Climate Uncertainty Modelling in Integrated Water Resources Management: Review

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Abstract. Integrated water resources management is exposed to the effects of several risks (climatic, socio-economic, and political). Currently, climate change represents one of the greatest risks for many countries around the world and the agricultural sector in particular. In the literature, climate change is sufficiently researched but there are scarce studies that deal with the theme of risk in agricultural water management and in particular the management under climate change. In the paper, we first define out the characteristics and particularity of climate change risk and then we point the different approaches and methods for taking into consideration for climate change risk in the integrated water resources management models for the agriculture sector. In this work, we aim to appraise the quantification of uncertainties in systems modelling in watersheds and discuss various water resource management and operation models. ***Keywords***: Integrated water resources management, climate change, risk, Uncertainty, modelling review.

1 Introduction

According to IPCC Report, climate change is likely to have a complex set of impacts on water resources throughout the world [1]. Climate change will affect the ocean and surface temperatures, precipitation patterns, agricultural water demand, evapotranspiration rates, frequency, storm intensity, timing, the magnitude of runoff, and sea level in coastal communities [2]. In this context, the problem of climate change and fear of its serious negative impacts has gained vast socio-economic, hydrologic, and agronomic interest.
In order to assess the impacts of climate change and to propose adaptation measures, integrated water resources management models have been developed by academics and policy-makers in recent decades. The consideration of potential CC effects on IWRM models introduces many forms of uncertainties in these models.
In the literature, climate change is sufficiently researched but there are scarce studies that deal with the theme of risk in agricultural water management.
This study aims to offer an updated review of the advances in hydro-agro-economic modeling in the last decade, focusing on the assessment of water management for the agriculture sector under climate change. In this paper, we first define the characteristics and particularity of climate change risk and then we review various approaches so far applied to address various sources of uncertainties in integrated water resource management models for the agriculture sector by highlighting key findings.

2 Characteristics and particularity of climate change risk for the agriculture

It is commonly acknowledged that most climate change impacts will relate to water [3]. How water is managed will be at the center of climate change adaptation strategies. Globally, the negative impacts of climate change on water systems are expected to outweigh the benefits. This is particularly true in the agriculture sector, the largest consumer of water globally (agricultural water withdrawal represents 70 percent of all withdrawal) and where water plays a critical role in crop and animal production.
Although agriculture is highly dependent on climate, so far evidence of observed changes related to regional climate changes, and specifically to water, has been difficult to find. One of the reasons for this is that agriculture is strongly influenced by factors unrelated to climate, especially management practices, technological advances, market prices, and agricultural policies. These factors have more immediate impacts on the water than those induced by climate change [4]. For this reason, it is important to understand the characteristics and particularity of climate change risk for water resources management particularly for the agricultural sector before assessing the potential impact of climate change. This part identifies the key risks and opportunities associated with long-term climate change by exploring the future impacts of climate change.

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2.1 Climate change and crop production

Throughout the production season, crops are sensitive in varying degrees to different weather events. Global warming changes not only the climate's mean state but also its variability, which is projected to increase in most areas [5,6]. Both inter- and intra-annual rainfall variability affect the outcome of cropping systems during any particular season [7,8]. Increasing climate variability will put the sustainability of crop production at risk. The timing and interactions of stresses at different crop growth stages may cause higher losses and increase food insecurity in the future [9]. Many studies have gone into assessing the vulnerability agricultural sector to climate change. However, the time dimension of increased risk is often only implicitly included in the modelling, statistical and empirical studies.

2.1.1 Inter- and intra-annual rainfall variability:

- Growing research addresses the role of the timing and severity of climate hazards, to identify the adaptation policies required to improve resilience at the farm level [10,11]. Agronomy research typically uses experiments and modelling to discern cause-and-effect relationships between weather variables, and crop yields but generally does not consider hazard frequency and associated vulnerability. For most crops, upper and lower thresholds of climatic parameters have been established for different phenological stages [12].

2.1.2 Extremes values:

- Weather parameter values extreme at different stages affect crop production [13,14]. Both Temperature and rainfall extremes, in the form of heat stress, cold stress, drought, and flood can damage crop production differently at different stages [15]. Temperature thresholds, critical months, and thresholds for critical crop stages have been studied at the regional level, such as for rice crops in Asia [16]. Rains with storms can be particularly damaging and mostly cause lodging that leads to heavy losses for example 60–70% diminishment of yield in wheat [17]. Other studies have further differentiated crop sensitivities to the time duration of exposure. Short exposure to high temperatures at anthesis drastically reduces spikelet fertility, which drops from 80% to 20% with a two-hour exposure to 38 ◦C, and falls to zero if a rice crop is exposed to 41 ◦C for more than one hour [18].

2.2 Climate change and farm income

Net farm income is affected by crop yield and production costs [19]. If a weather event coincides with a sensitive crop stage, the level of risk of impact on net farm income becomes significant [20,21]. In addition to impacting crop yields and quality, Climate change may also disrupt farm operations and field workability, affecting production costs. Even if farmers cope with a hazard, there may be a cost associated with these coping measures [22]. Socio-economic research analyses associations between, yields, hazards, and farm income, but often neglected the taking into account the risk aversion of farmers in terms of adaptation to climate change.

3 Approach and methods

The climate is a very complex system composed of a large number of highly interconnected components and parameters. The Relationships between the components are non-linear and very complex. According to the IPCC rapport, Climate change will increase in the coming decades due to past greenhouse gas emissions and the inertia of the climate system [23]. However, the adaptation to climate change impacts has become a major source of concern for human development and optimal water resources management. In this context, the scientific community is devoted considerable efforts to addressing various aspects of climate change, including how to best adapt to future climatic conditions given the uncertainty associated with climate change [24,25]. Water resource management models have been involved in the past four decades in several aspects of single and multi-purpose reservoirs, optimization models, imprecision and uncertainty quantifications, and climate change [26].

Agronomy modelling helps to quantify the effect of weather stresses on yield by crop stage but generally does not consider hazard frequency, the effectiveness, and costs of coping and associated vulnerability at the crop production system level. recently, integrated regional water resource management models (or hydro-agro-economic modelling) have been applied for the assessment of impacts and adaptation to climate change, and the associated uncertainties[27,28,29,30]. These models can represent climate change impacts on water resources and agricultural production based on economic sciences.

The integrated regional water resource management models are associated with various forms of climate change uncertainties accumulating from various stages of decision-making [31]. Uncertainties arise at each stage of the modelling and decision-making process due to the random nature of input variables, various parameters, models, imprecise goals of the users, priorities, and social importance in decision-making by various stakeholders. Addressing these uncertainties is very important for precise decision-making and avoiding the failure of water resource system management [32]. Identifying and addressing various sources of uncertainties is one of the crucial tasks in water resource modelling to have better water resources management policies

Several review studies have articulated the evolution of water resource management systems modelling, focusing on several key aspects in terms of the application of evolutionary algorithms and metaheuristic optimizations for optimal strategies of the planning and management of water resource systems [33,34].

Review papers that can articulate various studies of water resource management and associated uncertainties are limited in the literature.
In this article, we review various approaches so far applied to address various sources of uncertainties in integrated water resource management models for the agriculture sector by highlighting key findings.

3.1 Data and input-parameter uncertainty

Due to the conjunction of hydrological, agronomic, and economic components, IWRM models are prone to data and input-parameter uncertainty from both the physical side of water availability as well as the socio-economic side of data demand and its complex interlinkages.
Regarding physical and climatic input parameters, it is mainly about:
- Inherent model uncertainty of climate models [35];
- Model chain uncertainty from deriving information from global to regional data and from regional to spatially more explicit climate data [36];
- Biases involved when using upscaling and downscaling methods [37];
- Economic inputs (water prices and cost of adaptation measures) [36].

Input parameter and data uncertainty can be addressed by: (a) various scenarios combined with a sensitivity analysis in the case of simulation IWRM models, or (b) stochastic programming, that is, through the introduction of a stochastic component in the optimization of the model [38].

3.1.1 Sensitivity analyses:

Are commonly used in IRWR models s to define the response of input parameters that are likely to suffer from uncertainty. In IWRM models it is used on outcomes of groundwater recharge, runoff, or crop evaporation, and crop yield under changing rainfall and temperatures [39]. D'Agostino et al. [27] used a sensitivity analysis of the major water balance components and agricultural water use for their integrated hydro-economic model for the case study area of Apulia in Italy to assess the impacts of Climate change. They explicitly accounted for uncertainty by considering different scenarios climatic and by conducting a nominal range sensitivity analysis. Sensitivity analyses were employed to determine the contribution of single-input parameters to variations in the simulation model output [38]. Their results revealed that climatic conditions, soil type, and cropping patterns exerted a major impact on the outcome of the model. The variance of the upper and lower bounds of irrigation water.

El ouadi [40], used an integrated model for the case study area of Ait Ben Yacoub located in east Morocco to assess the impacts of CC on the agriculture sector. To identify the model input parameters that influence the results of the model and, taking into account the uncertainty, parametric sensitivity analysis is performed by the" One-Factor-At-A-Time" approach within the" Screening Designs" method. The results of this analysis show that 6 parameters affect significantly the objective function of the model, it is in order of influence: i) Coefficient of crop yield response to water, ii) Average daily gain in weight of livestock, iii) Exchange of livestock reproduction, iv) maximum yield of crops, v) Supply of irrigation water and vi) precipitation. These six parameters register sensitivity indexes ranging between 0.22 and 1.28. Those results show high uncertainties on these parameters that can dramatically skew the results of the model or the need to pay particular attention to their estimates. Keywords: water, agriculture, modelling, optimal allocation, parametric sensitivity analysis, Screening Designs, One-Factor-At-A-Time, agricultural policy, climate change.

3.1.2 *Climate modelling*

To account for Climate change impact uncertainties, different climate scenarios can be applied to IWRM models. To this end, local HEMs need to be combined with global or regional climate models. Modelling global climate change is a branch of geophysical sciences that is hard to solve due to the difficulty of interpreting the cause-effect chains in a complex system driven by multiple factors. Many recent climate studies make use of simulations with the help of general climate models (GCMs) that represent mathematically the behavior of the global climate system and simulate the interactions of the oceans, atmosphere (temperature, wind, water vapor...), land surface, including the carbon cycle, biosphere, and water storage. Global climate models have been extensively used to simulate observed climate change during the 20th century [41]. Such models were fed with combinations of natural and anthropogenic forcings and proved to be able to reproduce broad, large-scale, features of the observed Earth's climate of the past century. However, they cannot mimic important details of observed climate. This holds in particular for the global variability of climate and extreme values.

3.1.3 *Upscaling/downscaling biases*

Feeding IWRM models for basin scales with output data generated by climate models requires the downscaling of results from regional climate models that in turn derive their outcomes from global climate models. This process involves additional uncertainty and biases that are often ignored in HEMs [42]. Sophisticated methods are available to conduct downscaling with bias-correction methods of global to regional information regarding land use and climate change [43,44]. To address model uncertainty upscaling/downscaling biases, various global models can be applied as robustness checks of the analysis [45]. It is recommended to employ several hydrological models and various emission or climate scenarios [45]. Wada et al. [45] suggested a multi-model approach to address uncertainties arising from model uncertainty and CC uncertainty in their analysis of irrigation water demand to provide robust modeling results.

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The majority of IWRM models addressing CC risks and uncertainties apply simulation models. Escriva-Bou et al. [46] selected six regional climate models that showed the best-fitting results when compared to historical precipitation and temperature data in the basin analysed (Jucar River basin, Spain). Graveline et al. [47] constructed one CC scenario by downscaling precipitation, temperature, and climate data from regional climate models and combined them with two catchment-specific agricultural management scenarios to address the effect of climate and socio-economic changes on water resources in the Gallego catchment area (Spain).

3.1.4 *Stochastic method*

D'Agostino et al. [27] included stochastic components in their optimization model. The non-linear stochastic economic component of the HEM that maximizes farmers' utilities takes uncertainties concerning prices and yields into account. As a framework for planning investments and considering the interrelationships between CC and water resource systems, the concept of hydro-economics was used by Jeunland et al. [48]. These last two studies included both physical aspects of CC (changes in runoff, net evaporation, water demand, and flood and drought risks) as well as economic uncertainties (e.g., real value and productivity of water-system-related goods and services). The innovation of this approach involves extending a hydrological water-resource planning model to include economic uncertainty. Additionally, Jeuland [48] accounted for uncertainties by using a stochastic streamflow generator, a hydrological simulation model, and an economic appraisal model. The economic appraisal model calculates the net present value (NPV) of hydrologic projects under a Monte Carlo simulation and considers various possible physical and economic states. Reynaud and Leenhardt [49] took economic risk into account by introducing a probabilistic component in the microeconomic production model and represented each farmer's behavior in their integrated water-management framework, thereby representing agricultural, urban, and environmental water demand in the case of the river Neste (France). This model includes climate and crop price variation and farmers' risk preferences and influences farmers' choices regarding land use, sowing dates, and water use. Also, [50] considered climate change uncertainties via stochastic programming methods in the economic model, which is combined with a hydrological model to form IWRM models. Graveline et al. [51] conducted Monte Carlo simulations to account for input-parameter uncertainty in their farm-scale model applied to two regions in France.

3.2 Imprecise goals of the users

The next prevailing uncertainty in integrated water models is the imprecise goals of the users, which have been conventionally addressed using fuzzy set theory [52]. Ahmad [52] reviewed reservoir operation models with fuzzy optimization along with other optimization methods such as Artificial Neural Network (ANN), Genetic Algorithm (GA), artificial bee colony, and Gravitational Search Algorithm (GSA).

4 Conclusion

In recent years, several IWRM models have taken into account uncertainties associated with Climate change and their feedback links, but limitations still persist. In this context, this study highlighted the mains uncertainties that have to be addressed by the integrated water resources management models for the agriculture sector in particular (input-parameter uncertainty; scenario uncertainty; model chain uncertainty).
Additionally, this paper has reviewed the different approaches and methods for taking into consideration climate change risk in the integrated water resources management models for the agriculture sector.
To summarize, Climate change uncertainties can be addressed by (a) including diverse climate change scenarios representing different states of certain aspects in optimization IWRM models (water availability, temperature, associated costs, and benefits, environmental or (b) incorporating stochastic components in optimization models. The hybrid approaches combining simulation and optimization network-based IWRN models may be well suited to analyze water policies under CC at a river-basin scale.
Currently, the current challenges for the hydro-agro-economic models are to include the food-energy-water nexus and the successful representation of micro-macro linkages and feedback under climate change uncertainties and risks.

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References

1. IPCC, Climate change 2007: The physical science basis, Agenda. Intergovernmental Panel on Climate Change, p. 333 (2007).

2. K.D. Frederick and D.C. Major, *Climatic Change*, **37**, 7-23 (1997), http://dx.doi.org/10.1023/A:1005336924908

3. United Nations UN-Water Annual Report (2012).

4. B.C. Bates, Z.W. Kundzewicz, S. Wu and J.P. Palutikof, Climate Change and Water. *Technical. Paper of the IPCC*, Eds. (2008).

5. A. Pandey, R.K. Chakrabarty, L. Liu, and M.I. Mishchenko, *Opt. Express*, **23**, A1354-A1362, (2015) http://dx.doi.org/10.1364/OE.23.0A1354.

6. C. Schär, P. L. Vidale, D. Lüthi, C. Frei, C. Häberli, M. A. Liniger, C. Appenzeller, *Nature*, **427**, 332-336 (2004).

7. IPCC, A special report of working group I and II of the intergovernmental panel on climate change.*Cambridge University Press, Cambridge UK and New York, NY, USA* (2012).

8. J. B. Nippert, A. K., Knapp, & J. M. Briggs, *Plant, Ecology,* **184**, 65-74 (2006).

9. P.K. Thornton, P.J. Ericksen, M., Herrero, A.J., Challinor, *Glob. Change Biol*. **20**, 3313-3328 (2014).

10. R. Heltberg, P. B. Siegel, S. L. Jorgensen, *Global Environ. Change* **19**, 89–99 (2009).

11. R. L. Wilby, S. Dessai, *Weather*, **65**, 180-185 (2010).

12. Q. Luo, *Clim. Change* **109**, 583-598 (2011).

13. S. Chakraborty, A. C. Newton, *Plant. Pathol.* **60**, 2-14 (2011).

14. P. Juroszek, A.Von Tiedemann, *Eur. J. Plant Pathol.* **136**, 21–33 (2013)

15. K., Bhandari, K.D. Sharma, B. Hanumantha Rao, K.H.M. Siddique, P. Gaur, S.K. Agrawal, R.M. Nair, H. Nayyar, Temperature sensitivity of food legumes: a physiological insight. *Acta Physiol. Plant.* **39**, 1-22 (2017).

16. R. Wassmann, S. Jagadish, K. Sumfleth, H. Pathak, G. Howell, A. Ismail, R. Serraj, E. Redona, R. Singh, S. Heuer, *Adv. Agron.* **102**, 91-133 (2009a).

17. P. M. Berry, J. Spink, *Field Crops Res.* **137**, 19–26 (2012).

18. S. Yoshida, Fundamentals of rice crop science. International Rice Research Institute (IRRI), Los Banos, Philippines (1981).

19. T. Thamo, D. Addai, D. J. Pannell, M.J. Robertson, D. T. Thomas, J.M. Young, *Agric. Syst.* **150**, 99–108 (2017).

20. H. Shah, C. Siderius, P. Hellegers, *Agric. Syst.,* **178**, 10274 (2020).

21. C. Toeglhofer, R. Mestel, F. Prettenthaler, *Weather Clim. Soc.* **4**, 190–199 (2012).

22. M. Mandryk, P. Reidsma, M. K. Van Ittersum, *Agric. Syst.* **152**, 154–164 (2017).

23. IPCC, Climate change: impacts, adaptation, and vulnerability: contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press (2001).

24. R. Pielke, G. Prins, S. Rayner, D. Sarewitz, *Nature*, 445(7128), 597-598 (2007). http://dx.doi.org/10.1038/445597a.

25. P, Reidsma F. Ewert, A. O. Lansink and R. Leemans, *Eur. J. Agron*. **32**, 91-102 (2010).

26. D. P. Loucks, *Water Resour. Manag*, **31**(10), 2905-2916 (2017).

27. D.R. D'Agostino, A. Scardigno, N. Lamaddalena, D. El Chami, *Water Resour. Manag*. **28**, 4303–4318 (2014).

28. B. H., Hurd, and J. Coonrod, *Climate Res.* **53**, 103-118 (2012).

29. M. Jeuland, D. Whittington, *Water Resour. Res.* **50**, 2086–2107 (2014).

30. J. Medellín-Azuara, L. G. Mendoza-Espinosa, J. R. Lund, J. J. Harou, R. E. Howitt, *J. Environ. Manag.* **90**, 3470–3478 (2009).

31. B. H., Hurd, and J. Coonrod, *Climate Res.* **53**(2), 103-118 (2012).

32. M.T. Kahil, F.A. Ward, J. Albiac, J. Eggleston, D. Sanz, *J. Hydrol.* **539**, 510-524 (2016).

33. M.T. Kahil, F. A. Ward, J. Albiac, J. Eggleston, D. Sanz, *J. Hydrol.* **539**, 510–524 (2016).

34. F.A. Ward, R. Young, R. Lacewell, J.P. King, M. Frasier, J.T. McGuckin, New Mexico Water Resources Research Institute: Las Cruces, NM, USA, (2001).

35. IPCC, Intergovernmental Panel on Climate Change Fifth Assessment Report (AR5) No. WGII; WMO (World Meteorological Organization): Geneve, Switzerland; UNEP: Geneve, Switzerland, (2014).

36. S. Stoll, H. J. H. Franssen, R. Barthel, W. Kinzelbach, *Hydrol. Earth Syst. Sci.***15**, 3861-3875, (2011).

37. G. N. Souza da Silva, M. M. Alcoforado de Moraes, *Reg. Environ. Chang.* **18**, 1957-1967 (2018).

38. D. R. D'Agostino, A. Scardigno, N. Lamaddalena, D. El Chami, *Water Resour. Manag.* **28**, 4303–4318 (2014).

39. R. N. Jones, F. H. S. Chiew, W.C. Boughton, L. Zhang, *Adv. Water Resour*. **29**, 1419–1429 (2006).

40. I. El Ouadi, Parametric sensitivity analysis of an agro-economic model of management of irrigation, Water Conference: EGU General Assembly, Vienna, Austria (2015).

41. P. Goderniaux, S. Brouyère, H.J. Fowler, S. Blenkinsop, R. Therrien, P. Orban, A. Dassargues, *J. Hydrol.* **373**, 122–138 (2009).

42. P. Goderniaux, S. Brouyère, H.J. Fowler, S. Blenkinsop, R. Therrien, P. Orban, A. Dassargues, *J. Hydrol.* **373**, 122-138 (2009).

43. Y.C.E. Yang, C.M. Brown, W. Yu, A. Savitsky, *Water Int.* **38**, 632–650 (2013).

44. H.J. Fowler, S. Blenkinsop, C. Tebaldi, *Int. J. Climatol.* 27, 1547–1578 (2007).

45. Y. Wada, D. Wisser, S. Eisner, M. Flörke, D. Gerten, I. Haddeland, N. Hanasaki, *Geophys. Res. Lett.* **40**, 4626–4632 (2013).

46. A. Escriva-Bou, M. Pulido-Velazquez, D. Pulido-Velazquez, *J. Water Resour. Plan. Manag*. **143**, 0401700 (2017).

47. N. Graveline, B. Majone, R. Van Duinen, E. Ansink, *Reg. Environ. Chang.* **14**, 119-132 (2014).

48. M. Jeuland (2010). *Water Resour. Res.* **46**(11) (2010). https://doi.org/10.1029/2010WR009428

49. A. Reynaud, D. Leenhardt, MoGIRE: A model for integrated water management. *In Proceedings of the 4th International Congress on Environmental Modelling and Software*, Barcelona, Spain, 7–10 (2008).

50. C. Varela-Ortega, I. Blanco-Gutiérrez, H.S. Swartz, T.E. Downing, *Glob. Environ. Chang.* **21**, 604–619 (2011)

51. N.; Graveline, S.; Loubier, G.; Gleyses, J.D. Rinaudo, *Agric. Syst.* **108**, 29-41 (2012).

52. A. Ahmad, A. El-Shafie, S. Razali, Z. Mohamad, *Water Resour. Manag.* **28**, 3391-3405 (2014).