal and spatial features (Meiyappan et al., 2014). The behavior of each feature is controlled by its own components (Jajarmizadeh et al., 2012). Accordingly, models are a simplified representations of the real processes (Anothai et al., 2008). Models can be either: physical (physical representation of the original system, reproduced by scaled parameters) electrical analogue (electrical circuit similar to the investigated system, composed of electrical component) or mathematical (mathematical/stochastic equations that describe physical characteristics of the system) (Gutzler et al., 2015).

* Corresponding author.
E-mail address: mokrane.siadsi@poliba.it (S.M. Siad).

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The physical and analogue models have been very important in the past (Refsgaard, 1996). Nowadays, the mathematical group of models is by far the most easily and universally applicable, the most widespread and rapidly developing with regards to scientific basis and application (van Kraalingen et al., 2003).

2.1. Crop growth modeling

Crop models are tools that help estimating crop yields as a function of weather, soil conditions and the applied management practices (Hoogenboom et al., 2002). There are several types of models that have been developed over the years. They can be classified into various groups or types, ranging from empirical to explanatory models (Hoogenboom, 1999).

Empirical models are based on direct descriptions of observed data, expressed as regression equations and used for estimation of crop yields. Empirical approach analyzes data and fits an equation, or a set of equations to the data. These models have no information on the mechanisms that control the outputs (Phakamas et al., 2013). In contrast, mechanistic models explain not only the relationships between weather parameters and crop yields, but also the mechanisms that control these relationships (Bannayan et al., 2003).

In Stochastic models, each output is attached to a probability element. For each set of inputs, different outputs are given along with probabilities. These models define a state of dependent of model variables at a given rate (Etkin et al., 2008). Explanatory models consist of quantitative description of the mechanisms that cause a behavior. In such models, the processes are separately quantified, and then integrated into the entire system (Hoogenboom, 1994).

Among the models successfully used to simulate maize growth and yield are the EPIC (Williams, 1990), CERES-maize (Bao et al., 2017), ALMANAC (Kiniry et al., 2005), CROPSYST (Stöckle et al., 2003), WOFOST (van Diepen et al., 1989) and ADEL (Fournier et al., 2003) for simulating maize growth and yield. The SORKAM (Rosenthal et al., 1989), SorModel (Arora, 1982), SORGF (Wiegand and Richardson, 1984), and ALMANAC are used for sorghum crop management. CERES-pearl millet model (Santos et al., 2016), CROPSYST, and PM Models (Boylan and Russell, 2006) are used for simulating of pearl millet genotypes across the globe. Similarly, the PNUTGRO (Hoogenboom et al., 1992) is used for groundnut, CHIKPGRO (Singh and Virmani, 1996) for chick pea, WTGROWS (Sehgal and Sastri, 2005) for wheat, SOYGRO (Hoogenboom et al., 1990) for soybean, QSUN (Schnable et al., 2009) for sunflower, and GOSSYM(Boone et al., 1993) and COTONS (Jallas et al., 2000) for cotton. The above mentioned models are those currently in use for meeting the requirements by farmers, scientists, and decision makers.

2.2. Hydrologic modeling

Hydrologic models are developed for estimating, predicting and managing water distribution and fluxes, at the soil-atmosphere interface, as a function of various parameters that are used for describing soil and watershed characteristics (e.g. Gioia et al., 2011; Manfreda et al., 2005). The commonly required inputs are atmospheric data (e.g. rainfall and temperature) while the model parameterization includes watershed characteristics like the topographic relief, geomorphology, bedrock, soil and vegetation properties (i.e.: models based on physical concepts).

When restricted to land surface processes, hydrologic models are referred to as Rainfall-Runoff models and are often based on a conceptual representation of physical processes (Iacobellis et al., 2015). In general, they can be classified as lumped or distributed models (e.g. Milella et al., 2012), depending on the spatial discretization of parameters. In lumped models, the entire watershed is taken as a single unit and the spatial variability of input variables, parameters and outputs are disregarded (Breuer et al., 2009). On the other hand, distributed models can deal with space distributed quantities by dividing the catchment into subunits, usually square cells or triangulated irregular network, so that the parameters, inputs and outputs can vary spatially.

A large number of models have developed different application ranges, from small catchments to global models, has been developed, such as DHSVM (Wigmosta et al., 2002), MIKE-SHE (Refsgaard and Storm, 1995), TOPLATS (Bormann, 2006), WASIM-ETH (Schulla and Jasper, 2007), SWAT (Santhi et al., 2001), PRMS (Heckerman et al., 2007), SLURP (Barr et al., 1997), HBV (Lindstrom et al., 1997), LASCAM (Viney and Sivapalan, 2001), IHACRES (Croke et al., 2005), DREAM (Manfreda et al., 2005), etc., where each model has its own unique characteristics and respective applications. The model choice and implementation are basically constraint by data availability (e.g. gauged or ungauged catchment) and modeling purpose such as streamflow and flood forecasting, water resource management, evaluation of water quality, erosion, nutrient and pesticide circulation, etc. (Di Modugno et al., 2015; Gorgoglione et al., 2016; Manfreda et al., 2015).

2.3. Complementarily of simulation processes

In order to guarantee the efficiency of crop production assessment, the role of hydrological modeling is to provide accurate soil moisture distribution in space and time accounting for basin scale water dynamics (Balenzano et al., 2013; Dokoohaki et al., 2016; Iacobellis et al., 2013). Rainfall amount and its space-time distribution determine the quantity of water that reaches the land's surface. Temperature, humidity, vegetation cover (i.e. type, amount and distribution) determine the proportion of evaporated water. Vegetation productivity, and soil conditions, while topography determines the quantity of water that infiltrates into the soil versus water that runs on the ground surface (Gioia et al., 2014). It is the interactions among these complex processes that define the effective water available for crops in the rhizosphere (Fig. 1.

Vegetation affects water balance by evapotranspiration (ET) and interception. Canopy properties such as the leaf area index (LAI) and the rooting depth, are obtained offline (externally) and are considered as parameters in most physically based hydrological models (Gigante et al., 2009; McNider et al., 2015b). LAI estimates provide an indication of vegetation growth cycle and of plant activity in terms of water transpiration. Keeping LAI constant throughout a model simulation may lead to errors in the model results. LAI may also be treated as an input variable, being regularly updated by means of earth observation products (Balacco et al., 2015; Milella et al., 2012). Yet, exploiting crop growth models, the hydrological model could be enhanced with a module able to simulate vegetation development. Crop growth models, which accurately reproduce soil-water flow processes, should be given preference when compared to other methods for evaluating vegetation stats (Betts, 2005). Crop models can be improved by a proper modeling of water flow distribution for a better estimation of ET rates. Since all these processes are represented in hydrological models, the coupling of hydrologic and crop growth models can be expected to be beneficial for both simulations (Manfreda et al., 2010).

2.4. Coupling models

Coupling is used in the context of feedbacks between various processes. It does refer to physics, but it happens on software-development base with numerical implications. There are several methods of coupling models, ranging between simple hand-made data exchanges and automated frameworks of integration as follow:

1. Sequential coupling: Models are completely decoupled
2. Loose coupling: Models exchange I/O data
3. Shared coupling:
   a) *Unified GUI:* Models share graphical user interface (GUI)

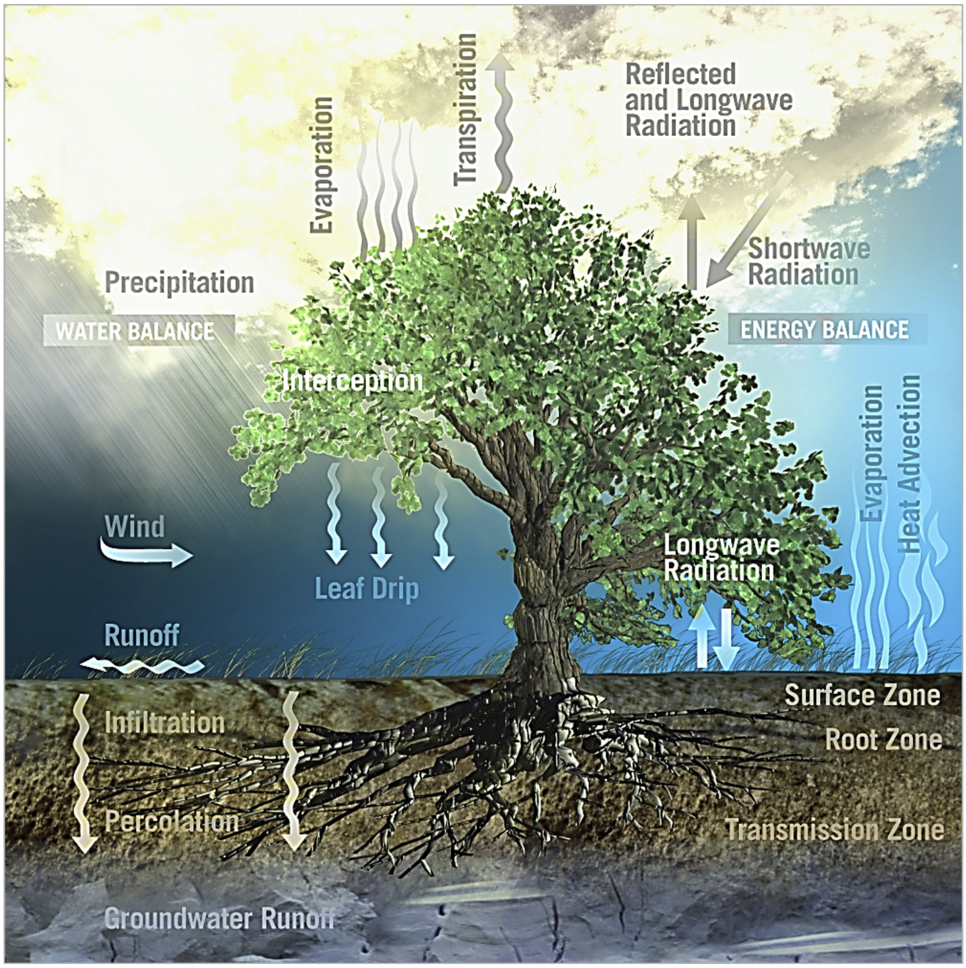

Fig. 1. Soil-water balance interaction with vegetation (ESA/AOES-Medialab, 2004).

b) *Shared data:* Models share I/O database

4. Embedded: One model is completely contained in the other (usually as a subroutine)
5. Integrated: Models are merged at the code source level in one coherent model.
6. Framework: Using an overall modeling framework, where the models are coupled using a third-part tool commonly called "Coupler" based on a combination of the previous methods.

The level of coupling refers to the degree to which model variables depend upon each other. In high-level coupling (i.e. embedded, integrated) each component and its linked one must be presented in a way allowing a code or a framework to be executed. At the same time, low level coupling (i.e. shared and loose coupling) allows components to be autonomously managed and communicate among themselves. In a completely decoupled coupling (i.e. sequential coupling), components operate separately and independently).

2.5. Open- and Closed-source models

The notion of openness/closeness of a source can be applied either for the code source of a model and/or its data. Flexibility, use and modification of closed-source models are predetermined by the creator (s), which is subjected to copyright and limit their accessibility and modification. At the same time, open sources allow more freedom in modification, reproduction and use according to needs. Also, open sources, with the possibility to change their codes, develop more rapidly. Generally, we may define three level of openness to third party models:

- Open Source: A completely open source code.
- Partially Open Source: part of the source code is restricted.
- Close Source: An entirely restricted source code.

And three other level for third party data:

- Heterogeneous: No restriction for third party data source.
- Partially Heterogeneous: Some data sources are restricted.
- Homogeneous: Only pre-determined data source is accepted.

These characteristics have to be considered for model development, based on coupling. An integrated method offers a highly cohesive system but makes its maintenance and upgradability harder, such as if new versions of the legacy models are released. In contrast, less invasive methods offer easier maintenance and more homogeneity, but with weak cohesiveness (Fig. 2).

2.6. Challenges of model coupling

In order to be coupled, models must be interoperable, a term often used but lacking a single and precise definition. For instance, Wileden and Kaplan (1999) defined interoperable as the capability of two or more programs to share and process information irrespective of their implementation of language and platform. Similarly, Bühler and McKee, 1996,defined interoperable geo processing as "the ability of digital systems to: (i) freely exchange all kinds of spatial information

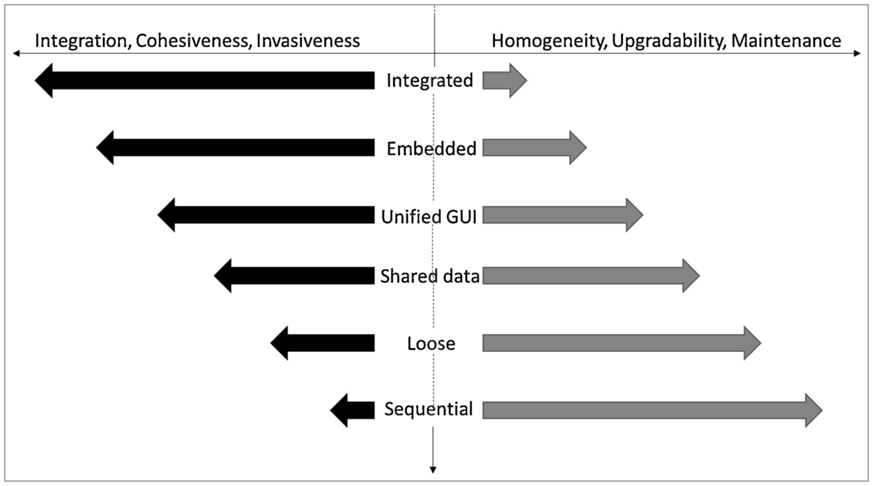

Fig. 2. Compromise between methods and integration.

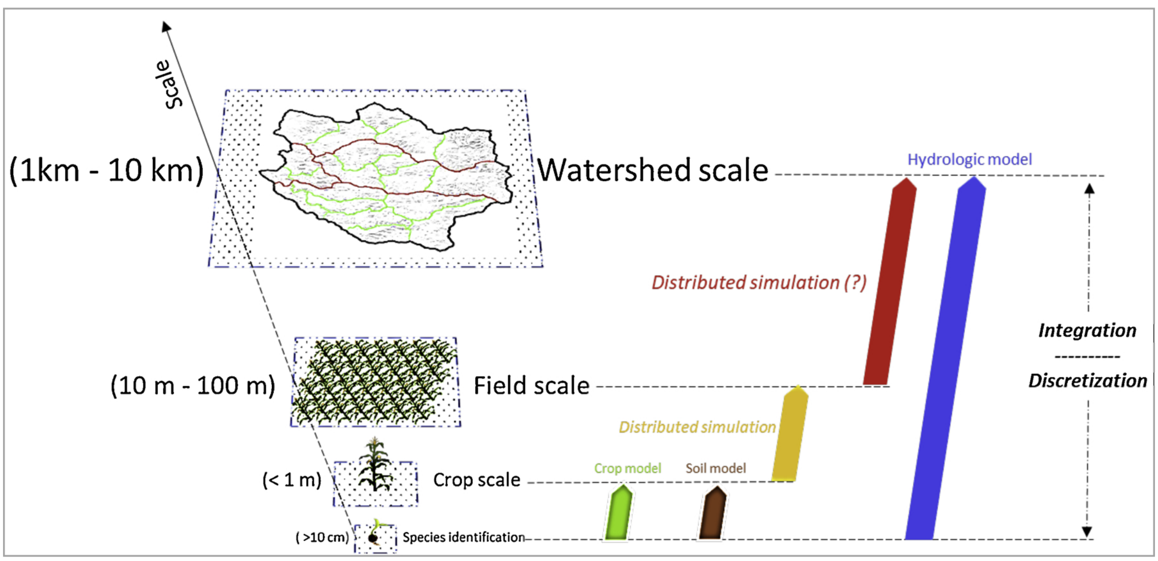

Fig. 3. Up/down simulation scaling - integration /discretization of point-based/distributed simulation.

about the Earth and about objects and phenomena on, above, and below the Earth's surface; and (ii) cooperatively, over networks, run software capable of manipulating such information." Both definitions apply to computer programs, hardwares, and data file formats.

Models and their respective data must be interoperable with both spatial and temporal scales. If a scale difference cannot be resolved, then the models cannot be meaningfully coupled. Although the models may share information, if the models' scales are different, the results from the coupled system are meaningless. In such cases, an intermediate program is required to reconcile the scales. For example, two models may assume the same data type with the same dimensions and extends. However, if the output is in the time unit, but one is in minute and the second is in month, a temporal scale conversion for interoperability is required. Similarly, if the spatial scale is different, a spatial conversion is required (Hu and Bian, 2009; Kumar et al., 2006).

Due to the substantial number of available models and practical tools, and the diff ;erent approaches (e.g., from empirical to mechanistic) that characterize them, choosing a suitable model to be coupled and the specific method of data processing may be difficult. Moreover, a lack of knowledge about the domain heterogeneity can make models' application entirely misleading.

Often, computer resources encompass a restrictive factor for such combinations. Nevertheless, reasonable computational time and precision can be achieved when simulated processes are not overloaded (i.e. in the Random-Access-Memory (RAM) or Central Processing Unit (CPU)). In addition to hardware resources, both programming languages and framework of combination, play a key role in managing the available resources. These aspects are purely computer science-oriented criteria, and may represent a serious barrier for the combination of source models.

Many factors should be considered prior to the selection of an appropriate methodology and framework for coupling. These factors include the nature and relative scale of the crop system, basin characteristics, data and information availability, method requirements, time constraints for producing an assessment, and the required accuracy. In some cases, process selection is a context-shaped approach. Therefore, the process should be transparent, where the assumptions, simplifications, and other limitations are clearly indicated. It would assist in validating the results with observation data. The process also needs to be adaptive, so that new or improved information can be incorporated (Fig. 3).

3. Overview of coupled hydrologic and crop growth model

Coupling hydrologic and crop model's studies are relatively scarce and is still at early stage of development. Nevertheless, it is an

Table 1
List of coupled hydrologic and crop models' studies. Note: Not all studies do use the nomenclature shown previously in "2.4. Coupling models" for describing the coupling method. In such case, the coupling method is drawn from the description of the coupling process when enough information is provided.

Method	Models			Description	Study focus	Reference study
	Hydrology	Crop	Coupled			
-/-	Built from scratch	Built from scratch	-/-	Coupling based on a predetermined empirical relationship.	Seasonality and energy balance effect on rice.	(Maruyama and Kuwagata, 2010)
Integrated	CHAIN-2D	EPIC	-/-	Models' subroutines/functions codded with FORTRAN 90.	Simulation of furrow irrigation and crop yield.	(Wang et al., 2014)
Loose coupling	CMF	PMF	CMF-PMF	Follow recommendation of (Perkel, 2015).	Effect of CO_2 on grassland	(Kellner et al., 2017)
Integrated	DRAINMOD	DSSAT	DRAINMOD–DSSAT	Modular codes integration.	Integrated agricultural system modelling.	(Negm et al., 2014)
Integrated	HYDRUS 1D	DSSAT	-/-	Simplified version of HYDRUS 1D integrated to DSSAT Code source.	Simulations of Soil Water Dynamics in the Soil-Plant-Atmosphere System.	(Shelia et al., 2017)
Integrated	HYDRUS 1D	EPIC	-/-	Models' subroutines/functions codded with FORTRAN 90.	Irrigation water salinity impacts assessment.	(Wang et al., 2017)
Embedded	HYDRUS 1D	EPIC based	-/-	*HYDRUS 1D is the host model and the SWAT's EPIC crop module is simplified and added.*	Impacts of groundwater balance on cotton growth.	(Han et al., 2015)
Integrated	HYDRUS 1D	PS123	WHCNS	The models are integrated in whole WHCNS modelling framework	Water and nitrogen management.	(Liang et al., 2016)
Framework	HYDRUS 1D	WOFOST	-/-	OMS V.3 framework	Agricultural water management.	(Zhang et al., 2012)
Integrated	HYDRUS 1D	WOFOST	-/-	Modules and functions integration.	Irrigation modeling of wheat cultivation.	(Zhou et al., 2012)
Loose coupling	JULES	InfoCrop	-/-	One-ways data exchange	Estimation of evapotranspiration	(Tsarouchi et al., 2014)
Integrated	JULES	SUCROS	JULES-SUCROS	Modular incorporation of derived SUCROS model to JULES.	Crop growth simulation.	(Van den Hoof et al., 2011)
Loose coupling	LSP	DSSAT	-/-	Synchronized two-ways data exchange.	Estimation of energy and moisture fluxes for dynamic vegetation	(Casanova and Judge, 2008)
Framework	MIKE-SHE	DAISY	DAISY-MIKE SHE	OpenMI framework	Nitrate leaching.	(Thirup, 2013; Thirup et al., 2014)
Integrated	MIKE-SHE	DAISY	-/-	Hard code integration of models.	Macropore flow and transport processes modeling.	(Skovdal Christiansen et al., 2004)
Integrated	MIKE-SHE	DAISY	-/-	Hard code integration of models.	Integration of remote sensing in agro-hydrologic modeling.	(Boegh et al., 2004)
Loose coupling	ORCHIDEE	STICS	-/-	One-way data exchange with shared inputs.	Croplands influence water and carbon balance.	(De Noblet-Ducoudré et al., 2004)
Embedded	RZWQM	DSSAT	RZWQM2	Wrapping approach for model integration.	Presentation of the RZWQM2	(Ma et al., 2012)
Embedded	RZWQM	DSSAT-CERES	RZWQM-CERES	CERES-Maize added as a module to RZWQM.	Maize crop growth and yield modelling.	(Ma et al., 2006)
Embedded	RZWQM	DSSAT-CROPGRO	RZWQM-CROPGRO	*CROPGRO* added as a module to RZWQM.	Model coupling for soybean production modeling.	(Ma et al., 2005)
Loose coupling	SHAW	WOFOST	-/-	Custom framework with dynamic feedback	Irrigated maize study for water, carbon and energy balance.	(Li et al., 2013)
Not indicated	SiB2	SiBcrop	-/-	Daily-base data exchange coupling.	ET and carbon exchange in wheat-maize croplands.	(Lei et al., 2010)
Integrated	SWAP	EPIC	-/-	Substitution of the WOFOST model in SWAP by EPIC	Ground water level effects on soil salinity and wheat yield.	(Xu et al., 2013)
Integrated	SWAP	WOFOST	SWAP	WOFOST integrated as a submodule in SWAP.	Presentation of the integrated SWAP model.	(Kroes et al., 2000)
Integrated	SWAT	EPIC	HE^XM	*Upgraded hydrologic module in SWAT with original EPIC module.*	Integrated hydrologic system modelling	(Zhang et al., 2014)
Integrated	VIC	CropSyst	VIC–CropSyst	Tightly source code integration with modular approach.	Presentation of the VIC–CropSyst-v2	(Malek et al., 2017)
Framework	VIC	DSSAT	-/-	RHEAS framework	RHEAS framework presentation.	(Andreadis et al., 2017)
Loose coupling	WaSSI	DSSAT	GriDSSAT	GIS based I/O exchange coupling.	Hydrological impacts of irrigation.	(McNider et al., 2015b)
Framework	WRFV.3.3-CLM4	AgroIBIS	WRF3.3-CLM4crop	*CESM1* framework	Crop growth and irrigation interact to influence surface fluxes	(Lu et al., 2015)
Loose coupling	WEP-L	WOFOST	-/-	One-ways data exchange with feedback.	Climate change impact on winter wheat.	(Jia, 2011)
Embedded	TOPLATS	WOFOST	WOFOST	WOFOST is coupled as subroutine to TOPLATS.	Coupled model optimization using LAI/soil moisture.	(Pauwels et al., 2007)

Notes: Models references: AgroIBIS (Kucharik, 2003); CESM1 (Kay et al., 2015); CHAIN-2D (Simunek and Van Genuchten, 1994); CMF (Kraft et al., 2011); DRAINMOD (Skaggs et al., 1996); HYDRUS 1D (Simunek et al., 2005); InfoCrop (Aggarwal et al., 2006); JULES (Best et al., 2011); LSP (Yuei-An and England, 1998); OMS (David et al., 2002); OpenMI (Gijsbers et al., 2002); PILOTE (Mailhol et al., 1997); PMF (Multsch et al., 2011); PS123 (Driessen and Konijn, 1992); RHEAS (Andreadis et al., 2017); RZWQM (Ahuja et al., 2000); SiB2 (Sellers et al., 1996); SiBcrop (Lokupitiya et al., 2009); STICS (Brisson et al., 1998); SUCROS (Goudriaan and Van Laar, 2012); SWAP (Kroes et al., 2000); SWAT (Santhi et al., 2001); VIC (Liang et al., 1994); WaSSI (Averyt et al., 2013); WEP-L (Jia et al., 2001); WOFOST (Diepen et al., 1989).

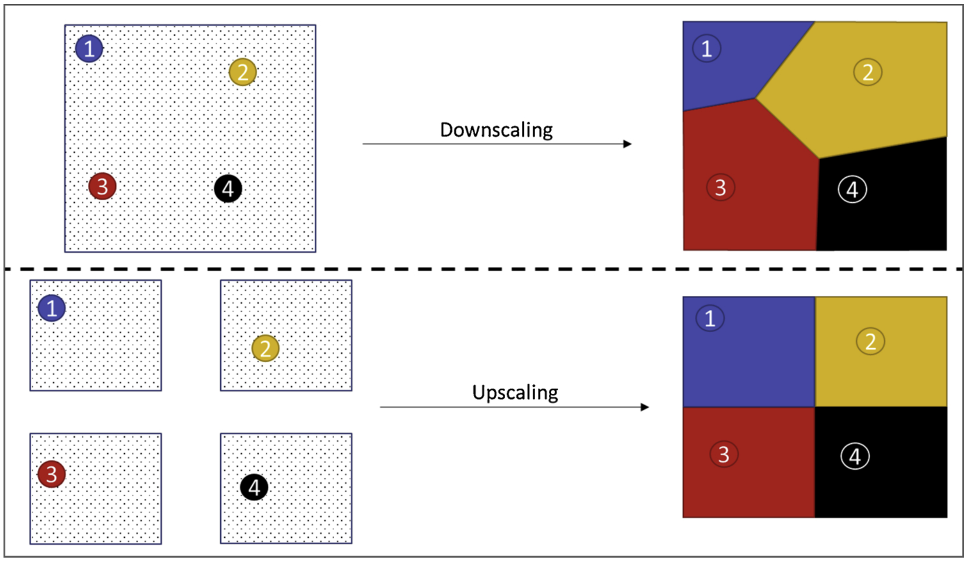

Fig. 4. Example of up/downscaling of rainfall data.

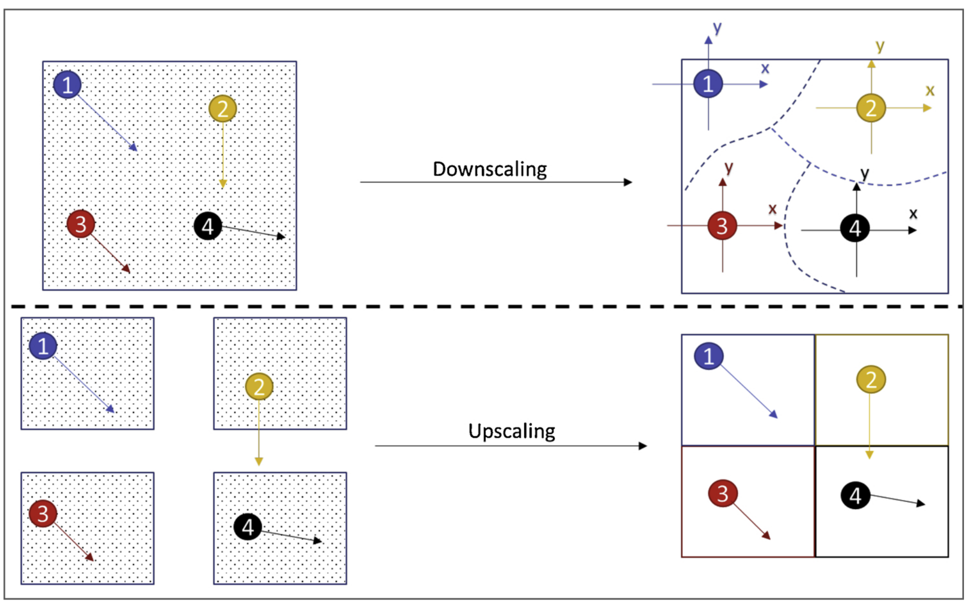

Fig. 5. Example of up/downscaling of wind data.

important task for the scientific modelling community dealing with sustainable water resources management for crop system improvement. The principal objectives of the reviewed studies (Table 1) concern better quantification of ET, CO_2, water and nutrients flux estimation with dynamic vegetation, along with the cost and time saving involved in the model development. For this reason, exchanges between atmosphere– surface–subsurface water fluxes need to be complemented with crop development and other physiological processes.

The developed models have been parameterized for a given target crop(s) according to the area extend and/or relevance for the study focus. All studies' results show that hydrological processes are sensitive to changes led by the incorporation of crop dynamics in the hydrologic models and significantly improve fluxes estimation (compared to the original hydrological models in case distributed hydrological models, where some zones of the watershed present specificity regarding the cropping pattern). It was concluded (case study related) that improving the estimation of energy, ET, CO_2, pollutants and water fluxes over croplands is achieved through a more accurate description of vegetation dynamics.

Regardless, with the numerous crop models available and their different levels of sophistication, water requirement and availability are basic inputs. Increased accuracy of soil hydrology strengthens the understanding of temporal dynamics as a function of agricultural production and inter-seasonal plant physiological changes, while at the same time improvement to irrigation practices.

4. General discussion and implications

Meteorological observations, crop production, soil samples and other data pertinent to watershed system are gathered at local scale. Current research supports integrated assessments of complex systems based on place-oriented assessments. 'Results of this review show that building larger-scale understandings from localized case studies is an upscaling task (aggregation). Nonetheless, not all data are prompt to aggregation to estimate larger scale values, such as vector (i.e. wind) or intensive (i.e. temperature) data. However, technical solution for problems in upscaling exists, such as linking models between scales, changing model resolution or comparing aggregates with overall records (Fig. 3).

Challenges related to data availability at detailed scales, the increasing complexity of causal relationships, and capturing contextual detail, led to another essential aspect of coupling – downscaling. Because many driving forces (i.e. rainfall, topography, etc.) operate at watershed scale, they shape on-field realities. However, this is not easily attainable by interpolating spatially data, which results in great uncertainties (Fig. 4 and 5, examples for rainfall and wind data; downscaling often use a triangularization process, where upscaling is proceeded through grids aggregation). In addition, validation processes of the model's outputs are not always attainable, due to lack of detailed observational datasets.

Assuming that all relevant data are converted to a common metric data, the coupling challenge has been greatly simplified. If the aim is to attain an integrated understanding of processes, simply converting numbers to a common spatial scale does not necessarily assures conceptual integration, as contrasted with computational integration where coupling method has a crucial role in the system processes assimilation. It is often a matter of reconciling differences in process assumptions, theoretical foundations and perceived standards.

Last but not least, distributed hydrological models are land-use dependent for soil functions and rainfall distribution. Land-use can significantly alter the seasonal and annual hydrological response within a catchment. Nevertheless, cropping systems represent one category among others (i.e. urban areas, forests, etc.). The prevalence of agricultural activity in a given hydrological system will determine the potential benefit of incorporating crop model in hydrological simulation.

The first criterion for modeler when selecting models to be coupled should be the end purposes, followed by the selection of the adequate compromise between precision and ease-of-use for investigating the models' assumptions and qualifications. This implies that the addressed user should have a comprehensive overview on the selected models' purposes, metrics, capabilities, and field of validity. Then, the user has to consider the biophysical cycles that have to be modeled along with the crop and hydrological cycle. The greater is the number of simulated processes, the larger is the complexity of the resulting coupled model.

Going on through the choice of models, specific purposes regarding the investigated agro-hydrological system and climatic regions, such as their ecological relevance, economic importance, expected risks, etc., should be defined. Hence, it is necessary to refer to the geographic regions where models have been already applied. Successful studies for assessments and analyses serve as guides towards most suitable planning for coupling, especially those targeting climate changes and adaptation issues. Literature provides several models' reviews, mostly focused on topics of specific interests, such as the description of general approaches and evaluation, inter-comparison of models' performance, forecasts, and gaps analysis.

5. Conclusion

The objective of our work was to review studies involving coupled hydrologic and crop growth models. The study provides useful examples for practical information and purposes of this new tendency in model development. This study can be of interest for researchers, practitioners, and policymakers involved in agro-hydrological studies and projects. Particularly, this study may help understanding the potential benefit raising from incorporating crop models in hydrological simulation for water resources conservation, sustainability, and performance improvement of crop and irrigation systems.

Despite its potential, the study results suggest that the current interest trend in coupling hydrologic and crop models is limited to improvement of crop systems performance and environmental impacts assessment. Hydrologic systems resilience to imported/exported quantities (i.e.: soil nutrients and water) for agricultural practices is an important aspect that has to be given more consideration for sustainable crop production and resource conservation concerns.

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