Usefulness of Information for Drought Management Decisions: Data and User Perspectives

Lines Diaz, C.

DOI
10.4233/uuid:915b322a-ade1-476b-a0d8-610a0b1f8500

Publication date
2025

Document Version
Final published version

Citation (APA)
Lines Diaz, C. (2025). *Usefulness of Information for Drought Management Decisions: Data and User Perspectives*. [Dissertation (TU Delft), Delft University of Technology]. IHE Delft Institute for Water Education. https://doi.org/10.4233/uuid:915b322a-ade1-476b-a0d8-610a0b1f8500

Usefulness of Information for Drought Management Decisions:

Data and User Perspectives

Clara Lines Diaz

USEFULNESS OF INFORMATION FOR DROUGHT MANAGEMENT DECISIONS: DATA AND USER PERSPECTIVES

Clara Lines Diaz

USEFULNESS OF INFORMATION FOR DROUGHT MANAGEMENT DECISIONS: DATA AND USER PERSPECTIVES

DISSERTATION

for the purpose of obtaining the degree of doctor
at Delft University of Technology
by the authority of the Rector Magnificus Prof.dr.ir. T.H.J.J. van der Hagen,
chair of the Board for Doctorates
and
in fulfilment of the requirement of the Rector of IHE Delft
Institute for Water Education, Prof.dr. E.J. Moors,
to be defended in public on
Monday, 7 April 2025 at 12:30 hours

by

Clara LINES DIAZ

This dissertation has been approved by the (co)promotor.

Composition of the doctoral committee:

Rector Magnificus TU Delft	chairperson
Rector IHE Delft	vice-chairperson
Prof.dr. G.P.W. Jewitt	TU Delft / IHE Delft, promotor
Dr.ir. M.G.F. Werner	IHE Delft, copromotor

Independent members:

Prof.dr.ir. S.C. Steele-Dunne	TU Delft
Dr. L. De Stefano	Complutense University of Madrid, Spain
Dr.ir. A. van Loon	VU Amsterdam
Dr. M. Ramos	INRAE / Sorbonne University, France
Prof.dr. T.A. Boogaard	TU Delft, reserve member

This research was conducted under the auspices of the Graduate School for Socio-Economic and Natural Sciences of the Environment (SENSE)

Published by IHE Delft Institute for Water Education
www.un-ihe.org
ISBN 978-90-73445-71-0

To all those who helped keep this project going

ACKNOWLEDGEMENTS

This (long) journey would not have been possible without the support of many people and organisations. Firstly, I would like to thank my supervisory team. Many thanks to Micha for his guidance, encouragement and good mood throughout the whole process; for his thorough and useful comments to improve my drafts, and for the long chats to discuss ideas or results. A big thanks also to my promotors for their support during the different phases of this research: to Prof. Arthur Mynett for his help in the first steps of the journey; to Prof. Wim Bastiaansen, for enthusiastically embracing my research project after Arthur retired, his encouragement and the inspiring discussions about remote sensing, and to Prof. Graham Jewitt, for taking over, unsticking the situation and facilitating its successful conclusion. I would also like to thank here my doctoral committee for taking the time to review this work.

I gratefully acknowledge the funding from the European Union Seventh Framework Programme Earth2Observe project (Global Earth Observations for integrated water resources) for my time at IHE-Delft and for the travel to the project meetings, research trips and conferences. I really enjoyed being part of the project and having the opportunity to work with and learn from such an interesting, knowledgeable and friendly team from around the world. I would like to thank in particular the colleagues involved in the Mediterranean case study: Pere Quintana Seguí, Gonzalo Miguez-Macho, and Anaïs Barella-Ortiz on the Spanish side (it was a pleasure to work with all of you in the Ebro case study), and Patricia López-López, Stefan Strohmeier, Mohammed Karrou, and Vinay Nangia on the Morrocan side (many thanks in particular for the very instructive visit to the Tadla irrigation district). A special thanks also to Alex Kaune, my project and PhD companion in IHE-Delft. I would also like to extend my thanks the Hymex community, for their useful and well organised conferences and their welcoming members.

Many thanks to the CEIGRAM for hosting me for two months in Madrid, which allowed me to travel repeatedly to the Ebro basin to meet the different stakeholders, and thanks to all the people I found there (especially to Esperanza and Ivanka) for making me feel part of the team from the first moment. I had a lovely time at CEIGRAM with all of you. Special thanks to Ana Iglesias for helping arrange both my time at CEIGRAM and part of the meetings with the stakeholders; to Luis Garrote and Vicente Sotes for helping with the visits to the Canal de Aragón y Cataluña (CAyC) and Raimat, and to the three of them for the insights and helpful discussions about water managers and farmers decisions in the area.

I'm very grateful to all the people in the Ebro basin who spent time helping me understand the context and their decision processes. Your contribution has been fundamental for this thesis. Thanks to Miguel Ángel Galván, Rogelio García Vera, Rafael Moneo from the

Ebro Basin Authority; to Roberto Quintilla, Jose Luis Pérez from the CAyC, to Daniel García and Juan Carlos from Agropixel and Raimat. An immense thank you also to the Ebro Basin Authority for their excellent and open hydrological data.

Thanks to Jolanda, Anique, and Floor for their support with the paperwork, to Vera for helping with the summary in Dutch, and to Lindsay, James and Kevin for being supportive of this project and offering me flexibility when needed. Many thanks also to my colleagues at Scottish Water who broadened my view and knowledge of water management.

During my time at IHE-Delft I had the pleasure to meet lots of amazing people, more that I could possibly name here, but I would like to thank especially Tarn, Yuli, Fiona, Polpat, Selvi, Isnaeni, Sha, Leo, Lihn and Mona for warmly welcoming me into their lunch table and lives and filling my time in IHE with joy and delicious food, and my lovely desk neighbours Jeewa, Mia and Mawiti.

Thanks to Cristian for, among other things, being very good at knowing when I could be encouraged back to work and when I just needed a break from it all, and to my family, for their enthusiasm and motivation.

SUMMARY

This thesis examines how information can benefit drought management decisions at the basin scale. Three perspectives are tested. The question is first approached from a data-centric perspective, assessing the usefulness of remotely sensed datasets to detect early stages of drought and determining how much time can be gained to inform operational land and water management practices. A user-centric approach is then followed, identifying through semi-structured interviews the information use and needs voiced by farmers and reservoir operators to support water allocation decisions during droughts, and quantifying the value of (new) information to support these decisions through modelling. Lastly, the user-centric and data-centric perspectives are combined to assess the usefulness of seasonal forecasts of water availability to support water allocation decisions in irrigated agriculture through a risk-based approach and the factors that have an impact on that usefulness.

The assessment from the user-centric perspective provided essential knowledge on the decisions, the courses of action available to decision makers, and the conditions that determine the selection of one of the available courses of action at each decision point. This knowledge is necessary to assess whether the information can change the decision outcome, which is a prerequisite for its usefulness. The user perspective also helped confirm there is a perceived need for additional information among the decision makers interviewed. The assessment from the data-centric perspective showed the ability of the selected datasets to provide key information required by the decision makers in a timely manner, while the combined perspective allowed to demonstrate the capacity of information available from seasonal forecasts to actually impact the outcome of the decision. These three perspectives show that there are multiple factors that need to be considered when assessing the usefulness of information. Notably, these are (i) the ability of information to provide either the observations or predictions that are needed by the decision maker at the time when they are needed, and (ii) the capacity of the decision maker to change the course of action as a result of the available information. The results show that both of these factors depend on the options available to the decision maker. These may differ for different individuals, depending also on the level of risk aversion decision makers have as well as their technical capacities, and the context of the decision. Changes in the market value of goods, or weather variability, may also impact the usefulness of information for the decisions analysed in this research.

Bringing these perspectives and their respective methods together contributes to fill the gap between technical and human-centred approaches to assess the usefulness of information for drought management decisions.

SAMENVATTING

Dit proefschrift onderzoekt hoe bruikaar informatie is bij het ondersteunen van beslissingen in het beheer van droogte op stroomgebiedsschaal. Drie perspectieven worden getoetst. Eerst wordt het vraagstuk benaderd vanuit een perspectief waarbij de data die gebruikt wordt centraal staat. De bruikbaarheid van een geselecteerd aantal sattelietdataproducten bij het detecteren van droogte in een vroeg stadium is geëvalueerd en er is onderzocht hoeveel tijd hiermee gewonnen kan worden bij het nemen van beslissingen voor het inzetten van operationale maatregelen in de allocatie van water en de keuzes die boeren maken tussen geïrrigeerde en niet-geïrrigeerde gewassen. Het tweede perspectief benadert het vraagstuk vanuit een hoek waarbij de gebruiker van de informatie centraal staat. Middels semi-gestructureerde interviews met boeren en reservoirbeheerders is onderzocht wat de informatiebehoefte is en hoe ze die informatie gebruiken om de beslissingen te ondersteunen die zij nemen ten aanzien van het beheer van het beschikbare water. Hiermee wordt vervolgens met een model onderzocht wat de toegevoegde waarde van die (nieuwe) informatie is bij het nemen van die beslissingen. Het derde perspectief combineert de twee voorgaande perspectieven. De bruikbaarheid van seizoensvoorspellingen van waterbeschikbaarheid bij het nemen van beslissingen, ten aanzien van de allocatie van water aan geirrigeerde landbouw, wordt getoetst. Hierin wordt een risico-gestuurde aanpak toegepast bij het nemen van beslissingen, gegeven de (onzekere) seizoensvoorspellingen, en de factoren die de bruikbaarheid van die informatie beïnvloeden worden getoetst.

Bij de evaluatie vanuit het perspectief van de gebruikers is essentiële kennis opgedaan over de beslissingen die worden genomen, de mogelijkheden die de besluitvormers tot hun beschikking hebben en de voorwaarden die zij daarbij gebruiken om op elk beslissingsmoment te kiezen tussen de beschikbare mogelijkheden. Deze kennis is onmisbaar bij het toetsen of nieuwe en/of beschikbare informatie de uitkomst van een beslissing kan bepalen, hetgeen een voorwaarde is voor de bruikbaarheid van die informatie. Bovendien kon de in de interviews geuite perceptie dat er additionele informatie nodig was om de beslissing te ondersteunen worden bevestigd.

Kijkend vanuit het perspectief van de data, is in dit onderzoek aangetoond dat de geselecteerde satelietdatasets belangrijke informatie bevatten, die de gebruikers in de interviews als benodigd hadden geïdentificeerd. Bovendien kon worden aangetoond dat deze informatie tijdig beschikbaar is. Vanuit het derde, gecombineerde perspectief, kwam duidelijk naar voren dat de informatie die de seizoensvoorspellingen toevoegen inderdaad het vermogen hebben om de uitkomst van gemaakte beslissingen te beïnvloeden. Deze drie perspectieven laten zien dat er meerdere factoren zijn die moeten worden meegenomen bij het onderzoeken van de bruikbaarheid van informatie. Deze zijn met name: (i) het vermogen van de informatie, bestaande uit hetzij waarnemingen of

voorspellingen om toegenseden te zijn op de informatiebehoefte van de besluitvormer en om op het juiste moment voor het nemen van een beslissing beschikbaar te zijn; (ii) de mogelijkheden die de besluitvormer heeft om de uitkomst van de beslissing te kunnen bepalen aan de hand van de beschikbaar gestelde informatie. Resultaten van dit onderzoek tonen aan dat deze factoren bovendien afhankelijk zijn van de opties die een besluitvormer tot haar of zijn beschikking heeft. Voor verschillende individuen zijn deze verschillend en worden bovendien beïnvloed door een aantal factoren: hoe risicomijdend een beslisingnemer is, de technische capaciteiten en de context waarin de beslissing wordt genomen. Veranderingen in martkwaarde van goederen, of de variabileit van het klimaat, kunnen eveneens invloed hebben op hoe bruikbaar informatie is in het ondersteunen van de beslissingen die in deze studie zijn onderzocht.

De perspectieven en de daarbij gebruikte methoden die in dit onderzoek worden samengebracht, dragen bij door een brug te slaan tussen de tot nu toe uiteenlopende benaderingen om de bruikbaarheid van informatie in het ondersteunen van beslissingen in het droogtebeheer te toetsen: die waarbij de bruikbaarheid vanuit een puur technisch perspectief wordt bekeken en die waarbij dat wordt gedaan vanuit het perspectief van de mens die de beslissing neemt.

CONTENTS

Acknowledgements vii
Summary ix
Samenvatting xi
Contents xiii
1 Introduction 1
1.1 Drought information in water resources management 2
1.2 Key concepts in decisions and information assessment 3
1.2.1 Value of information 4
1.2.2 Usability 6
1.3 Research objectives and aim 6
1.4 Outline 8
2 The predictability of reported drought events and impacts in the Ebro Basin using six different remote sensing datasets 9
2.1 Introduction 11
2.2 Materials and methods 13
2.2.1 The Ebro Basin 13
2.2.2 Input datasets 15
2.2.3 Correlation between remote sensing data and the bench-marking datasets 20
2.3 Results 22
2.3.1 Drought events and impacts 22
2.3.2 Correlation of text-based records and remote sensing indicators 23
2.3.3 Correlation of crop yield and remote sensing indicators 27
2.4 Discussion 31
2.4.1 Use of impact records as drought reference 31
2.4.2 Early drought detection with remote sensing products 34
2.5 Conclusions 35
3 Do users benefit from additional information in support of operational drought management decisions in the Ebro basin? 37
3.1 Introduction 39
3.2 Study area and approach 41
3.2.1 The Ebro basin 41
3.2.2 Approach 42
3.3 Stakeholder consultation 43
3.3.1 Method 43

3.3.2 Confederación Hidrográfica del Ebro 44
3.3.3 Canal de Aragón y Cataluña (CAyC) 45
3.3.4 Farmers in the Canal de Aragón y Cataluña Irrigated Area 46
3.4 Decision model 47
3.4.1 Farmer decision: crop areas 47
3.4.2 Reservoir operation decision: water restrictions 50
3.4.3 Crop water demand and benefit 51
3.5 Quantifying the effect of additional information 51
3.5.1 Input data 53
3.5.2 Model options 54
3.6 Results 57
3.6.1 Selection of optimal thresholds 57
3.6.2 Quantifying the effect of additional information 61
3.7 Discussion 63
3.7.1 Potential value of additional information 63
3.7.2 Effect of the cost of planting on the value of information 65
3.7.3 Value of the information for the different types of farmers 65
3.8 Conclusions 66
4 How useful are seasonal forecasts for farmers facing drought? A user-based modelling approach 69
4.1 Introduction 71
4.2 Methods 73
4.2.1 Study area 73
Observed data 74
4.2.2 Seasonal forecasting of precipitation and streamflow 74
4.2.3 Modelling the cropping decisions of the farmers 75
4.2.4 Evaluating the benefit of decisions 78
4.3 Results 80
4.3.1 Seasonal forecast of water availability to end of season 80
4.3.2 Comparison of decisions made under the different information scenarios 82
4.3.3 Influence of farmer type on forecast value 84
4.4 Discussion 88
4.4.1 Is the forecast information good enough to be useful? 88
4.4.2 In what context is the forecast information useful? 89
4.4.3 To whom is the information useful? 90
4.5 Conclusions 91
5 Synthesis 93
5.1 Main results 94

5.2 How to assess the usefulness of information 96
5.3 Bridging the gap between technical and human-centred approaches 96
5.4 Interplay between information and decisions 97
5.5 Opportunities for further investigation 98
References 101
Code and data availability 123
Chapter 2 123
Chapter 3 123
Chapter 4 123
Appendices 125
Appendix A: The Ebro basin 125
Appendix B: Supplementary materials chapter 3 127
B1 Total benefit for different costs 127
B2 Yearly relative value 128
Appendix C: Supplementary materials chapter 4 130
C1 Seasonal Forecast Data, bias correction and skill assessment 133
C2 Crop yields 139
List of acronyms 141
List of Tables 143
List of Figures 145
About the author 147

1

INTRODUCTION

1.1 DROUGHT INFORMATION IN WATER RESOURCES MANAGEMENT

Droughts are natural hazards caused by a deficiency in precipitation over a prolonged period of time. Despite this apparently simple definition, droughts are notoriously difficult to characterise (Kiem et al., 2016; Wilhite et al., 2007) and different choices in the characterisation might result in different conclusions about the drought event (Hisdal et al., 2024). Droughts are a complex and recurring phenomenon that can occur practically anywhere, have multiple contributing factors, and affect the entire water cycle. They may lead to a wide range of negative environmental, economic, and social effects that vary from region to region. To help the characterisation of droughts, four drought types and definitions are commonly distinguished in the scientific literature (Mishra and Singh, 2010; Wilhite and Glantz, 1985): meteorological drought, resulting from lower than average precipitation for an extended period; agricultural drought, better defined as soil moisture drought (Berg and Sheffield, 2018), resulting from reduced soil water levels associated with water stress for vegetation; hydrological drought, resulting from anomalous lack of water in one or more of the components of surface or subsurface water supply such as streamflow, reservoir storage or groundwater, and socioeconomic drought, that occurs when the demand for an economic good exceeds the supply as a result of a weather-related water deficit.

In the same way that water deficits propagate through the hydrologic, agricultural, and social systems, drought impacts cascade through all natural and human systems that depend on water. Drought impacts are varied and far-reaching, affecting water supply for domestic and industrial use, agriculture, energy generation, and the natural environment among others. However, despite their importance, drought impacts are still understudied in the context of drought characterisation (Enenkel et al., 2020; Urquijo-Reguera et al., 2022).

Drought management plans aim at guiding the decisions water resources managers take to prepare for and mitigate these drought impacts. Their implementation requires reliable and timely information on the occurrence and characteristics of drought events (Vicente-Serrano et al., 2012). Droughts are commonly characterised in terms of severity, duration, spatial extent, and frequency. However, as it is not possible to support this characterisation through a single observable variable, normally drought management plans rely on indicators and indices that combine different kinds of data to support managers in identifying the characteristics of ongoing or predicted droughts. Drought indicators may consider essential climate variables such as precipitation, temperature, streamflow, water levels, soil moisture, or evapotranspiration, that can help identify drought conditions, while drought indices are numerical characterizations of drought usually based on the data from one or more indicators (Svoboda and Fuchs, 2016). Threshold values of the indices are then typically defined in drought management plans to classify a drought event into categories of severity and to identify decision points at which the managers should decide whether to apply the mitigation measures associated with each level of severity, as defined in the drought management plan. The selection of indicators and thresholds, as well as the uncertainties in the data sources used to establish the indicators, can have a significant impact on the outcome of the water resources management decisions in which they are used.

There is an ongoing and continuous research effort into developing, assessing, and improving drought indices and information services to detect, monitor and predict droughts (Mishra and Singh, 2010; Yihdego et al., 2019; Alahacoon and Edirisinghe, 2022). Numerous indices have been developed and used over the years to identify and characterise drought. Among the most widely used are the Standardised Precipitation Index (SPI, McKee et al., 1993), the Standardised Precipitation Evapotranspiration Index (SPEI, Beguería and Vicente-Serrano, 2013) and the Normalised Difference Vegetation Index (NDVI, Rouse et al., 1974) (See Zargar et al., 2011; Niemeyer, 2008; Mishra and Singh, 2010; Heim, 2002 for additional examples of drought indices). Each index has its own strengths and weaknesses, and is suited for a specific context, e.g. a type of drought, a climatic area, or an impacted sector (Svoboda and Fuchs, 2016).

Despite drought indices and related information products having a clear potential to help drought management decisions, they are usually developed by researchers with little input from end users (Purdy et al., 2019). As a result, there is a gap between what scientists consider a useful information index or product and what decision makers recognize as usable (Lemos et al., 2012; Raaphorst et al., 2020; Jebeile and Roussos, 2023). This thesis aims to contribute to reducing that gap by researching the usefulness of information for drought management decisions from both the data and the user perspectives.

1.2 KEY CONCEPTS IN DECISIONS AND INFORMATION ASSESSMENT

A decision is the selection of one alternative from two or more different possibilities. A common approach to study decision problems consists of identifying all the possible actions that can be taken and the possible outcomes of those actions.

Two levels can be distinguished in management decisions: planning decisions and operational decisions. Planning decisions involve the definition of plans and methods to achieve defined strategic objectives. In the case of drought management, these decisions may include the selection of indicators, thresholds, and mitigation measures. On the other hand, operational decisions are required to put the plans into action. These decisions are made on a regular basis and are usually informed by real-time data supported by indicators and thresholds. For example, the decision of whether to apply the mitigation measures defined in the drought management plan once an indicator threshold is crossed, is an operational decision.

Depending on the level of knowledge about the outcomes of the actions and their probability of occurrence, decision problems can be classified in the following categories (Hansson, 2005, 2022):

i. Decisions under certainty: correspond to a situation of deterministic knowledge, in which the outcomes of actions are invariable and known.

ii. Decisions under risk: correspond to a situation of complete probabilistic knowledge, in which the probability of occurrence of each of the possible outcomes for an action is known.

iii. Decisions under uncertainty: correspond to a situation of partial probabilistic knowledge, in which the probability of occurrence of the possible outcomes for an action is only partially known.

iv. Decisions under ignorance: correspond to a situation of no probabilistic knowledge, in which the probability of occurrence of the possible outcomes for an action is unknown.

Water management decisions tend to fall in the category of decisions under uncertainty, as they depend on variable and uncertain water availability and demands. Sources of uncertainty in this field include lack of reliable data, unpredictability of the future state of the system both because of environmental and socio-political components, and the complexity and lack of understanding of some aspects of the hydrological systems (UNESCO, 2012). Information, such as that obtained from drought monitoring or seasonal weather forecasts, can contribute to reduce part of this uncertainty by helping to quantify and estimate the availability of water resources.

The attractiveness for decision makers of each possible course of action in the decision depends both on the likelihood of the possible outcomes and their preferences for those outcomes (Keeney, 1982). In decisions under uncertainty, the latter also involves the decision maker’s attitude to risk (Cerdá Tena and Quiroga Gómez, 2008).

1.2.1 Value of information

One of the motivations for decision analysis is to compute the potential value of information (Wilks, 1997). Information can be defined as a set of data organised for a particular purpose with the potential to change the state of knowledge of the user. Two categories can be distinguished in relation to the practical value of information: value in use and the exchange value. The first is related to the benefits derived from the use of the data, while the second corresponds to the value of the information in the market (Repo, 1986). In this thesis we focus on the first category, and from that perspective, the value of information (VOI) is related to the potential of information to increase knowledge, which may lead to a change in the outcome of a decision. In the case of drought management, improved information about the characteristics of an event could contribute to the selection of more appropriate mitigation measures and therefore to reduce the impacts and/or optimise the cost of prevention measures. The potential of improved information to generate benefits, or savings, or reduced impacts makes it valuable.

There are some essential conditions required for information to have value. A good overview of those conditions is presented by Macauley (2006), who reviews studies about the value of information derived from remote sensing in the context of environmental management and points out the need for a better understanding and assessment of the benefits of the operational use of earth science data. From her review, she observes that the value of information depends largely on:

i. The potential contribution of the added information in reducing uncertainty or error. The value of information in reducing uncertainty is larger when the individual is more uncertain, while when there is a conviction about the occurrence or non-occurrence of an event, then the value of information is zero.

ii. The potential earnings or savings that can be achieved with better information. When the making of a wrong decision has no cost, then value of information is also zero.

iii. The capacity of the user to change the course of action as a result of new information. The value of information is lower when there are less available actions to take.

iv. The cost of using the information, as well as the cost of using alternative sources of information.

Usually, methods for VOI analysis begin by evaluating the Value of Perfect Information (VOPI). Perfect information corresponds to the situation where there is no uncertainty regarding the outcomes of the possible courses of action. VOPI serves as a reference of the maximum value of information in supporting a particular decision problem. However, new information will generally only reduce uncertainty. In some situations, new information may even increase the level of uncertainty. Therefore, methods for VOI analysis commonly include an evaluation of the Value of Imperfect Information as well, to estimate the worth of reducing uncertainty with additional or improved information.

The VOI is used in this thesis as a helpful framework to quantitatively assess the usefulness of information, which allows to compare different information scenarios and users of information.

1.2.2 Usability

Analysis of the value of information can help determine how useful information is for a particular decision. However, climate information considered potentially useful often ends up not being used for multiple reasons, calling for a need to understand the processes that takes information from being considered useful by the producers to being used by decision-makers (Kirchhoff et al., 2013; Lemos et al., 2012; Porter and Dessai, 2017). Cash et al. (2003) indicate that to be usable by decision-makers, information needs to be credible (scientifically sound), salient (relevant to their needs) and legitimate (unbiased and respectful with different views and values) and argue that to achieve this, a two-way communication and mutual understanding between information producers and decision-makers is needed. The latter is sometimes hindered by the different language and views of the two groups. A widely supported strategy to ensure the salience of information and increase its uptake is the co-production between science and users (Bruno Soares and Dessai, 2016; Cash et al., 2003; Lemos et al., 2012; Porter and Dessai, 2017).

Bruno Soares and Dessai (2016) investigate the barriers and enablers to the use of seasonal forecast in European organisations from different sectors through in-depth interviews (75). Their conclusions confirm the issues discussed by Cash et al. (2003); finding that the majority of organisations do not use information such as from seasonal forecast mostly because of the limited skill and reliability of the forecasts in Europe, but also because of the lack of salience (i.e. the data available not fitting in their way of work) and lack of awareness of the products and communication between producers and users. Not having enough resources or technical capacity available or unsuitable timing (information not available early enough to fit their planning) was also mentioned by a couple of organisations.

1.3 Research objectives and aim

This thesis examines the interplay of information and decisions in the context of water allocation in drought prone areas, with a focus on assessing the usefulness of information that could be considered in addition to in-situ measurements, such as remote sensing products and seasonal forecasts. The thesis revolves around the questions of how information can benefit drought management decisions at the basin scale, and how its usefulness can be assessed. These are multifaceted questions that cut across different fields of study: drought management, which looks into plans and actions to reduce the impacts of drought and make the best use of scarce or irregular water resources; climate and water information, and the products that can be generated to inform decisions that depend on them; and the study of decisions and information usefulness, which is multidisciplinary in itself, ranging from mathematical models to social aspects.

Each of these fields of study has their own motivations, perspectives, and methods to investigate the role of information in drought management decisions, and addresses the concerns and questions of different stakeholders:

- Managers: How can well-informed decisions help prepare for and reduce the impact of drought?
- Climate and water information providers: Are available information products fit for drought management decisions? How can these be improved to better support the decisions? What is the value of the information to users to justify investment needed to develop the products?
- Decision and information researchers: How to make better decisions? How can the value or usefulness of information be assessed?

These questions span from the more specific to the more abstract. From assessing how information can support a given drought management decision, with its existing information needs, gaps and limitations, to assess more broadly how information products can fulfil the information needs of a certain type of decisions, to reaching general rules that help understand the role of information in drought management decisions.

Although the multiple disciplines that deal with the usefulness of information for drought management all offer relevant concepts and methods to approach the question, each discipline normally works independently, focusing on specific aspects of the problem. However, understanding what makes information both useful and usable requires crossing the disciplinary boundaries and integrating their different methods to paint the whole picture of the role of information for drought management decisions. This thesis aims to bridge the gap between technical and human approaches by first exploring what insights a data-oriented perspective and a user-oriented perspective offer independently. Then a third perspective, resulting from the integration of the previous two approaches, is used to identify the overall factors that influence the usefulness of information for drought management decisions.

The data-centred analysis is designed to determine whether available information is potentially useful to support drought management decision at the basin scale, while the user-centred perspective aims to identify the options available to decision makers and whether they perceive a need for additional or improved information. Combining the two perspectives, the thesis explores whether additional information has the capacity to change the outcome of the decision given the available options and decision constraints, which is one of the main conditions for information to be useful. Throughout the three perspectives, the thesis also investigates what aspects of the decision, its context or the information used influence the usefulness of the information.

In addition to identifying the types of results that each of the perspectives can provide and their contribution to the assessment of the usefulness of information to support drought management decisions, with the analysis conducted from the different perspectives, this thesis also aims to explore how to assess the usefulness of information, how the gap between technical and human approaches can be bridged, and how different aspects of the decision and its context impact the usefulness of information.

1.4 Outline

This first chapter states the aims of the thesis and introduces the context and relevant concepts for the study of decisions and how these may benefit from information.

The subsequent chapters (2-4) approach the question of how information can benefit drought management decisions at the basin scale from different perspectives. In this research, the Ebro basin in Spain is used as a case study for the three chapters. Detailed information on the basin can be found in Appendix A.

Chapter 2 considers a data-centric perspective, assessing the usefulness of remotely sensed datasets to detect early stages of drought at the river basin scale and determine how much time can be gained to inform operational land and water management practices.

Chapter 3 follows a user-centric perspective. The information use and needs of farmers and reservoir operators that make decisions within the context of water resources allocation during droughts are identified through semi-structured interviews and the value of information to these decisions is quantified by building a model of the decisions described in the interviews.

The two approaches, data and user-centric, are combined in the analysis presented in Chapter 4 to assess the value of seasonal forecasts of precipitation to support water allocation decisions in irrigated agriculture through a risk-based approach.

A final synthesis and overall conclusions are presented in Chapter 5.

2

THE PREDICTABILITY OF REPORTED DROUGHT EVENTS AND IMPACTS IN THE EBRO BASIN USING SIX DIFFERENT REMOTE SENSING DATASETS

This chapter is based on:

Linés, C., Werner, M., and Bastiaanssen, W.: The predictability of reported drought events and impacts in the Ebro Basin using six different remote sensing data sets, Hydrol. Earth Syst. Sci., 21, 4747–4765, https://doi.org/10.5194/hess-21-4747-2017, 2017.

Abstract

The implementation of drought management plans contributes to reduce the wide range of adverse impacts caused by water shortage. A crucial element of the development of drought management plans is the selection of appropriate indicators and their associated thresholds to detect drought events and monitor the evolution. Drought indicators should be able to detect emerging drought processes that will lead to impacts with sufficient anticipation to allow measures to be undertaken effectively. However, in the selection of appropriate drought indicators, the connection to the final impacts is often disregarded. This paper explores the utility of remotely sensed datasets to detect early stages of drought at the river basin scale and determine how much time can be gained to inform operational land and water management practices. Six different remote sensing datasets with different spectral origins and measurement frequencies are considered, complemented by a group of classical in situ hydrologic indicators. Their predictive power to detect past drought events is tested in the Ebro Basin. Qualitative (binary information based on media records) and quantitative (crop yields) data of drought events and impacts spanning a period of 12 years are used as a benchmark in the analysis. Results show that early signs of drought impacts can be detected up to 6 months before impacts are reported in newspapers, with the best correlation–anticipation relationships for the standard precipitation index (SPI), the normalised difference vegetation index (NDVI) and evapotranspiration (ET). Soil moisture (SM) and land surface temperature (LST) offer also good anticipation but with weaker correlations, while gross primary production (GPP) presents moderate positive correlations only for some of the rain-fed areas. Although classical hydrological information from water levels and water flows provided better anticipation than remote sensing indicators in most of the areas, correlations were found to be weaker. The indicators show a consistent behaviour with respect to the different levels of crop yield in rain-fed areas among the analysed years, with SPI, NDVI and ET providing again the stronger correlations. Overall, the results confirm remote sensing products' ability to anticipate reported drought impacts and therefore appear as a useful source of information to support drought management decisions.

2.1 INTRODUCTION

Drought is defined as a temporary water shortage in part caused by anomalous climatic conditions but strongly influenced by socioeconomic factors (Kallis, 2008). The effects of drought propagate through all human and natural systems that depend on water directly or indirectly, producing substantial losses (Wilhite et al., 2007). Various economic sectors are adversely affected, in particular agricultural production, energy generation and water supply for domestic and industrial use. Habitat degradation, increased mortality of flora and fauna, and increased occurrence of wildfires are examples of the effects on the natural environment. Indirect impacts, such as increase of prices, unemployment or migration, arise as a consequence of the direct impacts and may be felt in a much wider area, even reaching the global scale (Wilhite and Vanyarkho, 2000).

The occurrence and severity of drought impacts depend on the intensity and duration of the event but also on the vulnerability of the society and the environment (Wilhite, 2000). As a consequence, the conditions that produce negative socioeconomic impacts are not necessarily the same for the different sectors that may be affected (Redmond, 2002). The timing of the event also influences the severity of impacts. Soil moisture deficit during the flowering stage of a crop or reduced domestic water supplies during the tourist season are examples of situations in which the socioeconomic impact is aggravated due to the timing of the drought. The aim of the current paper is to identify Earth observation datasets that can be used to detect early stages of drought at the basin scale, as well as to determine the extent to which these datasets can anticipate drought impacts and be used to inform operational land and water management.

The implementation of drought management plans by governing agencies can contribute to reducing the negative effects of drought by guiding decision-makers in taking appropriate mitigation actions. However, the effectiveness and cost efficiency of these actions rely on the selection of suitable indicators to monitor drought conditions and to detect events at an early stage, gaining valuable time for mitigation measures to be implemented effectively and impacts to be mitigated. Examples of actions that can be taken include retention of water; reallocation of available water resources; curtailment of current allocations; recommendations to plant less water-demanding or drought-resistant crops; or prohibition of certain water uses (e.g. watering gardens or washing cars).

Indicator systems consist of drought indices with associated thresholds that allow classifying the event in categories of drought severity. A classic example is the division of river flow into several categories. When the value of the indicator crosses one of the thresholds, managers should decide whether to activate the corresponding responses defined in the drought management plan for that situation. Indicators and associated thresholds should be problem, context and user-specific (Kallis, 2008), and therefore an integrated management of droughts in basins where there are multiple users requires advanced drought detection systems based on multiple indicators.

Measurements from in situ networks and from remote sensing are complementary sources that can be used to build the system of indicators for early detection and monitoring of drought conditions. In situ data are generally collected at specific points only. The advantage is the high temporal frequency of observations and the availability of longer-term records. Remote sensing techniques, on the other hand, offer cost-effective and spatially continuous information over extended regions. Satellites allow drought events to be categorised over a certain area, rather than at point locations (Famiglietti et al., 2015; Kogan, 2001). Several satellite datasets are now available at daily or at even shorter timescales, offering excellent potential to develop sound drought monitoring systems in real time and allowing to overcome the shortcomings of classical indicators based on in situ datasets that lack the spatial scale (e.g. Sheffield et al., 2014; Van Dijk and Renzullo, 2011).

Keyantash and Dracup (2002) analyse a set of criteria to assess the usefulness of drought indicators for the assessment of drought severity and point out that while the robustness of an indicator provides insight into its consistent behaviour across differing conditions, assessing the accuracy of the information provided by the indicator requires a standard or benchmark for comparison. This holds true for both remote-sensing-based and ground-based indicators. A standard that offers an absolute metric of drought is not easily available and likely does not exist, and as a result a common approach to evaluating the performance of remote-sensing-based drought indicators is to assess their robustness by comparing them with other indicators such as flow, reservoir levels or widely used drought indices (e.g. Morid et al., 2006; Tsakiris et al., 2007; Vasiliades et al., 2011). Expert knowledge may also be used in practical applications as a benchmark to assess drought indicators such as in Steinemann et al., (2015), who rely on regional water managers, drought decision-makers and other stakeholders' knowledge as a reference to develop, select and evaluate drought indicators. Expert judgement is also included, in combination with several indicators and model outputs, in the US drought monitor (Svoboda et al., 2002) to develop a weekly map of drought conditions in the US which itself is also frequently selected as a reference dataset in the evaluation of the performance of drought indicators in the country (e.g. Anderson et al., 2011; Brown et al., 2008).

Since mitigating impacts is the purpose of drought indicators included in drought management strategies, impact data are especially suitable as a benchmark in this case. Drought impacts, however, are difficult to evaluate and are rarely monitored (Lackstrom et al., 2013; Wilhite, 2011). Several studies have analysed the connections of drought indices to quantifiable effects on agriculture, hydrology or forests (see Vicente-Serrano et al., 2012, for a review), but very few have applied the impact data (mostly crop yields) as a benchmark to assess indicators for drought detection (e.g. Potop, 2011; Sepulcre-Canto et al., 2012; Stagge et al., 2015). Recognising the potential of this kind of data for drought management, two large-scale initiatives have recently been launched: the US Drought Impact Reporter (DIR) (Wilhite et al., 2007) and the European Drought Impact Report Inventory (EDII) (Stahl et al., 2016). These have the objective to collect text-based impact records systematically with the aim to increase their availability and accessibility. Recent studies have explored the links of the EDII records to drought indicators (Bachmair et al., 2015, 2016; Blauhut et al., 2015), though these have focused on the national scale, and it is recognised that further development is required to allow analysis at the subnational scale (Bachmair et al., 2016).

Despite their important role in mitigation of drought impacts, the selection and use of indicators and thresholds for decision-making often suffers from a lack of scientific justification: only a few studies have analysed the choice of drought indicators in relation to drought management in practice (Steinemann et al., 2015; Steinemann and Cavalcanti, 2006). Moreover, the thresholds that have been selected to declare droughts are only rarely connected to the specific impacts that need to be avoided (Wilhite, 2000). In this paper, quantitative and qualitative drought impact information is applied as a benchmark in evaluating the utility of indicators derived from six different remote sensing datasets at river basin scale. This implies that the analysis is not based on a definition of drought as a statistical extreme but as the occurrence of certain conditions of meteorological origin that will lead to impacts in sectors depending on water. Two aspects are considered in the assessment of the indicators against the benchmark data: how well these indicators reflect reported drought impacts and to what degree these indicators can be used to anticipate drought conditions and consequent impacts.

2.2 MATERIALS AND METHODS

2.2.1 The Ebro Basin

The Ebro Basin, with an extent of 85 600 km^2, is the largest catchment in Spain. It is located in the north-east, bounded by the Pyrenees and Cantabrian Mountain ranges to the north and the Iberian system to the south. It is a highly regulated basin with 51 reservoirs (> 1 Mm^3) and a total storage capacity of more than 7500 Mm^3, which supply water to more than 900 000 ha of irrigated agriculture and more than 450 hydroelectrical plants (Portal de CHEbro, 2017). Analysis of the impacts of a recent drought event (2005–2008) revealed that agriculture and food production are the main sectors affected by drought in the area, but impacts to hydropower production, water supply to villages, food industry, recreational activities and ecosystem functions were also identified (Hernández-Mora et al., 2013; Pérez Pérez and Barreiro Hurlé, 2009).

The period 2000–2012, selected for the analysis, encompasses a wide range of different conditions: the hydrological year 2004–2005 was characterised as one of the most intense droughts of the record in the Iberian Peninsula (García-Herrera et al., 2007), while 2003–2004 is considered one of the wettest hydrological years of the country's record (MMA, 2005).

The Confederación Hidrográfica del Ebro (CHE) is the organisation responsible for the management, regulation and conservation of water in the Ebro Basin. The basin is divided into 18 management units, each of which has a board constituted of representatives of the different water users as well as of the basin authority to coordinate the use of the hydraulic infrastructures and water resources in their area.

A drought management plan for the basin was developed in 2007 to guide drought management actions (CHE, 2007). The plan defines a set of indicators to detect situations of hydrological drought in the Ebro Basin and evaluate their severity. The indicators are built using observations from a rich network of in situ automatic stations. In the areas in which the flow is regulated by dams, water stored in reservoirs is considered the most robust indicator, but other variables such as water flow, snow depths or head levels in aquifers may also be taken into account. For areas with a natural or an almost natural flow regime without reservoirs, the 3-month water flow measured at representative stations is selected as the main indicator. In one of the management units, where there is no regulation and no representative rivers, groundwater levels are used as indicators.

The north-east of the basin, where the larger irrigation districts of the Ebro Basin are located, was selected to evaluate the set of drought indicators against the qualitative text reports (Figure 2-1). This area was also the most affected by the drought period 2005–2006 (Hernández-Mora et al., 2013). It is composed of four management units (management units 12 to 15). Figure 2-1 shows the management units further subdivided according to the main drought indicators currently selected in each: 3-month water flow in the northern sectors (zones 120, 130, 140 and 150) and reservoir levels in the southern sectors. To differentiate non-irrigated agricultural areas, Corine Land Cover 2006 (CLC06) map classes 211 (non-irrigated arable land), 242 (complex cultivation patterns) and 231 (pastures) have been used. The land cover class "irrigated agriculture" corresponds to the irrigation polygons provided by MAGRAMA (1997 version). The main irrigation districts are marked with dotted patterns and are identified by the name of the main canal that serves them. For the evaluation of quantitative crop yield data as a benchmark, only five of the districts within this area were selected: Hoya de Huesca (H), Somontano (S), La Litera (L), Monegros (M) and Bajo Cinca (B), including irrigated and rain-fed cropland.

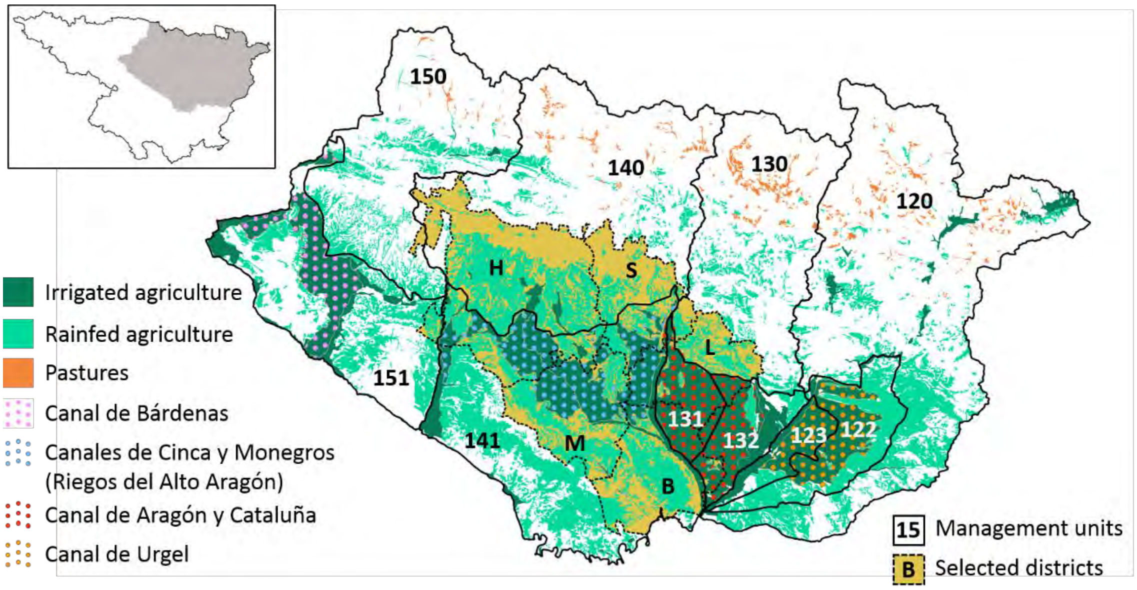


Figure 2-1. The north-eastern part of the Ebro Basin with selected agricultural land cover information.

2.2.2 Input datasets

Remote sensing data

The analysis focuses on medium-resolution global remote sensing products that are related to land surface hydrological and vegetation growth processes. Six commonly used remote sensing parameters were investigated: precipitation (P), land surface temperature (LST), normalised difference vegetation index (NDVI), gross primary production (GPP), top soil moisture (SM) and actual evapotranspiration (ET). The selected datasets are the following:

- **Precipitation (P):** The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a gridded precipitation dataset based on satellite and station data, designed with the main objective to support agricultural drought monitoring. It is a daily, quasi-global product, with a resolution of 0.05°. The dataset is available from 1981 to the near present. It is based on top cloud temperature measured by geostationary satellites and the Tropical Rainfall Measuring Mission (TRMM) satellite with a rainfall radar aboard. A detailed description of the product can be found in Funk et al. (2015). In this study, monthly aggregated rainfall values have been converted into standard precipitation index (SPI) datasets. The SPI (McKee et al., 1993) is a normalised rainfall anomaly, computed by comparing the accumulated rainfall over a given period with the long-term record. The standardised precipitation–

evapotranspiration index (SPEI) R package developed by Beguería and Vicente-Serrano (2013) was used to calculate SPI for periods of 1, 3, 6, 9 and 12 months. The possibility to calculate the index for different periods is one of the strengths of SPI as it allows to explore the effects of rainfall anomalies of different duration. SPI values calculated for shorter periods are associated with meteorological drought, while those calculated for longer periods are often associated with hydrological drought (WMO, 2012).

- **Land surface temperature (LST):** The MODIS (Moderate Resolution Imaging Spectroradiometer) product MOD11A2 offers day and night LST datasets, available at 1 km resolution as daily and 8-day products (http://modis.gsfc.nasa.gov/data/dataprod/mod11.php). The daily daytime LST data have been used for the current study. LST is based on long-wave emissions in the thermal infrared range (10 to 12 µm).
- **Vegetation health (normalised difference vegetation index – NDVI):** The MODIS vegetation indices product (MOD13) provides information on the active leaf chlorophyll and thus indirectly on the photosynthetically active process. NDVI describes the ratio of the difference and sum of reflected radiances in the red (0.65 µm) and near-infrared parts of the spectrum (0.9 µm). MOD13 is available at different resolutions: 16-day (250, 500 m and 1 km) and monthly (1 km) (http://modis.gsfc.nasa.gov/data/dataprod/mod13.php). The monthly 1 km data product has been used in the current analysis.
- **Gross primary production (GPP) and PsnNet:** GPP describes the daily gross carbon flux as a result of the photosynthetic process and is thus suitable to detect the effects of drought on biomass production. The MODIS GPP product (MOD17) applies a light-use efficiency model based on MODIS FPAR (fraction of photosynthetically active radiation) data, meteorological data and biome-specific parameters. The product also includes net photosynthesis (PsnNet), which corresponds to the GPP minus the maintenance respiration for leaves and roots. It is available at 1 km spatial resolution as 8-day composites or annual values (http://modis.gsfc.nasa.gov/data/dataprod/mod17.php) and as monthly aggregates (Numerical Terradynamic Simulation Group – NTSG; http://www.ntsg.umt.edu/). Additional background information can be found in Running and Zhao (2015).
- **Soil moisture (SM):** The soil moisture product considered is taken from the Soil Moisture Climate Change Initiative (CCI) project, which is part of the ESA Programme on Global Monitoring of Essential Climate Variables (ECV) (Liu et al., 2011, 2012; Wagner et al., 2012). Three daily products are available (datasets based on active, passive or merged microwave instruments) for the period 1978 to 2014 at a spatial resolution of 0.25° (http://www.esa-soilmoisture-cci.org/).

Higher spatial resolution products are only available for certain areas. The product used in the current analysis is the merged CCI SM dataset. The data are based on C-band scatterometers and multi-frequency radiometers.

- **Evapotranspiration (ET):** There are currently three global datasets of actual ET in the public domain. These are the MODIS ET product (MOD16; https://modis.gsfc.nasa.gov/data/dataprod/mod16.php) developed by the University of Montana (Mu et al., 2007, 2011) and supported by NASA, the Surface Energy Balance System (SEBS) developed by Su (2002) and the Global Land Evaporation Amsterdam Model (GLEAM) developed by Miralles et al. (2011), which is available through www.gleam.eu. In addition, there are global ET products that are quasi-open-access, including the Atmosphere–Land Exchange Inverse Model (ALEXI) being developed by Anderson et al. (1997) from the USDA in conjunction with Hain et al. (2009) from NOAA; the Operational SEBS (SEBSop) of the USGS (Chen et al., 2016; Senay et al., 2013) and the CMRS evapotranspiration (CMRSET) published by Guerschman et al. (2009) from CSIRO in Australia. In this paper, an ensemble product based on these individual products with accumulated monthly ET values at a pixel resolution of 250 m × 250 m is used. This ensemble ET product (ETens v1.0) is available from the Water Accounting Group of IHE Delft (www.wateraccounting.org). The six individual ET models considered all use different parts of the spectrum, which reinforces the power of this tool.

In order to have one common time interval, precipitation data in mm day^{-1} were aggregated by a sum of the daily values for each pixel to obtain monthly data in mm month^{-1}, and LST and SM data were aggregated by averaging the daily values for each pixel (Table 2-1). Part of the input data (LST, NDVI, SM, ET, GPP and PsnNet) present a seasonal trend. For these, monthly anomalies were obtained by subtracting the mean for the whole period from each monthly average value, using these anomaly time series as input for the correlation. The remote sensing data have been aggregated per management unit. Pixels with at least 85 % of their area within the management unit (30 % in the case of soil moisture due to the coarse resolution) were considered in establishing the aggregate value for that unit. For the 1 km resolution LST, NDVI and ET remote sensing products, the results are also analysed by land cover type. This relates to pixels where at least 85 % of the area consists of irrigated and rain-fed agriculture land cover classes (see Figure 2-1).

In situ data

In situ data of reservoir levels and inflow and river flow from the basin measurement network were used to calculate the status index (I_e), a normalised monthly index used by CHE to homogenise the different indicators (CHJ, 2007):

$$\text{If } V_i \geq V_{avg} \rightarrow I_e = \frac{1}{2}\left[1 + \frac{V_i - V_{avg}}{V_{max} - V_{min}}\right] \tag{2.1}$$

$$\text{If } V_i < V_{avg} \rightarrow I_e = \frac{V_i - V_{min}}{2(V_{avg} - V_{min})} \tag{2.2}$$

where V_i is the value of the indicator for month i, and V_{avg}, V_{max} and V_{min} are, respectively, the average, maximum and minimum values of the indicator derived from historical data. Based on this index (which is a value between 0 and 1), the situation under analysis is classified by the authority as normal ($I_e > 0.5$), pre-alert ($0.5 > I_e > 0.3$), alert ($0.3 > I_e > 0.15$) or emergency ($I_e < 0.15$).

The indicators selected by CHE for each of the management areas were used for the analysis presented here. These are the values of reservoir volume for the regulated areas (122, 123, 131, 132, 141, 151), inflow into the corresponding reservoir(s) for the upstream areas (120, 140, 150) and runoff at a selected station for management area 130.

Table 2-1. Selected remote sensing products.

Parameter	Product	Pixel size	Original time interval
P	CHIRPS	0.05°	Daily
LST (day)	MOD11A2	1 km	Daily
NDVI	MOD13A3	1 km	Monthly
GPP and PsnNet	MOD17 (NTSG)	1 km	Monthly
SM	Merged SM product (CCI project)	0.25°	Daily
ET	Ensemble	250 m	Monthly

Benchmarking datasets

Two different tests were carried out using drought impact datasets as a benchmark to assess the ability of remote-sensing-based indicators to provide early drought detection information during the period 2000–2012. The short length of the remote sensing data series available was one of the reasons to base the definition of drought we use to build the reference not on a frequency analysis, in which drought is defined as an extreme event with respect to the historical series, but on the occurrence of drought impacts. The other reason is that managers need to identify the conditions that may lead to drought impacts in order to take mitigation actions. In the first test, text-based records of drought occurrence and impacts collected from a review of local news (i.e. qualitative information) were used to reconstruct the onset and evolution of drought conditions during the period of analysis and as a benchmark for the comparison of the remote sensing datasets. Newspaper records were selected as a data source because they allowed a systematic collection of impact occurrence data of all affected sectors with a monthly time step for the whole period of analysis. In the second test, the use of crop yield statistics (i.e. quantitative information) is considered as a benchmark of drought impact on agriculture. The correlation of remote sensing data, especially SPI and NDVI, to agriculture yield data has been widely researched and applied (see Bachmair et al., 2016, for a review). This second type of impact data was included to provide a comparison of the results obtained in the correlation to text-based impact data, and results obtained with the most commonly used type of impact data, and discuss the advantages and limitations of one with respect to the other.

Text-based datasets were collected from a review of regional news. “El periódico de Aragón”, the second largest newspaper in average daily circulation in the Aragón region was selected for the review because it has an online record going back to September 2001. All news items containing the word “drought” were reviewed and relevant records of drought events and impacts referring to the area of study were tabulated. For each entry, the location, period, description and, in the case of reported impacts, the affected sector were noted. The affected sectors were labelled as “rain-fed agriculture”, “irrigated agriculture”, “livestock”, “water quality”, “fire”, “water supply”, “energy” and “others”. The records of drought occurrence are classified according to the source of the information, making a distinction between non-official sources such as journalists and water users, labelled “mention of drought occurrence” in Figure 2-2, and official sources labelled as “drought acknowledged by the authorities”, “ongoing mitigation measures” and “periods retrospectively defined as anomalously dry”. This last type corresponds mainly to news about the publication or communication of analysis performed by the scientific community or the water managers describing an ongoing or past drought.

The limit between indicators and impacts is not always clear. For example, low flow or reservoir levels are considered an impact of meteorological drought in some analyses, while these serve as indicators of hydrological drought in others. Here, we limit the definition of drought impacts as the effects of drought on people, economy and/or the environment.

Crop yield data of winter cereals both for irrigated and rain-fed cropping systems were obtained for the five selected districts in Huesca (H, S, L, M and B). Winter cereals are the cereal crops that are planted in the autumn, and they are the crops that cover the largest surface area. Their importance for the region results in better data availability than for other crops, and for this reason this type of crops was selected for the analysis. Only winter cereal crops with larger cultivated areas were considered: two- and six-row barley (irrigated and rain-fed), wheat (irrigated and rain-fed) and rice (irrigated). The two- and six-row barley types refer to the number of fertile spikelets in the spike.

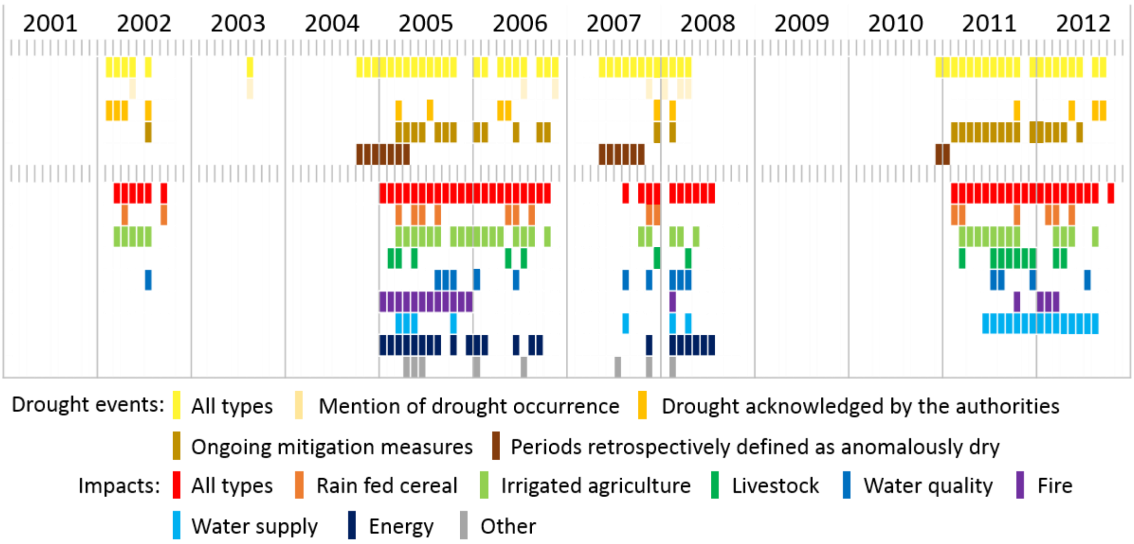


Figure 2-2. Timeline of drought events (upper part) and impacts (lower part) for the north-eastern Ebro Basin during the period 2001 to 2012

2.2.3 Correlation between remote sensing data and the benchmarking datasets

The correlation between each of the remote sensing parameters and both the timeline that aggregates all types of drought event records and the timeline that aggregates all types of drought impacts (Figure 2-2) was analysed in terms of strength of the relationship and anticipation. The strength of the relationship is a function of the predictability of the occurrence of drought and drought impacts provided by the remote sensing time series. Anticipation reflects the ability of the remote sensing datasets to provide early information and gain time to undertake actions. The aim of this analysis is to identify the datasets that can be useful for operational drought detection at the basin scale. Drought detection in this case is closely related to the predictability of impacts, as the conditions that need to be detected are those that may lead to impacts. However, these impacts do not necessarily occur immediately; their occurrence can be delayed as the effects of drought propagate through the different components of the hydrological cycle. To identify the remote sensing parameters that represent conditions that anticipate the occurrence of drought impacts, and therefore have potential to support the prediction of drought, we explore the correlation between the remote sensing data and the drought events and impacts at different time lags. The benchmark datasets were compared to the variables represented by the remote sensing time series in the 24 preceding and following months. While using correlation in this way may say less about the long-term correlation of two time series, it does provide insight in the relationship between correlation and lag.

The sample cross-correlation function (CCF), $r_{x,y}$, was used for the analysis. The CCF can be expressed as (Chatfield, 2004):

$$\boldsymbol{c_{x,y}(\tau) = \mathrm{cov}(X_t, Y_{t+\tau})} \qquad (2.3)$$

$$\boldsymbol{r_{x,y}(\tau) = \frac{c_{x,y}(\tau)}{\sigma_x \sigma_y}} \qquad (2.4)$$

Here, $\tau = \pm 1, \pm 2, \ldots,$ where τ is the lag, and σ_x and σ_y are the standard deviations of the time series x_t and y_t. The set of $c_{x,y}$ coefficients corresponds to the cross-covariance function. The CCF as implemented in R (R Core Team, 2016) was used for the calculations. To detect possible issues related to the stationarity or ergodicity of the series, their time autocorrelation and partial autocorrelation plots were considered.

The reference drought periods used for the correlation provide a binary record, indicating the occurrence or non-occurrence of drought events in each month, without quantifying their intensity. To obtain insight into the severity of the events, the use of annual crop yield data was explored. The correlation of each annual crop yield value to the monthly values of the remote sensing time series from the start of the hydrological year in September to the end of the following calendar year was analysed. This was done to detect the key months in which the occurrence of drought conditions led to impacts on the (annual) crop yield. The comparison was performed for three rain-fed areas and three irrigated areas. These were selected to correspond with the management units so that a relation could be established with the areas of influence of the reservoirs (Figure 2-1). The areas selected included the rain-fed agriculture areas of Hoya de Huesca (HH0, corresponding to management unit 140), Monegros–Bajo Cinca (MB0, corresponding to management unit 141) and the five districts together (AA0), and the irrigated agriculture in Hoya de Huesca–Monegros (HM1, corresponding to management unit 141), La Litera–Bajo Cinca (LB1, corresponding to management unit 131) and the five districts together (AA1).

2.3 RESULTS

2.3.1 Drought events and impacts

The timelines of drought events and impacts derived from the review of local news are illustrated in Figure 2-2. Three drought events can be distinguished in the Ebro Basin: a short drought event at the beginning of 2002, a multi-year drought from the end of 2004 to the spring of 2008 and a shorter duration drought during 2011 and 2012.

The first coloured row (yellow) in the figure represents the months in which drought was taking place according to the records found in the newspapers. The first line of the second block (red) reflects the occurrence of drought impacts described in the newspaper, while in the following rows these impacts are disaggregated by the affected sector.

Based on the records gathered from the newspaper records, the following descriptions of the hydrological years affected by drought episodes were constructed.

In 2002, after a dry winter, the availability of water in the reservoirs was low. A first reference to drought in the press appeared in February 2002. At the start of the spring, which is the beginning of the irrigation season, water curtailments were reported for the Bardenas irrigation system. In the beginning of April, agricultural associations reported losses of 20 % of rain-fed cereal crops in Aragón and at the end of the month the impact of drought in the area was acknowledged by the ministry as well as by the local government. In July, the flow of the Ebro in Zaragoza was half of the minimum 30 $m^3 s^{-1}$ that has been set to warrant water quality. In September, a reduction of 40–70 % in olive oil production in the areas of Bajo Cinca, Cinca Medio and La Litera was reported in the news. General mention of impacts on pastures, hydroelectricity production and employment in the primary sector during that drought period appeared in retrospect, but these reports did not go into detail.

The hydrological year 2004–2005 was depicted as the driest on record. The combination of cold and dry conditions during the first part of 2005 produced significant losses in the agriculture and livestock sectors. First impacts were reported in February 2005 (lack of pastures' production after 5 months without rain). From then until September 2006, the newspaper reflected a succession of impacts in different sectors, including all crop types, pastures, forests, livestock production, water supply to the population, wildlife, economy, recreational activities, hydroelectricity, water quality, employment and politics. The drought was already acknowledged by the authorities in March 2005, and the first mitigation measures were announced shortly after. This was that the regional government increased to 50 % the area of land, rain-fed or irrigated, that could be set aside to remain fallow. In June, aid measures were approved by royal decree.

Reservoir levels increased during the first half of the hydrological year 2005–2006, but the system failed to recover completely from drought before levels started decreasing again in April 2006, and at the beginning of the summer levels were lower than the previous year. After a hot summer, storage started to recover again, and in December 2006 the government considered the drought to have ended. Intense rains starting in February 2007 were followed by a period of precipitation deficit from May to February 2008. A few problems of water supply to certain villages were reported in August 2007 and flows were below the minimum required to warrant water quality in October. Impacts on agriculture and hydroelectricity started to be reported again in October. Abundant rains during spring 2008 constituted a first step towards the end of the drought episode.

The hydrological year 2010–2011 was characterised by lower-than-average precipitation and high temperatures. In February 2011, the newspaper showed the first reference to an emerging drought and its impact on the sprouting of winter cereal. This drought especially affected the Bardenas irrigation district. The Riegos del Alto Aragón and Canal de Aragón y Cataluña districts were also affected. All the systems managed to reach the end of the irrigation season, but with restrictions of more than 60 % on water quotas. Grapes and olives were the most damaged crops, but in general the food production in the area was defined as satisfactory at the end of the season. The following hydrological year (2011–2012) started with low reserves and a dry winter and spring, with the exception of November, which was a particularly wet month. In particular, the middle sector of Huesca revealed drought-affected areas. Extensive livestock farming, fodder and cereal production were the most impacted sectors. The risk of fire was reported to be high, even during the winter, which translated in a higher number of fires.

2.3.2 Correlation of text-based records and remote sensing indicators

The information on drought occurrence and impacts obtained in the previous step was used as a benchmark dataset to assess the ability of the remote-sensing-based datasets to provide early detection. Figure 2-3 and Figure 2-4 present the results of the cross correlation of the remote sensing datasets to the timelines of drought events (i.e. upper records in Figure 2-2) and impacts (i.e. all other records in Figure 2-2), respectively. The central line ($x = 0$) corresponds to the correlation of the two datasets in the same month. Negative values of x refer to correlations between impact time series at time t and remote sensing values at each of the 24 months before t ($\tau = -1, \tau = -2, \ldots, \tau = -24$). Strong correlations on the left side of the central line reflect the ability of the dataset to anticipate the occurrence of drought events and impacts. The positive side of the plots reflects the correlation of the drought occurrence and impact series with the values of the different datasets in later months. This type of correlation appears if the conditions that define the start of the event or impact occurrence last longer than 1 month. The positive correlations of the timelines of drought occurrence and impacts with the values of the indicator datasets with lags over 1 year (most notably at −15 and ±24 lags) are casual correlations.

Since the analysis presented here focuses on anticipations within a period of one hydrological year, the correlations should not be affected by this issue.

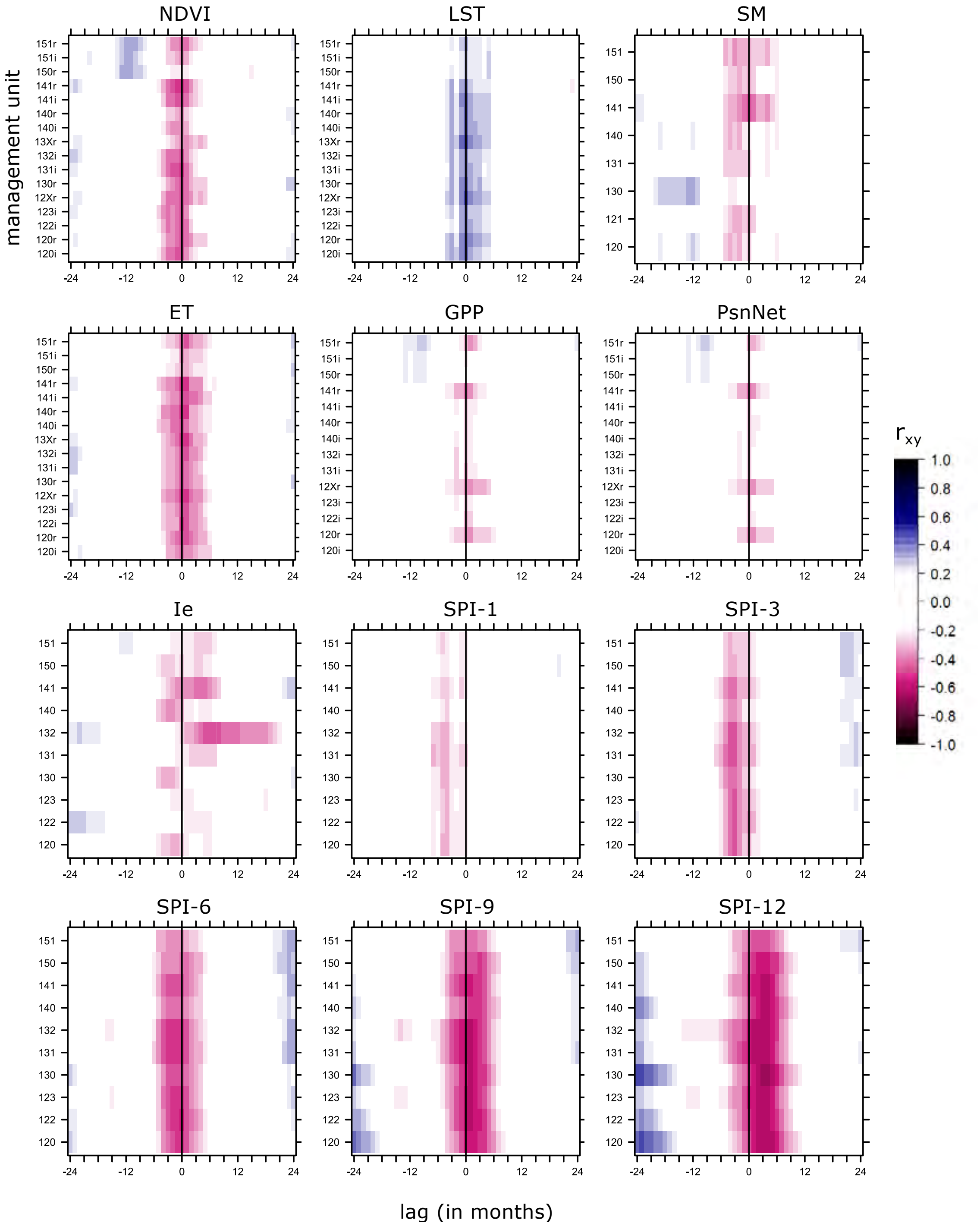


Figure 2-3. Cross correlation of drought indicators and drought events at multiple time lags. The numbers in the y axis represent the management areas depicted in Figure 2-1. For NDVI and LST, irrigated (i) and rain-fed (r) crops within the areas are

distinguished. The x axis represents the shift in months between the two data sets. The indicator built from in situ data (I_e) is also included.

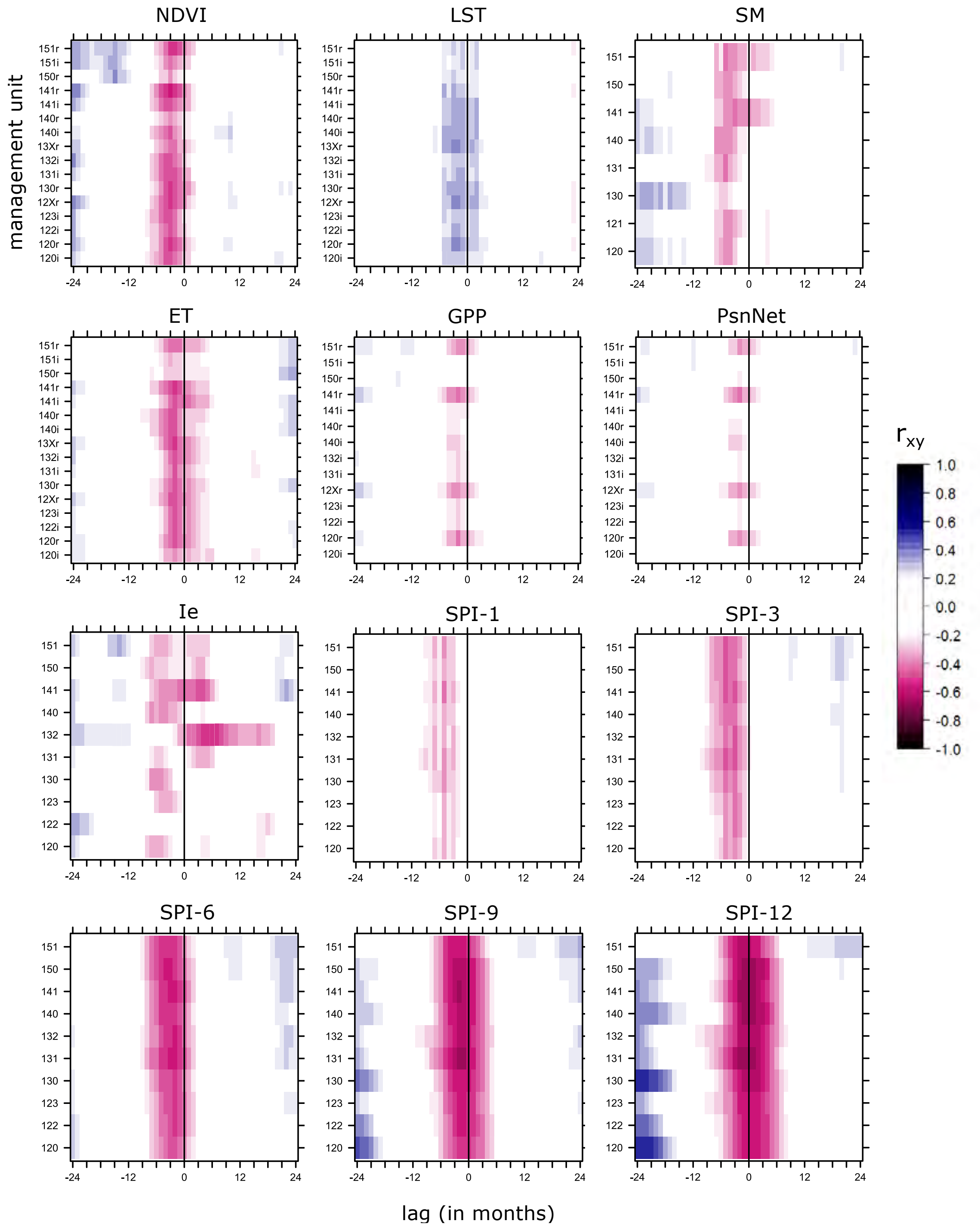


Figure 2-4. Cross correlation of remote sensing data sets against the timeline of reported drought impacts (all types).

Figure 2-3 and Figure 2-4 have similar correlation patterns, with the second showing higher anticipation. This result was expected because Figure 2-3 is based on records reflecting climatic and hydrologic anomalies and deficits, and these processes precede the impacts. SPI shows the strongest correlations for both events and impacts. For SPI values calculated for longer aggregation periods, the correlation grows stronger, while the anticipation is slightly reduced. The best correlation–anticipation relationship is obtained for SPI-6 and for SPI-9. For these indicators, the correlation is also stronger in the southern areas. This is probably because most of the socioeconomic activities are concentrated in these managed areas, and therefore the impacts and media attention are likely to be higher. The results show that SPI-6 and SPI-9 are most suitable for predicting impacts, together with NDVI and ET; achieving an anticipation of 6 months with a sufficient correlation ($r^2 > -0.6$). This provides useful information for activating drought mitigation measures. Soil moisture also shows good anticipation, albeit with weaker correlations. NDVI and ET datasets show a strong negative correlation with drought occurrence and impacts, which would be expected from a biophysical perspective. NDVI shows better anticipation, preceding the impacts in most of the units by more than 6 months. ET shows a slightly stronger correlation in the rain-fed areas, while no distinction is seen between rain-fed and irrigated areas for LST and NDVI. LST has a positive correlation because evaporative cooling is diminished during drought events, which prompts the land surface temperature to rise. LST correlation to events is stronger than to impacts, but the degree of anticipation is lower for the former. Indices derived from both GPP and PsnNet present weak or no correlation for most of the areas, with only some of the rain-fed areas showing moderate positive correlations. In situ indicators show varied levels of anticipation for the different areas. Most of them provide early information on drought occurrence and impacts from 6 to 9 months in advance, but there are two areas where the indicator offers no anticipation (management unit 140) or even no correlation with the benchmark datasets (management unit 123).

The time plots obtained for each of the parameters present no trends or discontinuities, and the values in the autocorrelation plots show that the autocorrelation diminishes quickly with increasing lag. An exception are the series of the reservoir indices. In that case, for some of the series, it is not clear from the plot if the series is stationary. For one of them (management unit 122), it clearly is not. This management unit corresponds to a reservoir (Rialb) that started to be filled in the year 2000, and therefore the levels cannot be considered stationary for the period of study. Most of the autocorrelation plots for the reservoir level series present a small peak of autocorrelation at a lag of 12 months, and one of them (management unit 132) presents autocorrelation values declining more slowly (significant values until lag 20). In the I_e plots in Figure 2-3 and Figure 2-4, it can be clearly seen that the two management units that do not satisfy the conditions for stationarity (management units 122 and 132) are those (at least two out of the three) that do not present anticipation. For the remaining products, autocorrelation for ET, LST, GPP, PsnNet, SM and SPI-3 dissipates mostly at a lag of 2 months. For SPI-1, it is quicker and is non-existent in some cases. NDVI takes 3–4 months and for SPIs with longer accumulation periods (SPI-6, 9 and 12) the correlation dissipates slower (4, 6 and 8 months, respectively), which is inherent to the product.

2.3.3 Correlation of crop yield and remote sensing indicators

The results of the correlation analysis between the remote sensing data time series and the annual crop yield for the main irrigated and rain-fed cereal crop types in the selected districts in Huesca are represented in Figure 2-5 and Figure 2-6. Every parameter is tested for the six areas. The crop types are represented on the y axis and the months on the x axis. The latter spans from the start of the agricultural year in September to the end of the following calendar year. The colour gradient reflects the sign and strength of the correlation, while the size of the inner grey circle corresponds to the reliability of the correlation.

NDVI and ET present some of the strongest positive correlations, especially between the remote sensing measurement during the spring (MAM) and the yield of rain-fed crops. LST shows also strong correlations with rain-fed crops in March and at the beginning of the season in September (S). The pattern is less clear for irrigated crops, probably because their water supply is less dependent on the rainfall. The strongest correlations in this case appear for rice crops with ET and NDVI, mainly at the start of the year.

Despite irrigated crops directly depending on reservoir supply, only rice shows significant positive correlations with the index based on reservoir levels for the two irrigated areas tested (HM, corresponding to management unit 141 and LB, corresponding to management unit 131). The reason can be that rice is especially drought sensitive, since it has shallow roots and consequently a low depth of readily available soil water, which is the fraction of total available soil water that crops can obtain from the root zone without experiencing water stress. This fraction is 0.2 for rice (Allen et al., 1998) and higher for the rest of the tested crops that therefore experience stress when more moisture is depleted. The rain-fed crops in the HH area (corresponding to management unit 140) show correlation with the status index based on reservoir inflow in April. Soil moisture, GPP and PsnNet do not show a clear pattern against reported crop yield, except for a strong positive correlation in one of the areas (MB). These correlations appear in the spring (especially for GPP and PsnNet) and at the beginning of the hydrological year. SPI has positive correlations at the start of the season, which are particularly strong in the MB area. In some cases, also a negative correlation during the summer emerges, especially for shorter-term SPIs. It can also be observed that the stronger correlations appear later with longer-term SPIs.

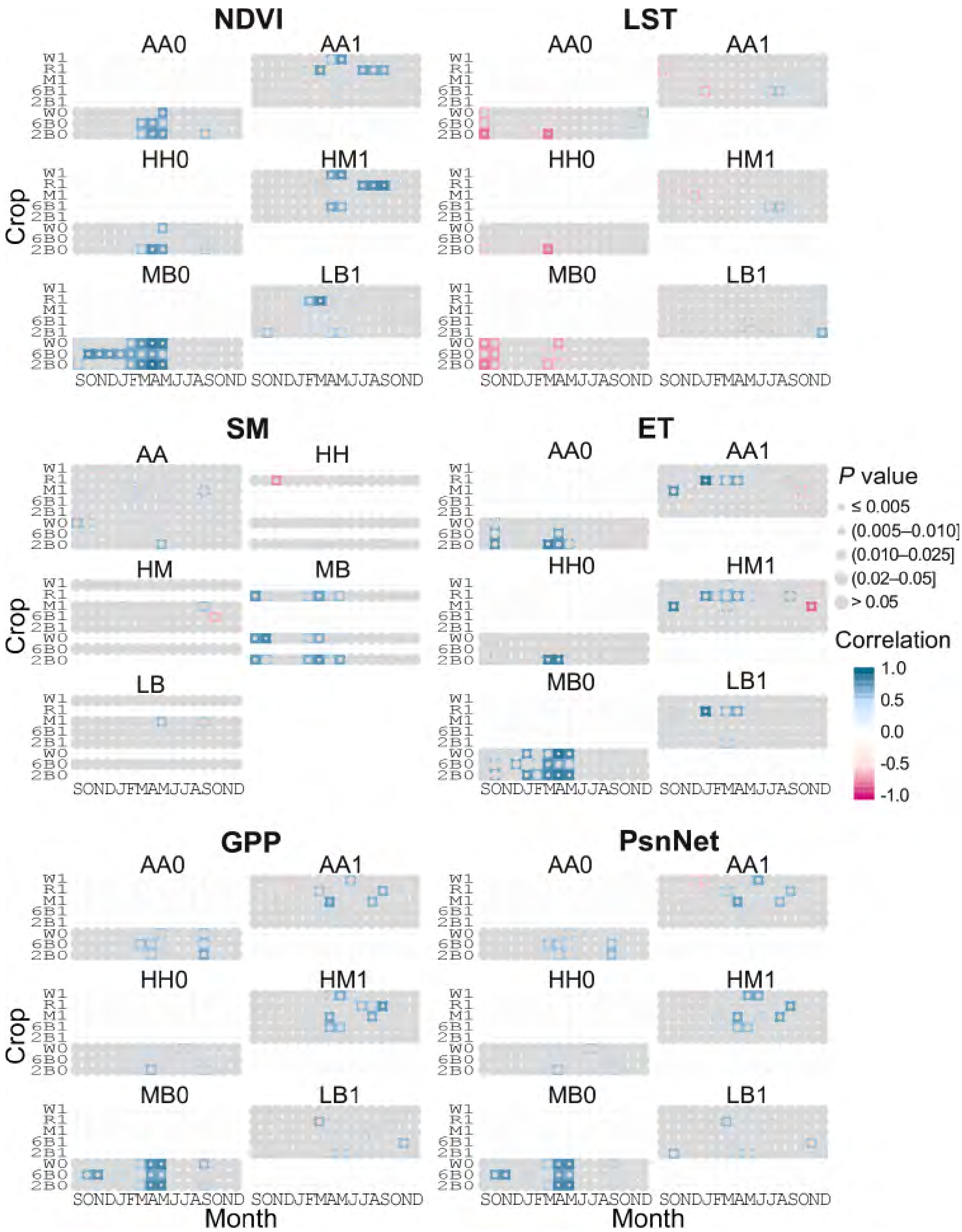


Figure 2-5. Correlation between remote sensing drought indicators and crop yield data. Rain-fed areas and crops are marked with 0 and irrigated areas and crops with 1. The crops are irrigated and rain-fed wheat (W1 and W0), irrigated rice (R1), irrigated maize (M1), irrigated and rain-fed six-row barley (6B1 and 6B0) and irrigated and rain-fed two-row barley (2B1 and 2B0).

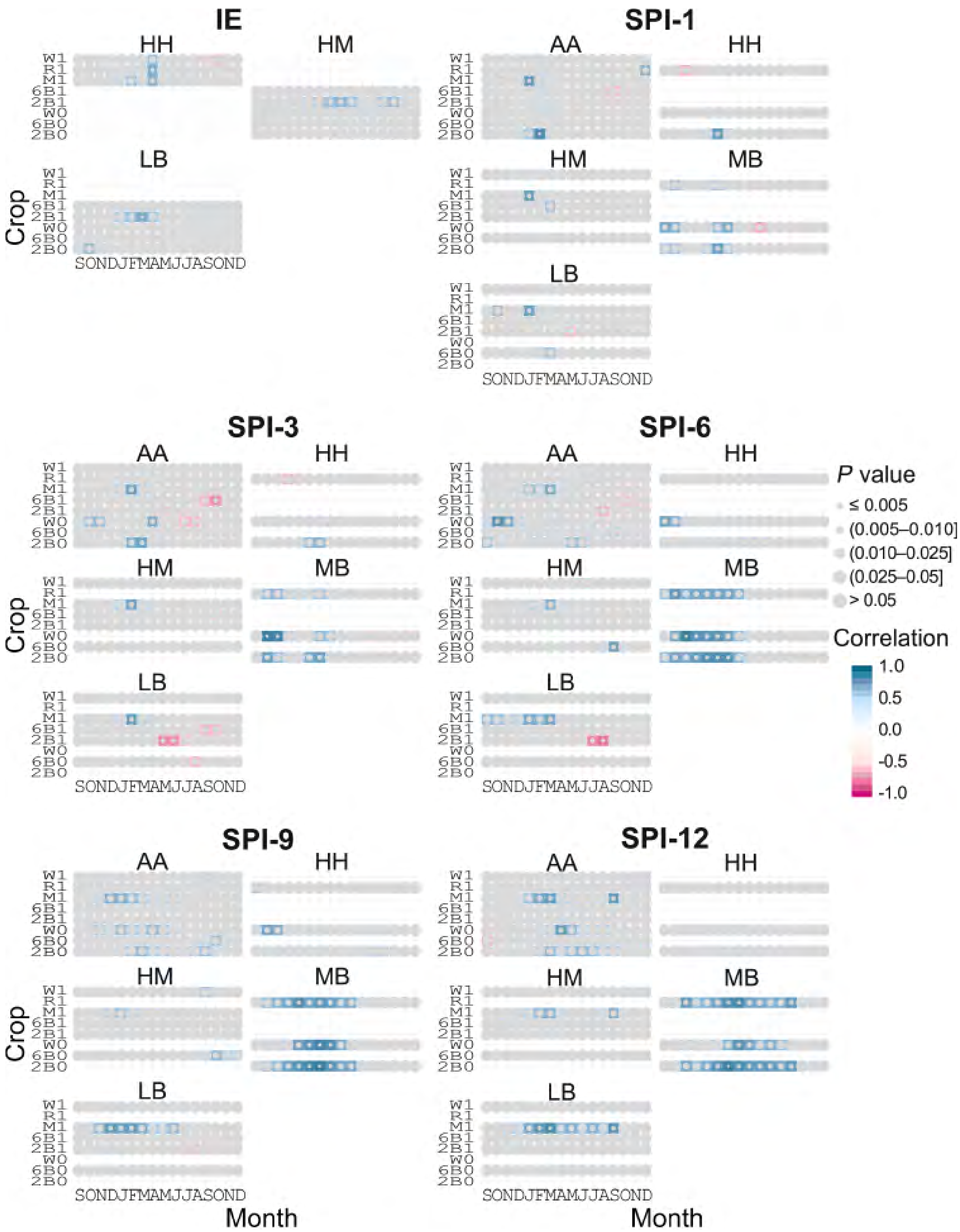


Figure 2-6. Correlation between drought indices (SPI and state index) and crop yield. Rain-fed areas and crops are marked with 0 and irrigated areas and crops with 1. The crops are irrigated and rain-fed wheat (W1 and W0), irrigated rice (R1), irrigated maize (M1), irrigated and rain-fed six-row barley (6B1 and 6B0) and irrigated and rain-fed two-row barley (2B1 and 2B0).

Rain-fed two-row barley (2B0) in March stands out as the crop with the stronger overall correlation with the different indicators. 2B0 is one of the major crops in the area, with a maximum cultivated surface for the period 2000–2012 of 170,914 ha of the total 204,614 ha dedicated to herbaceous crops (in 2008) and a minimum cultivated surface of 130,764 ha (2012). Maize is the second most common crop, with an average crop surface of 41,292 ha during the period. Figure 2-7illustrates the correlation of two-row barley to each of the indicators for the rain-fed crops in the Monegros–Bajo Cinca area (MB0), which has been selected as an example. This shows the crop yield for the different years against the value of each respective indicator.

Three years stand out in Figure 2-7 for having extreme low indicator values (high in the case of LST) for all variables: 2005, 2008 and 2012. Values are also low for the year 2000 for the datasets for which it is available. These three years correspond with hydrological years of reported impact in the area identified in the previous section. The lowest crop yields were obtained in 2012 (1342.5 kg ha^{-1}). Accordingly, the remote sensing parameters present some of the lowest (highest in the case of LST) values for the period. Only SPI-6 presents a value that is well above the minimum. This is caused by November 2011 being a particularly wet month in the middle of the drought period, thus moderating the value of SPI-6. For longer-term SPI values, this positive anomaly is compensated by the negative anomalies of the rest of the months.

Crop yields were very similar in 2005 and 2008 (1662.3 and 1800.1 kg ha^{-1}, respectively) and so was the behaviour of most of the variables. The main differences appear in LST, with the 2005 LST for March being more than 2°C higher than in 2008 (23.8 and 21.3°C, respectively), and SPI-3, which is less extreme in 2008 (−0.68 compared to −1.51 in 2005). The reason for this difference is the earlier start of spring rains in 2008. Both hydrological years start with an exceptionally dry period that extends to April in 2005 and to March in 2008 after which the spring rains improve the situation.

There is a second group in the middle sector of the plots that includes the rest of the years for which drought impacts on rain-fed agriculture were reported in the analysed media. This includes 2011 (3551 kg ha^{-1}), 2006 (3857 kg ha^{-1}) and 2002 (4249 kg ha^{-1}), together with the hydrological year 2006–2007 (3115 kg ha^{-1}), for which no impact was reported in the regional press. March values of SPI-3 for these years are close to the mean and only 2002 presents strong negative anomalies for SPI-6. In 2006 and 2007, the precipitation deficits start in April and May, respectively, and for 2006 the impacts are reported only after that month. Hydrological year 2001–2002 shows dryer autumn–winter conditions according to SPI-6.

The results of this second test present a consistent behaviour of the indicators with respect to the different levels of crop yield among the analysed years in rain-fed areas. As in the previous test, NDVI, ET and SPI stand out for having stronger correlations. Most indicators present similar March values for the years of severe drought, clearly differentiated from the behaviour of years of moderate drought and years of no drought. The only exception is LST, in which a year where drought was not reported and yields were normal, such as 2009, has similar LST values in March to the years of severe drought. This indicates that LST may not be a good indicator of drought on its own but can still be useful in combination with other indicators.

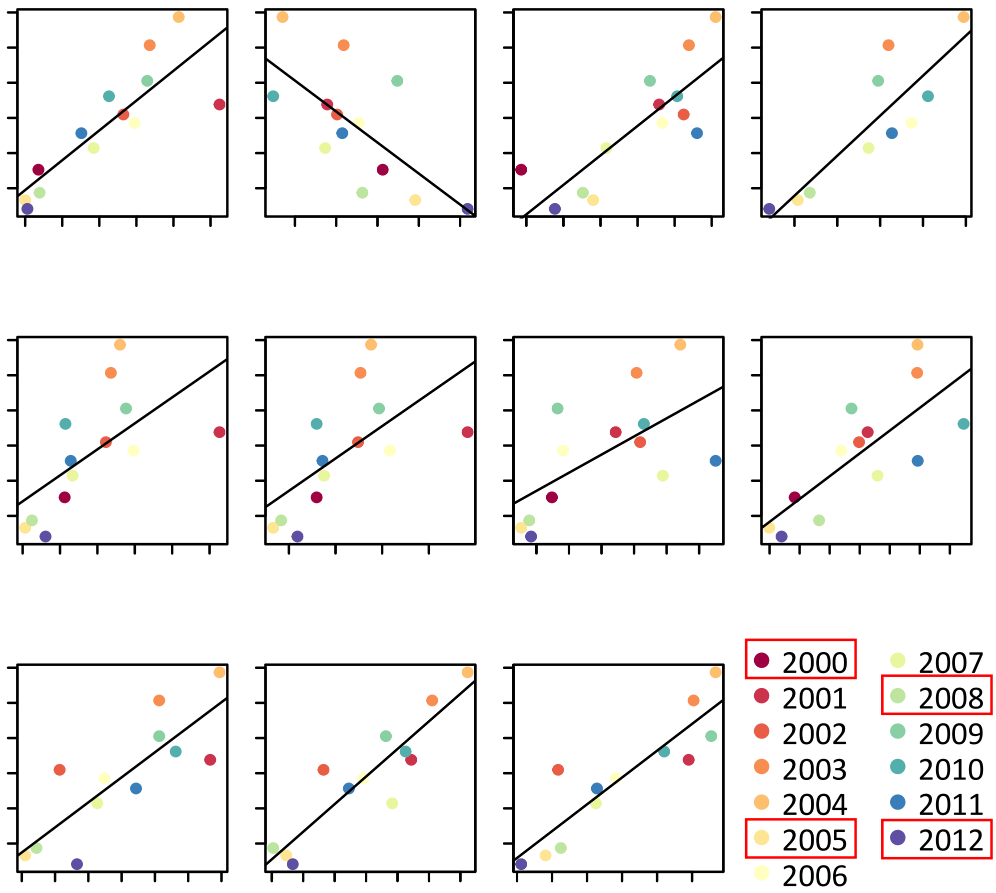


Figure 2-7. Correlation of the remote sensing drought indicators for the month of March to annual rain-fed two-row barley yield in Monegros-Bajo Cinca districts (MB). For LST, NDVI, SM, ET, GPP and PsnNet, monthly means were used.

2.4 Discussion

2.4.1 Use of impact records as drought reference

The review of text-based records allowed a detailed reconstruction of the drought events during the period studied. The cross correlation of the timelines of drought events derived from this review to the indices derived from remote sensing data revealed the potential of the latter to provide early detection of drought events. However, this binary information has the limitation that it does not allow to objectively quantify the severity of the events. For example, in the case of rain-fed agriculture, the information on impacts collected from the newspaper does not allow for differentiation between those years in which production was extremely low as a consequence of drought conditions and those years in which production was only partially affected by drought. Other studies have suggested a link between impact severity and the number of records reporting it (e.g. Hernández Varela et al., 2003; Bachmair et al., 2016), but this needs to be taken carefully since the media coverage of a drought event is highly influenced by the sociopolitical context in the affected area (Llasat et al., 2009; Sonnett et al., 2006).

A few additional aspects concerning reliability were noticed while processing the records from the press:

- **Accuracy**: The information on drought occurrence reported in the newspaper may not be accurate. For example, impacts due to other causes may be attributed to drought, or other phenomena such as normal summer shortages may be described as drought. This issue was the reason to classify the records of drought occurrence according to the source of the information to make a distinction between official sources such as mandated authorities, managers and scientists, and non-official sources such as journalists or water users. This second type of source is the one that is most susceptible to accuracy issues. Particularly for the case of the mandated authorities, there are clear procedures with which drought is officially acknowledged, which are defined in the drought management plan. In the records reviewed, only the mention of drought conditions recorded in 2003 is not backed up by the mention of drought from official sources during the same period and may therefore be regarded as a misuse of the word. Thus, we consider accuracy issues to have little impact on results.
- **Completeness**: Reporting of drought occurrence in the newspaper is not systematic, and therefore some impacts may be missing. In Figure 2-2, some unlikely situations can be identified. For example, there are impacts on livestock in May and July 2006 but not in June. Records referring to specific types of impacts are more likely to have gaps. However, when all types are aggregated, part of the gaps in each of the disaggregated datasets will likely be filled with records from the other datasets.
- **Scale:** Drought events affecting only a small area within the region covered by the newspaper may not be reported. The results of the test with crop yield data show values for the hydrological year 2006–2007 for which no drought impacts were identified in the reviewed regional newspaper that are similar to three other

hydrological years for which drought impacts were recorded. Local press for the specific area of the test (Alto Aragón), however, reported a lack of rain from October to March, aggravated by high temperatures, in Monegros and Bajo Cinca that had an impact on rain-fed cereals and pastures.

- **Bias**: Public or political interest or concern about drought (or even scarcity of other relevant news) can motivate overstatement of drought impacts. These do not have an influence in our analysis since we are only considering binary data of occurrence or non-occurrence, but this issue could have a significant impact on the reliability if the records were used to estimate the severity of the event.

The length of the period of analysis does not have an influence in the identification of drought events based on impact records. However, having a longer series, and therefore potentially a larger number of drought events, would provide more robust results in the correlation analysis. Ideally the results should be updated as the period of record of remote sensing data grows.

The drought events identified by the textual search for a sector of the Ebro Basin correspond with events observed at a larger scale. For example, Spinoni et al. (2015) use an indicator that combines three precipitation- and potential-evaporation-based indices to identify the drought events that occurred in different regions of Europe during the period 1950–2012. Following that approach, they identify three drought events for the Iberian Peninsula for the period 2000–2012 that match the ones obtained by the textual search, with the difference that the event starting in the hydrological year 2004–2005 has a shorter duration. This is caused by the different spatial scale of the analysis. While most of the basins in Spain received normal precipitation during the hydrological year 2006–2007, in the Ebro Basin, and especially in the inner part of Catalonia, it was still low during that year (MMA, 2007).

Crop yield data, on the other hand, allowed for a more objective identification of the drought events that had higher impact on agriculture, though the yield data do have the disadvantage that may only be reported on an annual basis. March was the month that presented higher correlations. This is in agreement with the results obtained by Vicente-Serrano et al. (2006), who observed a higher correlation between barley crop yield and NDVI for the month of March at a location in the Ebro River valley. The examination of the behaviour of the remote sensing parameters in the years with similar yield values provided insight on the reliability of the parameter as an index. Similar values of the parameter for years of similar final crop yield indicate the robustness of the indicator. For the period of analysis, the occurrence of drought in the years in which low yields were obtained is confirmed by the media records, but despite the water availability being a determinant factor for rain-fed winter cereal yield, other factors such as frost, floods, plagues and diseases could have further reduced the annual yield. However, for March values, there are no anomalies that suggest these factors had a strong influence in the low annual yield values. The lowest crop yields were obtained in 2012. This is in line with the information in newspapers reporting that drought that year especially affected cereal production in the middle sector of Huesca, the area of focus of this test.

Crop yield data can also be a useful reference to identify thresholds of drought severity classes. These thresholds could be derived based on the differences observed between the groups of years with severe, moderate and no drought conditions, although a longer data series than was used in this study is recommended to provide a more robust estimate of threshold values.

There are several factors that play a role in the severity of the impacts due to drought conditions, including coping capacities and water management (e.g. drought may not lead to impacts in irrigated areas). Variations in these factors can alter the relationship between the indicators and the impact. It should also be noted when using drought impacts as a benchmark of drought occurrence, the absence of certain types of impacts as a result of sound drought management does not imply that there is no drought (Smakhtin and Schipper, 2008), though even with perfect management there will always be some kind of impact. For example, a reduction of income as a consequence of substituting the usual crops with less productive alternatives with lower water requirements constitutes a clear impact, even if the yield in kg ha^{-1} is not affected. The influence of management is probably also the reason for irrigated land showing less clear correlation patterns than drought in rain-fed areas in both analyses. A wider view that considers as many different types of impacts and affected sectors as possible can help overcome the effect of management when using this type of data as a benchmark of drought occurrence. Initiatives such as the US Drought Impact Reporter and the European Drought Impact Report Inventory can play a useful role in providing that broader view.

2.4.2 Early drought detection with remote sensing products

Early information on emerging droughts benefits mitigation strategies by increasing the time available for managers and affected communities to take action. The requirements for drought early warning range from a few weeks to several months (UNISDR, 2009). The results show the potential of the tested products to anticipate up to 6 months reported drought impacts at the basin scale. SPI, NDVI and ET products stood out in both analyses as particularly suitable datasets to detect early stages of drought at the basin scale and anticipate drought impacts. However, while for most products the autocorrelation dissipates at a lag of 2 months, for NDVI and SPI-6 it takes 3–4 months, and this can have an influence on NDVI and SPI-6 showing stronger correlations. For SPIs with longer accumulation periods (SPI-9 and 12), the correlation dissipates even slower.

The weaker correlations obtained for SM data in the first test may be due to the coarser spatial resolution of the dataset. Higher-resolution soil moisture products (Alexandridis et al., 2016; Scott et al., 2003) could be considered for future studies. The reason for the weak or no correlations between both GPP and PsnNet and the text-based records may lie in the formulation of the MOD17 product. Indeed, limitations of the product in capturing spatial and temporal variability in croplands have been reported (Verma et al., 2014; Zhang et al., 2012).

The trade-off between the anticipation of the information and its reliability is also illustrated by the results. The lower reliability associated with earlier information detection of conditions that may lead to drought implies that often the situation may not evolve into a drought event. However, that information is still highly valuable as it allows the stakeholders to get ready to undertake mitigation actions if necessary.

The remote sensing products tested can enhance early warning capacity and therefore contribute to the shift from reactive to proactive management recommended by the European Commission (Commission of the European Communities, 2007) and the United Nations (UNISDR, 2009), and is being undertaken by many institutions (Iglesias et al., 2009). As remote sensing data products generally have a global coverage, this contribution would therefore be especially useful in areas with less in situ data available. Yet the most informative indicators of drought occurrence may vary depending on specific characteristics of the country or basin, such as management practices or dominant water uses (Stagge et al., 2015). Remote sensing products also have the potential to provide information at a finer spatial detail than the management units and land cover classes considered in this study, allowing the detection of local drought events that may remain unnoticed when the pixels are aggregated to the scale of the land cover classes considered.

2.5 CONCLUSIONS

The aim of this research was to test the ability of remotely sensed datasets to detect early stages of drought at the river basin scale, with particular attention to their capacity to anticipate drought impacts and gain time to inform operational land and water management. Media records from a regional newspaper proved to be a helpful source of information that allowed a detailed reconstruction of drought events and impacts. The analysis using these data as a benchmark revealed the potential of the tested medium-resolution remote sensing products to anticipate reported drought impacts on irrigated and rain-fed areas at basin scale up to 6 months. The best correlation–anticipation relationships were obtained for SPI, NDVI and ET. SM and LST also showed potential to anticipate drought but with weaker correlations. GPP and PsnNet from MOD17 presented weak or no correlation for most of the areas, with only some of the rain-fed areas having moderate positive correlations. The index based on in situ data currently used in the basin also provides early detection, and with the exception of two of the management units, the anticipation of drought impacts is better than that provided by the remote sensing indicators. However, the correlation of the indices based on SPI, NDVI and ET to anticipate drought impacts was found to be stronger. The use of quantitative impact data of crop yields as a benchmark showed a consistent behaviour of the remote sensing indicators with respect to the different levels of crop yield in rain-fed areas among the analysed years. SPI, NDVI and ET stand out for having stronger correlations, reinforcing the findings of the first analysis. In both analyses, drought on irrigated land showed less clear correlation patterns than drought in rain-fed areas.

Altogether, the results confirm remote sensing products' ability to anticipate reported drought impacts and therefore provide a useful source of information to support drought management decisions at the basin scale. However, further analysis of managers' information requirements and response options is required to better assess the usefulness of these types of products in informing specific operational drought management decisions.

3

DO USERS BENEFIT FROM ADDITIONAL INFORMATION IN SUPPORT OF OPERATIONAL DROUGHT MANAGEMENT DECISIONS IN THE EBRO BASIN?

This chapter is based on:

Linés, C., Iglesias, A., Garrote, L., Sotés, V., and Werner, M.: Do users benefit from additional information in support of operational drought management decisions in the Ebro basin?, Hydrol. Earth Syst. Sci., 22, 5901–5917, https://doi.org/10.5194/hess-22-5901-2018, 2018.

Abstract

We follow a user-based approach to examine how information supports operational drought management decisions in the Ebro basin and how these can benefit from additional information such as from remote sensing data. First, we consulted decision-makers at basin, irrigation district and farmer scale to investigate the drought-related decisions they make and the information they use to support their decisions. This allowed us to identify the courses of action available to the farmers and water managers, and to analyse their choices as a function of the information they have available to them. Based on the findings of the consultation, a decision model representing the interrelated decisions of the irrigation association and the farmers was built. The purpose of the model is to quantify the effect of additional information on the decisions made. The modelled decisions, which consider the allocation of water, are determined by the expected availability of water during the irrigation season. This is currently informed primarily by observed reservoir level data. The decision model was then extended to include additional

information on snow cover from remote sensing. The additional information was found to contribute to better decisions in the simulation and ultimately higher benefits for the farmers. However, the ratio between the cost of planting and the market value of the crop proved to be a critical aspect in determining the best course of action to be taken and the value of the (additional) information. Risk-averse farmers were found to benefit least from the additional information, while less risk-averse farmers stand to benefit most as the additional information helps them take better informed decisions when weighing their options.

3.1 INTRODUCTION

Water managers and farmers regularly make decisions on how to make the most of the available water resources. Information on the availability and variability of the resource is essential to allow these decision-makers to choose among the actions available to them, especially as water becomes scarce, for example during drought events. Improved information on the availability of water can then potentially lead to a more effective management and can therefore contribute to the mitigation of the impacts of drought events.

In situ meteorological and hydrological measurement networks have long served to inform these decisions, often providing accurate water resources observations at high temporal resolution. In addition, the potential of Earth observation (EO) from satellites to support water management has also been widely recognised (Famiglietti et al., 2015; Fernández-Prieto et al., 2012). The availability and quality of EO datasets has continuously improved during recent decades, providing an increasingly relevant source of globally consistent data that can be used to complement in situ data.

However, the increased quality and availability of information does not necessarily translate directly into benefits due to better decisions. How the information is used and distributed also plays a critical role (Williamson et al., 2002). It is the capacity of the user of information to change the course of action as a result of new information being available to them that largely determines the value of that new information (Macauley, 2006).

A good understanding of the role that information plays or could play in supporting decisions, as well as the resulting benefits, is useful both for the users and the data providers and helps improve the connection between these two groups. Onoda and Young (2017) present a series of analyses on the contribution of EO datasets in addressing environmental problems from a policy point of view and conclude recommending more stakeholder-oriented studies of the value of these data and the quantification of the benefits of this data through comparisons with current tools. The assessment of the role and impacts of remote sensing products is expected to help in fully achieving the potential of the products, maximising the socio-economic and environmental benefits, and contributing to justify the investment in developing and improving the products.

An example of a stakeholder-oriented approach to assess the value of satellite-based information in support of water management is presented by Bouma et al. (2009). They develop a framework to measure the benefits of satellite-based observations. The framework, which is based on Bayesian decision theory and expert consultation, is applied to water quality management in the North Sea (Bouma et al., 2009) and to coral reef protection (Bouma et al., 2011).

Macauley (2006) reviews studies on the value of information in Earth science applications, classifying the techniques that are used or that are potentially useful into three groups: studies that measure the value by gains in output or productivity; studies based on hedonic pricing, in which the value is inferred from models based on wages and housing prices; and studies that consider the willingness to pay. The main example of the first group of techniques are the studies that relate farm profits and weather information, especially in relation to weather forecasts. Early studies explore simplified cases of decisions such as whether to plant or to leave cultivable land fallow (Brown et al., 1986), or on what crop to plant (Wilks and Murphy, 1986).

From the user's perspectives, the optimal choice for a decision to be made is to take the course of action that results in the highest expected utility, which is defined as the weighted sum of the outcomes of the possible actions and the probability of a given state of nature such as a reduction in the available water resource. Clearly this includes undesirable outcomes, where an action is taken based on an expected state of nature that does not materialise. Additional information is then considered to have value if it can improve the advance knowledge on the probabilities of the different possible states of nature occurring, thus allowing the user to make a better-informed decision. A commonly used approach to evaluate the value of advance information, such as information provided through advanced warning, is the cost-loss framework (Mylne, 2002; Roulin, 2007; Verkade and Werner, 2011; Zhu et al., 2002). Often used to evaluate the potential benefit of (flood) warnings, this is the ratio of the costs of taking protective action to the losses incurred if that action is not taken. This framework has also been extended to water resources management decisions, such as in Quiroga et al. (2011), who analyse the value of climate projections to decisions on applying measures to reduce water demand in the Ebro basin. The cost-loss framework does assume a strictly rational behaviour of users in weighing the costs and probability of losses, which is a limitation as different users may make different decisions depending on their levels of risk averseness. This can, however, be incorporated through a function of risk aversion (Matte et al., 2017; Quiroga et al., 2011).

The aim of our paper is to explore the value of information to drought management decisions through a stakeholder-oriented analysis. We examine the operational decisions that stakeholders such as farmers and reservoir operators take within the context of water resources allocation during droughts. The proposed framework first uses interviews to identify the decisions stakeholders make, as well as the information they use to inform those decisions. A decision model is then established and applied to emulate the decision process and how additional information contributes to improving the decisions made. Our work contributes to the developing field of socio-hydrology (Sivapalan et al., 2012) in that it explores the co-evolution of the availability of water and the decisions made by humans (in this case farmer and irrigation operators). While the emerging field of socio-hydrology is broad (McMillan et al., 2016), we consider our work to be related most to that of the working group on drought in the Anthropocene (Van Loon et al., 2016), which explicitly addresses the inefficiency of drought management due to poorly understood feedback between people (and the decisions they make) and drought conditions.

3.2 STUDY AREA AND APPROACH

3.2.1 The Ebro basin

We explore the role of information in drought-related decisions in the Ebro basin. The Ebro Basin is the largest in Spain (85,600 km^2) and is a highly regulated basin with 125 reservoirs (>1 Mm^3) and a total storage capacity of approximately 8000 Mm^3. These reservoirs are used primarily to supply water to more than 900,000 ha of irrigated agriculture and 360 hydro-electrical plants (CHE, 2015).

The larger irrigation districts are located in the north-east of the basin (Figure 3-1). We have selected one of these, the irrigation district supplied by the Aragón and Cataluña channel (Canal de Aragón y Cataluña, CAyC), to examine the decisions made at the sub-basin scale.

Over 90 % of the water provided by CAyC is used for irrigation. The water it supplies is sourced from three reservoirs (Barasona, San Salvador and Santa Ana), and it is supplied to an irrigated area of around 98,000 ha. Two zones can be distinguished in the irrigated area: an upstream zone that can only be supplied from the Barasona reservoir as well as from the recently inaugurated San Salvador reservoir, and a downstream zone that can be supplied from all three reservoirs. These zones are 54,000 and 44,000 ha in size, respectively. The main crops grown in the area are fruit orchard (apple, pear, peach and nectarine) and extensive herbaceous crops, mainly maize, alfalfa and barley. The area cropped with wine vine surface is increasing, though it is still somewhat localised (CHE, 2018).

Three drought events that resulted in impacts to agriculture and other sectors have been recorded for the 2000–2014 period: a short drought spell in 2002, a multi-year event that lasted from the winter of 2004–2005 to the spring of 2008, and another during the years 2011 and 2012 (Linés et al., 2017). The impacts of the multi-year drought of 2004–2008 in the Ebro basin have been widely studied. The north-eastern part of the basin was the most impacted (Hernández-Mora et al., 2013) and agriculture was the most affected sector, with 540 million Euros of estimated losses to crop production during the hydrological year 2004–2005 and further losses of 272 million in related industries (Pérez Pérez and Barreiro Hurlé, 2009).

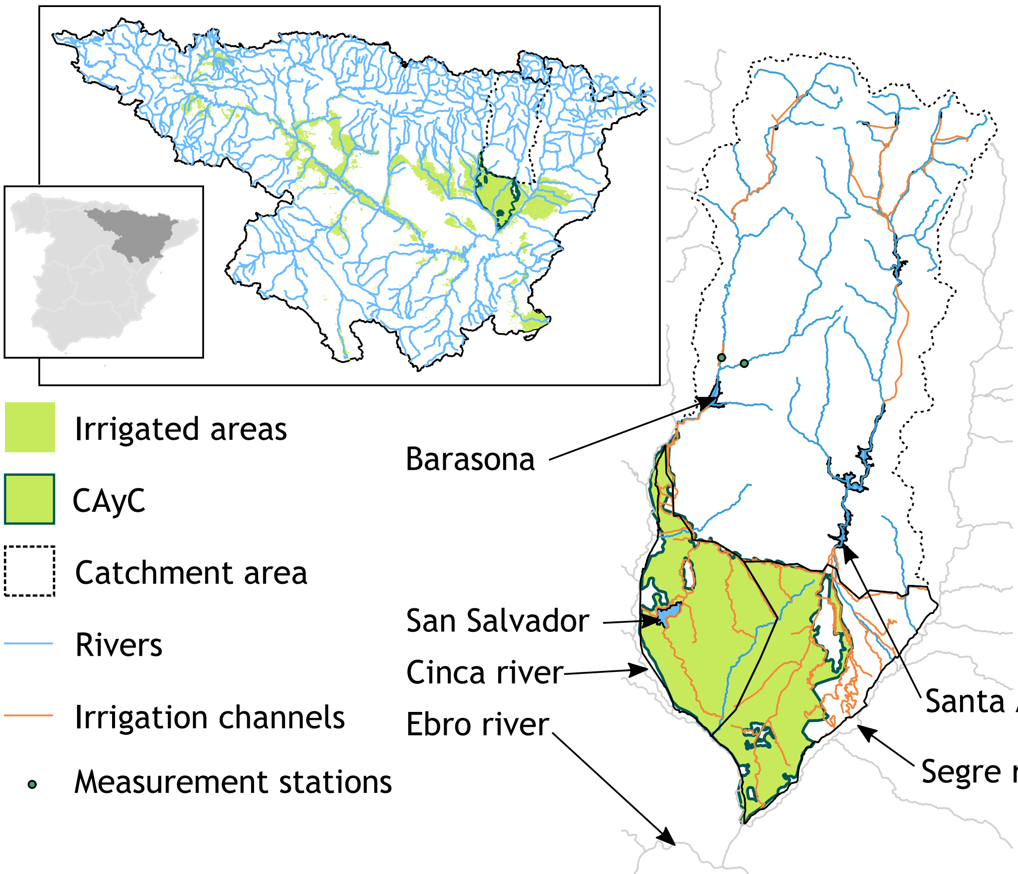


Figure 3-1. Canal de Aragón y Cataluña: irrigated area and catchment.

3.2.2 Approach

As the utility of information strongly depends on the particular details of the decisions and how information is used to support these, we first consulted decision-makers at the basin (Confederación Hidrográfica del Ebro, CHE), irrigation district (Comunidad de Regantes del Canal de Aragón y Cataluña) and farmer scale to better understand their decision processes, their information needs, and how they use information to support the decisions they make. For this analysis we focused on decisions regarding the allocation of water resources, in particular during drought, when curtailments may be applied (Figure 3-2). The methods followed for the consultation and a summary of the outputs of the interviews at each of the locations are provided in section 3.3.

The findings of the consultation phase were used to build a model of the decisions at irrigation district scale. The design of the model from these findings is described in sections 3.4.1 (farmer decisions) and 3.4.2 (reservoir operator decisions). The outputs of these components are the areas of different crops that are planted during the irrigation season and the curtailments applied. The crop yield is then calculated using the area of each crop and observed meteorological data in open-source crop models (introduced in section 3.4.3).

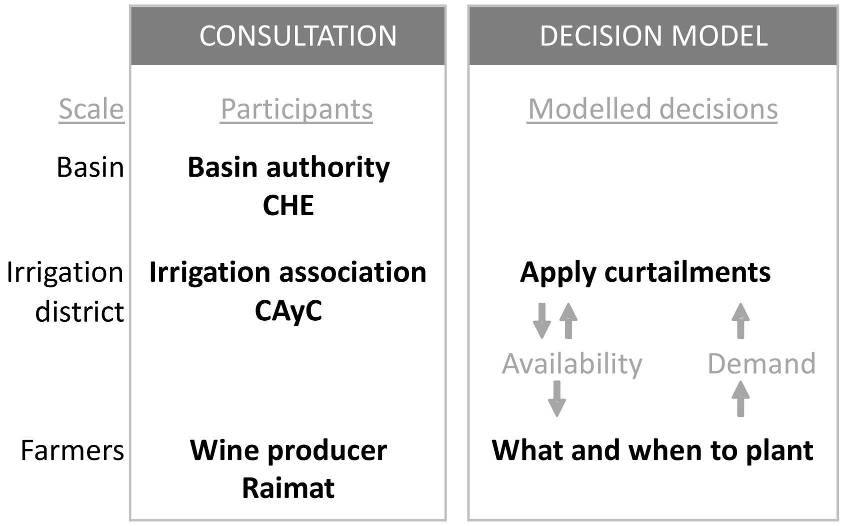


Figure 3-2. Research phases and spatial scales.

In order to test and quantify the effect that additional information has on the operational drought management decisions analysed, the decision model was run for two scenarios with different input information. The input data and specific parameters used in these two runs are described in section 3.5.

The expected final results of the analysis are the relative values of information in each of the tested scenarios. We calculate this based on the total net benefit obtained by farmers during the whole period of analysis. This benefit depends on the decisions made during each season, which in turn depend on the information used to inform them. The results are described in section 3.6 and followed by discussion and conclusions.

3.3 STAKEHOLDER CONSULTATION

3.3.1 Method

The stakeholders we consider are the different groups that have the capacity to modify the amount of water to be used for irrigation either by deciding on the volume of water to be supplied, or by deciding on the area and type of crops planted. This decision effectively also determines the irrigation demand. We use semi-structured interviews to develop our understanding of the decisions these stakeholders make in managing water resources and the possible adjustments to those decisions that they may make in view of water shortages. This method provides the possibility to discuss additional topics not originally envisioned by the research team in the interview guideline (Harrell and Bradley, 2009). O'Keeffe et al. (2016) and Carr et al. (2011) similarly apply semi-structured interviews to understand water use and management practices. Participants were asked to describe their own practices, as well as the practices of the groups they deal with in relation to drought management. A set of questions had been previously prepared but was only used to guide the interviews and ensure that topics not mentioned were addressed and that all required details about the decision processes were collected.

One interview session was held at each of the locations (the basin authority, the irrigation association and the farm) with two or three people participating in each. In the interview that was held at the basin authority, the participants included the head of one of the basin's management units and two members of the hydrological planning office, both with expertise in drought management in the basin. In the interview at the Irrigation Association, the participants were the head of the Irrigation Association and the engineer in charge of the information service about current and expected water availability. And in the interview at the farm level, two people participated: the head of viticulture and the engineer responsible for the information service.

The information about the practices and attitudes of farmers in the study area was to a great extent obtained from the interview with the staff at the Irrigation Association who work in close collaboration with all the farmers in the area and therefore have a wider view than individual farmers. We acknowledge that the sample of interviews we held is small. Although important to the assumptions made in the development of the decision model that we constructed, we would readily agree that our representation of the farmer behaviour and the diversity of responses across farmers may be over-simplified. A larger sample of interviews would reveal more information, but we feel that is outside the scope of this paper.

3.3.2 Confederación Hidrográfica del Ebro

The main operational decisions that the Ebro River basin authority (CHE) takes regarding drought are the declaration of drought conditions and the allocation of water in emergency situations. To guide these decisions, CHE defined a drought management plan in 2007 (CHE, 2007), which was the first of its kind in Europe. It is a very comprehensive plan and links hydro-meteorological indicators to drought severity levels. The decision to declare drought is informed by a set of indicators, derived from measurements from a dense network of in situ automatic stations. The plan establishes the main indicator to be used for each of the areas of the basin. Where applicable, water stored in the reservoir is used as the main indicator, since it is considered the most robust option. Otherwise, 3-month discharge or groundwater levels are used as indicators.

In the opinion of those interviewed at CHE, the declaration of drought is currently well informed and therefore they consider that additional information would be more useful after the declaration, when conditions must be monitored closely and decisions such as selecting the most cost-effective alternative sources of water or how to secure sufficient water to guarantee environmental flows must be taken. For these decisions timing is critical, and they point out that information should be available with a maximum delay of 1 week to be useful for decisions. In addition, they showed particular interest in remote sensing derived snow data to support the quantification of water availability in the basin.

3.3.3 Canal de Aragón y Cataluña (CAyC)

General Irrigation Associations such as Canal de Aragón y Cataluña (CAyC) are responsible for the distribution of water from the reservoir to the users. In drought situations they can decide to introduce restrictions to irrigation water quotas. The decisions they make on the application of these restrictions are informed by the availability of water in the reservoirs that feed the irrigation canal system.

The main decisions that CAyC make in relation to drought is to apply restrictions (curtailments) to the maximum amount of water that irrigators can request. They make this decision when they consider that the available water resource is insufficient to reach the end of the irrigation season if full irrigation supply to meet demand is maintained. They can also decide to move water among the three reservoirs in the area. When restrictions are necessary, these are applied to all users independently of the reservoirs that they can be supplied from to ensure curtailments are applied equitably across the district. However, when water is scarce, priority is given to perennial crops such as fruit orchards and vines to ensure their survival.

To make their decisions, the reservoir operators need information both on water availability and the expected demand until the end of the season. In the interviews, they indicated that they consider that they are well informed on the availability of water given the levels in the reservoir. However, the information on water demand is limited. The difficulty of knowing the demand is due to the fact that they lack information on what crops farmers are planning on cultivating that year, and especially if the farmers will decide to plant a second crop, thus increasing the demand towards the end of the season. Currently they use historic data to estimate the demand. They are also conducting studies on the feasibility of obtaining this information from remotely sensed NDVI data (Casterad

Seral, 2015; Quintilla et al., 2014), and although this will provide useful information on the current crops, it will not provide information on the future plans of the farmers.

Unlike the managers at the basin scale, CAyC indicated that they consider additional data on the snow cover in the headwaters to be of little use in quantifying the available resource. They argue that they tend to be cautious when accounting for snow in the estimation of total availability, since the reservoir capacity is rather small and therefore the possibility to store snowmelt runoff depends very much on the melt rate.

3.3.4 Farmers in the Canal de Aragón y Cataluña Irrigated Area

During the consultation, CAyC also provided details on the types of farmers present in their supply area as well as on the decisions these farmers make on what to plant. Typically, the proportion of crops planted is fruit orchards and vines for roughly a third of the area, alfalfa for another third, and annual crops for the remaining third. These annual crops are mostly winter cereals and maize. The cropping schedule adopted by farmers is mostly either a single crop of long-cycle maize or a winter cereal, or a double crop in which a winter cereal is followed by short cycle maize. The selection of one or the other by the farmers depends on the expected water availability and is currently mainly informed by the water level in the reservoir. CAyC shares this information with them in the form of biweekly reports. Conversely, the decisions farmers make in terms of what crop to plant, and if they plan to plant a double crop, determine the demand for the season, and will therefore also have an impact on the decision to apply curtailments that are taken by the CAyC.

A prominent farmer in the supply area of CAyC is the Raimat wine producer, who also participated in the consultation process. They provided details of their information use for water resources management. Their parcels extend over 3200 ha and are highly technified, with extensive use of detailed information. In addition to in situ measurements and meteorological station data, they use Landsat satellite data and perform flight campaigns to acquire spatial NDVI and thermal data. The thermal data are used to estimate the leaf water potential and, together with temperature data, calculate a crop water stress index. This information on crop condition is used to detect spatial differences in the crops to make the most of the limited water, select the optimal moment for irrigation and prevent plagues, as well as to ensure the production is as uniform and controlled as possible.

The decisions they make are already based on high-resolution data, and therefore additional medium-resolution global data are not likely to be a valuable contribution to this type of user. However, this extensive use of information is not representative of all the farmers in the basin and other farmers may indeed benefit from additional information.

3.4 DECISION MODEL

Two of the drought-related operational decisions described by the stakeholders were selected to be modelled. These are the decisions of the farmers on what to plant and the decision of the reservoir operators (part of the irrigation association, CAyC) to apply curtailments to the amount of water that farmers can request when this is considered necessary to avoid depleting the supply before the end of the irrigation season. The model represents both decisions as well as the interaction between the two. In the year-to-year planning of water allocation and crops to plant, the basin authority is of lesser relevance to the decision model as they are responsible for the longer-term planning through the basin hydrological plan. They are also in charge of developing the drought management plan, and although this plan provides guidelines on the measures to be taken during drought, it does not go into detail on the operational decisions to be taken on water allocation.

The decision model was built in R (R Core Team, 2016).

3.4.1 Farmer decision: crop areas

The farmers have a number of possible crop alternatives for each irrigation season. In this part of the model, we simulate the decision of the farmers to follow one of the possible courses of action available to them. The result of the decision is the planted area of the selected crops. Since fruit orchards, vines and alfalfa crops are perennial crops and are typically planted for several years, their approximate areal extent is known and is considered to be constant in the model. The farmer decision model therefore focuses on determining the variable areal extent of maize and winter cereal, as well as the decision as to whether to plant a single crop or also a second crop. In the model, barley is selected to represent the winter cereal crop since it is the most common winter cereal crop in the area.

The courses of action represented in the model consist of a series of decisions made during the irrigation season. The possible actions are depicted in Figure 3-3, which shows the choices that can be made at each decision stage in the calendar. At each of these decision points, the option that farmers would prefer to take if they perceive there are sufficient water resources available is indicated by a blue A. The preferred decision(s) if there are insufficient resources is marked with a red A. The choices and the calendar are based on the information provided by the stakeholders we interviewed, supported by literature sources (Espluga Trenc, 2016; Gil Martínez, 2013; Lloveras Vilamanyà et al., 2014). We consider two types of farmers in the model, with different options available to them: technified farmers managing large plots and smaller-scale farmers. In the model, technified farmers (marked with T1 in Figure 3-3) can support a double crop, and this is always their preferred option because of its higher productivity. However, in years of low water availability (red A in the figure) they may decide to leave the land fallow instead of planting a second crop. Smaller-scale farmers (T2) can only manage a single crop and in this case long-cycle maize is the most productive option. In years of low water availability, their decision will depend on the level of risk they are willing to take. We consider three levels of risk aversion (R1, R2 and R3 in the figure). The safest option to secure a crop is to plant long-cycle barley at the beginning of the season (R1), but they can also decide to wait for conditions to improve, taking the risk of having to leave the land fallow if there is no improvement (*R*>1). If, however, water availability increases by February, they can decide to plant long-cycle maize. If availability is still low, they can secure a crop by planting a short-cycle barley (a less productive option than the long-cycle version) (R2), or they can decide to wait longer (R3). In April, they can still plant a long-cycle maize crop if availability has improved, but, if it has not, then it is too late to plant barley, and they have no other option than to leave the land fallow.

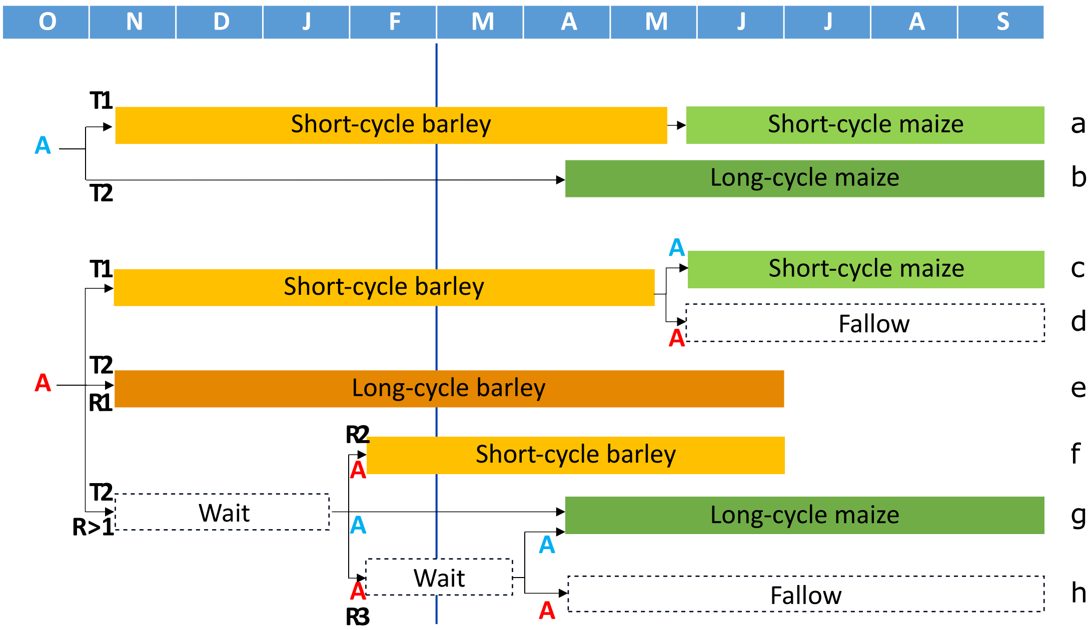
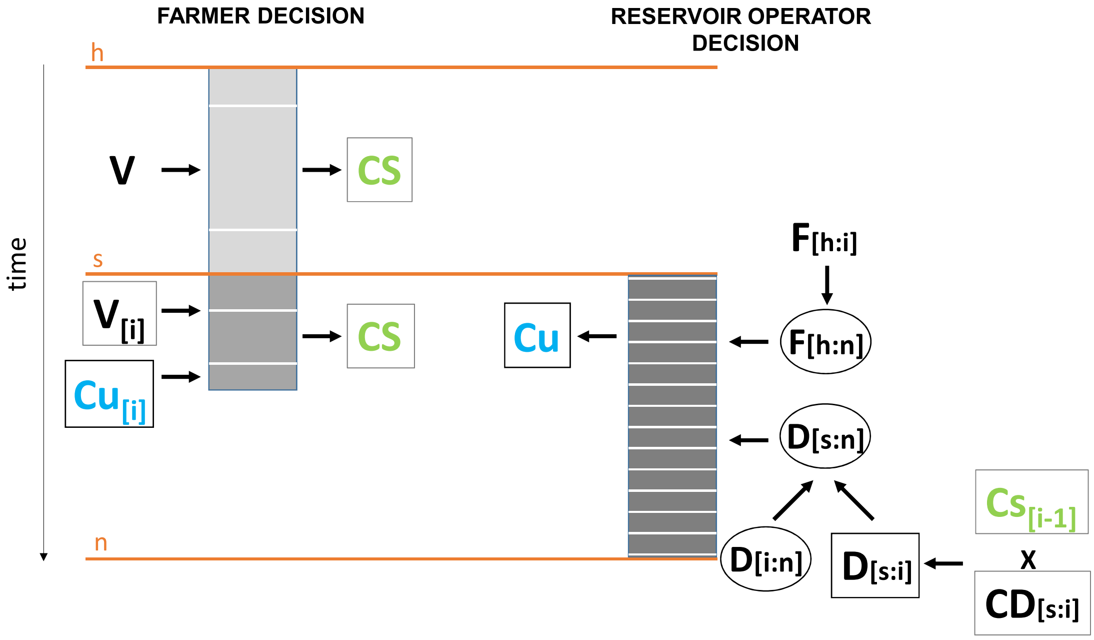


Figure 3-3. Crop options considered in the model for farmers. Blue and red As represent respectively good and poor water availability at the moment of the decision. R1, R2 and R3 mark the different courses of action that farmers can follow depending on the risk they are willing to take, with R1 being the most risk averse and R3 the least risk averse. The lower-case letters a–h indicate the end points of the possible decision paths. The blue vertical line marks the start of the irrigation season.



Parameters	Time [ ]	Availability and sources	
F – Inflow	h – start of hydrological season	V	known to decision maker (from data)
D – Demand	i – decision date		known to decision maker (from model)
V – Volume	s – start of irrigation season		unknown to decision maker (estimated)
CS – Crop surface	n – end of season		
CD – Crop demand			
Cu - Curtailments	[s:i] from s to i		

Figure 3-4. Model decisions, parameters that inform them and decision outputs. A description of the abbreviations is included below. The period considered for each parameter is given in between square brackets. The shapes indicate the availability and source of the information. The parameters representing the information that is exchanged between the two decision models are coloured in green (crop surface, CS) and blue (curtailments, Cu). The grey boxes represent different blocks of the decision models. The reservoir operation decision has the same kind of input and output for each decision date, while the farmer's decision has different inputs before and after the start of the irrigation season. The white lines within the blocks represent the moments at which decisions are made (time i*).*

The choice of a particular course of action in the model is based on the water availability at the moment of the decision and is used as an indicator of the expected availability of water during the remaining season. For the decisions made before the start of the irrigation season (November and February), the availability is based on the observed volume in the reservoir since these decisions have no influence on the level of the reservoir until the actual start of the irrigation season. For the decisions after the start of the irrigation season (decision points in April and May) a simulated volume is used (Figure 3-4). The simulated volume is based on the observed volume at the beginning of the irrigation season and the accumulated inflow from the beginning of the irrigation season until the decision date. From the start of the irrigation season the decisions made will have an influence on the level of the reservoir and therefore observed levels are not representative as an input for further decisions. Note that the barley crop is not irrigated and therefore does not pose a demand on the available water resource. However, as can be seen in Figure 3-3 the choice for planting a barley crop will have implications for the available options later in the season and therefore indirectly influences the irrigation demand.

3.4.2 Reservoir operation decision: water restrictions

Every 2 weeks during the irrigation season (March–October), the decision on whether to apply curtailments to the maximum amount of water that irrigators can request is re-examined. This decision requires an estimate of the total amount of available water during the season and the total water demand. To estimate the total amount of water that will be available during the season, the inflow into the reservoir from the beginning of the hydrological year in October up to the week of the decision (represented as $F_{[h:i]}$ in Figure 3-4) is compared with the percentiles of historic data. Data of accumulated inflow in the reservoir are preferred to reservoir levels as input information for the reservoir operator decision model to avoid the influence of the actual decisions of the managers and simulate them independently. The percentile curve in which the value of the current year is positioned is then used to sample from the climatological record a projection of the inflow series into the reservoir until the end of the season.

The total water demand for irrigation until the end of the season ($D_{[s:n]}$) is calculated as the sum of the demand until the decision day ($D_{[s:i]}$) and the expected demand from the decision day until the end of the season ($D_{[i:n]}$). The first is the product of the crop surfaces already planted ($\mathrm{Cs}_{[i-1]}$), which is the output of the farmer decision model, and the resulting crop demand ($\mathrm{CD}_{[s:i]}$) obtained from the crop models using observed meteorological data. The latter ($D_{[i:n]}$) is unknown to the managers. In the model, an average demand per unit area of crop calculated with the crop model data for the period 2000–2014 is used as an estimate to inform their decision. This is a simplification, as the demand to the end of season will depend on the expected climatological conditions and the crop surfaces planted. The actual demand up to the decision day could be used as an estimate of the expected demand until the end of the season. However, while that could provide an indication of the climatological conditions, the decisions made by farmers on which crops to plant at future decision moments are unknown.

When the estimated total amount of available water during the season is insufficient to fulfil the total demand, curtailments are applied. Conversely, if in a later week the expected total available water is found to be enough to fulfil the total demand, restrictions are lifted.

The output of the farmer model are the areas of each of the crops planted each year by the farmers. These crop areas determine the demand in the reservoir operator decision model. The outputs of the operator decision model on the other hand are the curtailments posed on the water supplied to the farmers until the end of the season, which is determined every 2 weeks. These curtailments may reduce the yield of the crops, if these are already planted and the demand cannot be satisfied, but will also influence the farmer decisions within the irrigation season. If curtailments are in force when the farmers are deciding what to plant (April and May), then the model assumes that the farmers do not consider water availability to be good, leading to decisions commensurate with low water availability being made. These decisions will consequently influence the demand.

3.4.3 Crop water demand and benefit

AquaCrop-OS (Foster et al., 2017) was used to simulate barley and maize yields. These crops are the main focus of the analysis and they require a more detailed and flexible simulation to differentiate the different growing cycles and planting dates. Default parameters for maize and barley were adapted for the diverse cycles using data from Lloveras Vilamanyà et al. (2014), Gil Martínez (2013) and Gutiérrez López (2011).

CropWat 8.0 (FAO, 2000) was used for alfalfa and fruit orchards, the crops that are considered to have a constant crop surface in the analysis. Default parameters were used but were adapted to the cropping calendar in the Ebro basin. Peach tree was selected as the representative fruit orchard crop. An irrigation calendar of 14 days was selected to match the reservoir operators' decision.

The percentage of reduction in crop yield was calculated as the maximum percentage of unsatisfied demand during the season. The reason for this is that, when there is insufficient water, farmers prefer to stop watering a part of the area, rather than apply insufficient water to the whole area. These percentages were calculated using the same 2-week time step of the operator decision. The areas in which irrigation was stopped were considered to have no yield and their contribution was subtracted from the full supply yield values derived from the crop models to obtain the final yield for each crop and year. Priority is given to the perennial crops, with the curtailments then being applied to the maize crops.

3.5 QUANTIFYING THE EFFECT OF ADDITIONAL INFORMATION

Expected availability of water during the irrigation season is the main variable used by both the reservoir operators and the farmers to inform their decisions. Information on that availability can, however, be obtained from different sources. Currently the main source of information that is used is the volume stored in the reservoirs, obtained through observations of the reservoir levels. Stakeholders indicated that they may also consider the available water resource in the snowpack in the headwaters upstream of the reservoirs, though there are currently no systematic observations of this resource that are formally included in their decision processes. Satellite images can, however, routinely provide estimates of this resource. Two information scenarios were therefore simulated: the expected water resource availability as informed by the reservoir levels alone, and the expected availability based on the reservoir levels with the addition of satellite-based data on snow cover in the headwaters.

Output benefit values using either of the two information scenarios were evaluated against the value (Val) of uninformed decisions and decisions under perfect information following the usual form of skill scores (Stanski et al., 1989):

$$RV = \frac{Val_{information} - Val_{uninformed\ decision}}{Val_{perfect\ information} - Val_{uninformed\ decision}} \tag{3.1}$$

The relative value (RV) is therefore a score between −∞ and 1, with RV =1 meaning that the information is perfect and RV ≤0 meaning that the information does not contribute to improving the decisions made.

The value of perfect information and uninformed decisions was calculated by running the model for all possible courses of action represented in Figure 3-3. The value of perfect information was then obtained by selecting for each season the best performing course of action, while the value of the uninformed decisions was defined as the result of selecting the course of action that performs best on average for all years.

Analysing the pathways in Figure 3-3 results in seven possible courses of action. These are summarised in Table 3-1, where the columns represent the four decision points and the colours the course that is followed. Blue and red indicate that the good or the poor water availability option is followed, respectively. The points at which no decision is required are marked in yellow. This happens when previous decisions already determine the course of action for later months. Option 7 corresponds to the situation in which the availability of water is good at the beginning of the hydrological year, so farmers already select to plant the most productive crops in November and no further decisions are required in the following months. The other six options correspond to situations in which the availability of water is not considered to be good at the beginning of the hydrological year. In options 3 and 6, the situation improves by February, so small-scale farmers decide to plant the preferred option (long-cycle maize) at this point and do not require further decisions. The difference between these two options results from the decision taken by technified farmers on whether to plant a second crop in May. They will do this if they consider the availability of water to be good (option 6), otherwise they will leave the land fallow (option 3).

Table 3-1. Possible paths for farmers. The paths are the result of the water availability (red – poor availability, blue – good availability, yellow – indifferent) at the four decision moments. The letters and coloured boxes in the last four columns correspond to the courses of action in Figure 3-3 for each of the farmer types given good or poor availability at the four decision moments. The crops planted when following each of the paths are indicated using the same colours as in Figure 3-3.

Path	Decision moments				Decision by farmer type			
	Nov	Feb	Apr	May	T1	T2-R1	T2-R2	T2-R3
1					d	e	f	h
2					d	e	f	g
3					d	e	g	g
4					c	e	f	h
5					c	e	f	g
6					c	e	g	g
7					a	b	b	b

3.5.1 Input data

Reservoir and meteorological data

In situ data on reservoir levels were obtained from the automatic measurement stations (SAIH, Automatic Hydrologic Information System). These data are available from http://sig.mapama.es/redes-seguimiento/ (last access: 12 November 2018).

Reservoir volume data for Barasona reservoir and river flow data from the stations at the upstream tributaries (stations located at Graus on the Ésera river and at Capella on Isábena river, Figure 3-1) were used to estimate the availability of water during the season. We focus on the Barasona reservoir as it is the levels in this reservoir that trigger the restrictions in the area supplied by CAyC. SAIH provides data for the Barasona reservoir from 1931 to September 2014, though there are some data gaps in the first few decades. The reservoir was enlarged in 1972 to a capacity of 84.71 hm^3 and we therefore consider only the values after that year.

In addition, daily precipitation and temperature data, as well as monthly relative humidity data from the meteorological station located just outside the basin at the University of Lleida (station 9771C), were used to provide meteorological inputs to the crop model. Data from this station are available from 1983 through 2014 and can be obtained from https://opendata.aemet.es/centrodedescargas/productosAEMET (last access: 12 November 2018).

Snow cover data

MODIS 8-day snow cover 500 m grid data (MOD10A2; Hall et al., 2006) were used to calculate the percentage of snow cover in the headwaters of the reservoirs (Figure 3-1) as an additional source of water availability information. This dataset covers the period from 26 February 2000 to the end of 2016 and was downloaded from the EartH2Observe Water Cycle Integrator (http://wci.earth2observe.eu, last access: 12 November 2018).

3.5.2 Model options

Availability thresholds

Thresholds are needed to define at what reservoir level, or at what combination of reservoir level and snow cover, the water availability is regarded by the farmers as good. This judgement is made at each of the decision points. If the availability is above the threshold, then the farmer would follow the decision path associated with good expected availability of water (this corresponds to following the paths marked with a blue A in Figure 3-3), while if it is below the threshold then the alternative, poor expected availability path will be followed. These thresholds are currently not formally defined and may also differ between farmers as individual farmers will assess water availability differently, depending on how risk averse they are.

In the first test we identified the thresholds that maximise the sensitivity (rate of true positives) for all years analysed and for each of the farmers decision moments (November, February, April, May). This is a measure of the goodness of a binary classification that in this case refers to the points correctly classified as having good availability of water. To assess the performance of the classification the decisions made with perfect information are used as a reference. This results in a set of four optimised thresholds, which may be different for each of the decision points. The optimised threshold values at each decision point are kept the same for all years analysed.

In addition to the optimised set of thresholds, the model is run with 10 extra sets of thresholds to explore the sensitivity to these thresholds. In this case, the thresholds are kept the same at each decision point, and the values range from low (35 hm^3) to almost full capacity (80 hm^3).

The effect of the additional snow cover information on the expected available water resource is incorporated in the decision model by considering the expected contribution of snowmelt to the available water resource. When the snow cover is below a certain threshold, indicating lower than normal expected runoff from snowmelt, the farmers would require the reservoir level threshold to be higher to regard water availability as being good and thus follow the higher water demanding path. The snow cover thresholds used for this test are again determined using a goodness-of-fit measure of the binary classification of the decision points correctly identified as having good or poor availability. For the decisions made in May the snow information was not considered since snow cover is already very limited in that period.

Allocation factor

An allocation factor is applied to the accumulated inflow in the reservoir to obtain the proportion of the available resources that effectively reaches the crops. This factor accounts for water supplied to other uses, water losses due to evaporation, efficiency of the distribution network and releases from the reservoir to the downstream river. The allocation factor determines the amount of water that is available for irrigation and therefore has significant influence on the decisions made by the farmers and operators. As the true allocation factor is not known for the area, the sensitivity to this factor is tested by running the model with different allocation factors, considering perfect knowledge of the expected availability of water.

The most profitable choices for farmers were identified for different allocation factors under perfect information and are shown in Table 3-2. The first row (AF =1) represents the hypothetical situation in which all the water that enters the reservoir is available to the farmers to irrigate the crops. The following rows represent different levels of allocation of water for irrigation. The results show that when more water is available, farmers already choose to plant the most productive option in November or February (options 7 and 6 respectively). When there is less water, they select to plant less maize or nothing at all (option 1). In years of water scarcity, such as 2005, we can see in the table that this is the case even if 80 % of the total water is used for irrigation.

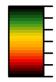
An allocation factor of 0.55 was selected for the following tests, since it is found to be a tipping point between good and poor availability for many of the years in the tested period and therefore allows for a higher range of represented situations. With this level of allocation, the area receives an amount of water that would be able to satisfy the full demand of the most productive alternative of crops in 10 out of the 14 years, with 4 years experiencing water shortages, which reflects the number of drought events in the 2000–2014 period.

To calculate the crop demand, an irrigation efficiency of 80 % is considered.

Table 3-2. Most profitable choice for the farmers for each of the years of the period 2001–2014 (represented in the columns) in function of the available water determined by the allocation factor (AF). The numbers of the options refer to the alternatives included in Table 3-1. The colours for the years represent the SPI-12 for the month of September for the catchment area of Barasona and Santa Ana reservoirs, calculated with CHIRPS precipitation data for the period 1981–2015.

	Years													
AF	**01**	**02**	**03**	**04**	**05**	**06**	**07**	**08**	**09**	**10**	**11**	**12**	**13**	**14**
1	7	7	6	6	7	6	7	7	6	7	6	6	7	6
0.8	7	7	6	6	3	6	7	7	6	7	6	6	7	6
0.6	7	6	6	6	1	4	7	7	6	7	6	6	7	6
0.55	7	4	6	6	1	1	7	7	6	7	6	5	7	6
0.5	7	3	6	6	1	1	7	5	6	6	6	3	7	6
0.475	7	2	6	6	1	1	6	4	6	6	4	2	7	6
0.45	7	1	6	6	1	1	4	4	6	4	1	1	7	4
0.425	7	1	6	6	1	1	3	4	6	4	1	1	7	4
0.4	7	1	6	6	1	1	2	4	1	4	1	1	7	4
0.2	4	1	1	1	1	1	1	1	1	1	1	1	1	4

SPI-12 (Sep.)



Farmer types

The distribution of the types of farmer was kept constant for all the years and runs. The proportions of technified and smaller-scale farmers was established as the mid-range of the yearly ratio between farmers sowing transgenic maize (considered to be technified) and farmers sowing conventional maize (considered to be small-scale farmers) observed in the area for the period 2010–2015 (Espluga Trenc, 2016; Gutiérrez López, 2016). This resulted in 65 % of the area being exploited by farmers considered to be technified, and 35 % by small-scale farmers. The proportion of risk aversion used in the model is R1 = 0.4, R2 = 0.3, R3 = 0.3, with R1 being the most risk averse and R3 the most risk acceptant.

Different distributions of farmer types would result in different levels of demand and therefore different optimal paths. The proportion between technified farmers and smaller-scale farmers also gives more weight to different decision moments. For example, the decision in May on whether to plant a second crop is only relevant to the technified farmers.

Costs and benefits

Planting costs and selling prices were used to calculate the value of the yield for the variable crops. The planting costs considered are 496 EUR ha^{-1} for barley and 1807 EUR ha^{-1} for maize (MAGRAMA, 2015) and the selling prices are EUR 159 per 1000 kg for barley and EUR 171.3 per 1000 kg for maize (Aragon Statistics Institute, 2015). Average yields are 2349.75 kg ha^{-1} for rainfed barley and 12 179.34 kg ha^{-1} for irrigated maize (MAGRAMA, 2015). No differences in price or cost between the varieties of a same crop type were considered, although the higher productivity of long-cycle varieties results in these varieties being more profitable in the model.

3.6 RESULTS

3.6.1 Selection of optimal thresholds

We first ran all possible decisions paths and identified the decisions that result in the highest benefits to the farmers for each season. These decisions are represented in Figure 3-5 by the coloured points, with the volume of the reservoir on the *y* axis. If the point is red, then the best decision is for the farmer to follow the path marked with a red A in Figure 3-3. If it is blue, then it is best to follow the blue A path. If the point is yellow, then it does not matter which of the paths is followed.

We use the optimal decisions based on perfect information to establish a threshold for the reservoir level to divide between good and poor water availability. A perfect threshold would be selected such that all the red points are below and all the blue points are above the threshold. This perfect threshold would always allow the farmer to make the decision that results in a higher benefit at the end of the season.

However, as can be seen in Figure 3-5, it is not possible to obtain a perfect classification of the reservoir levels with a single threshold. The dashed lines mark the thresholds that maximise the points correctly classified. The fact that the classification cannot be perfect means that the reservoir level alone does not provide enough information on what is the best decision to make. Additional information will be valuable if it contributes to improving the classification and, therefore, results in the decision that maximises the benefits being made more often. In this case the additional information we consider is the snow cover data. This is shown in the lower part of the figure. The coloured points again indicate the decision path that would be taken based on perfect information. Again, the figure shows that it is not possible to select a threshold value (dashed lines) where all the red points are below the threshold, and all blue points are above the threshold. This again indicates that this information alone does not lead to a perfect classification either.

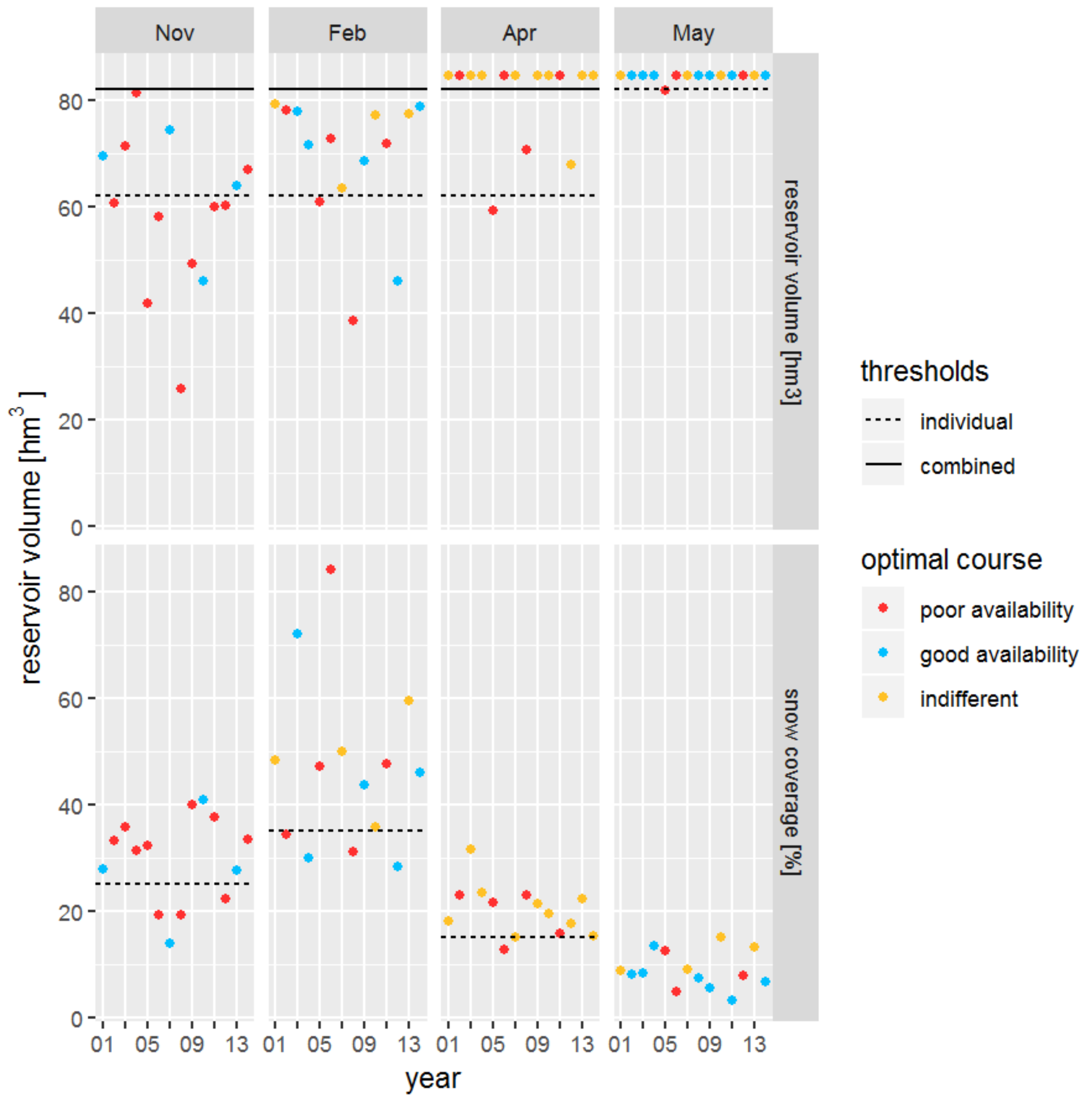


Figure 3-5. The position of the points represents reservoir levels (a) and snow cover (b) for the period 2001–2014. The points are coloured according to the decisions made with perfect information at those decision points, which are considered to be the "optimal course", and refer to the paths illustrated in Figure 3-3. The individual thresholds mark the threshold for reservoir level or snow cover when considered independently, while the combined thresholds are the modified thresholds for reservoir level for years in which the snow cover threshold is not reached.

This is different when the combined information of reservoir level and snow cover extent is used to inform the expectation of water availability. We incorporate this additional information by amending the threshold of the reservoir level. This is the solid line in the figure for the months November, February and April. Snow cover is not considered in May as that is too late in the season for snow to be of significance. When snow covers an area larger than the threshold coverage (dashed line in the lower plot), then the original threshold for the reservoir level is used. However, when the snow cover is smaller than the identified threshold, and therefore the future contribution to the reservoir volume from snowmelt is expected to be low, a second, more conservative threshold for the reservoir level is used (solid line). With the second threshold some of the red points incorrectly classified above the original threshold are now classified below the threshold.

The optimised thresholds for the reservoir level were established at 62 hm^3 for November, February and April, and 82 hm^3 for May; the thresholds for snow cover were set at 25 %, 35 % and 15 % for November, February and April respectively, while the increase in the reservoir level threshold for the years that are below the snow threshold was set at 20 hm^3.

Value of additional information for the decisions

The value of information is assessed here in terms of the total and relative benefit for the farmers during the whole period of analysis in each of the information scenarios. Figure 3-6 shows the total benefits obtained considering the two information scenarios with each of the 10 sets of thresholds. The benefits obtained using the optimised set identified in the previous step is also included (labelled as 62 in the figure). The columns are coloured to show the net benefit in terms of total gain (above 0) or loss (below 0) of each of the years in the period. The black dot represents the net benefit taken over the whole period.

The two reference scenarios are included in the first two columns. These show the net benefits using the uninformed decision and decisions made using perfect information, which are independent of the thresholds.

The difference between the perfect information (column labelled P) and the no information (labelled A) reference scenarios shows the potential value of using information, as the use of uncertain information is expected to scale between these two extreme situations. However, as can be seen in the following columns that represent the net benefits of the informed scenarios as a function of the threshold (labelled R for information from reservoir levels only and S for information from both reservoir levels and snow cover), the use of non-perfect information in this case results in losses for some of the years. This is particularly so for the lower thresholds, as water availability is often judged to be good when in fact it is poor.

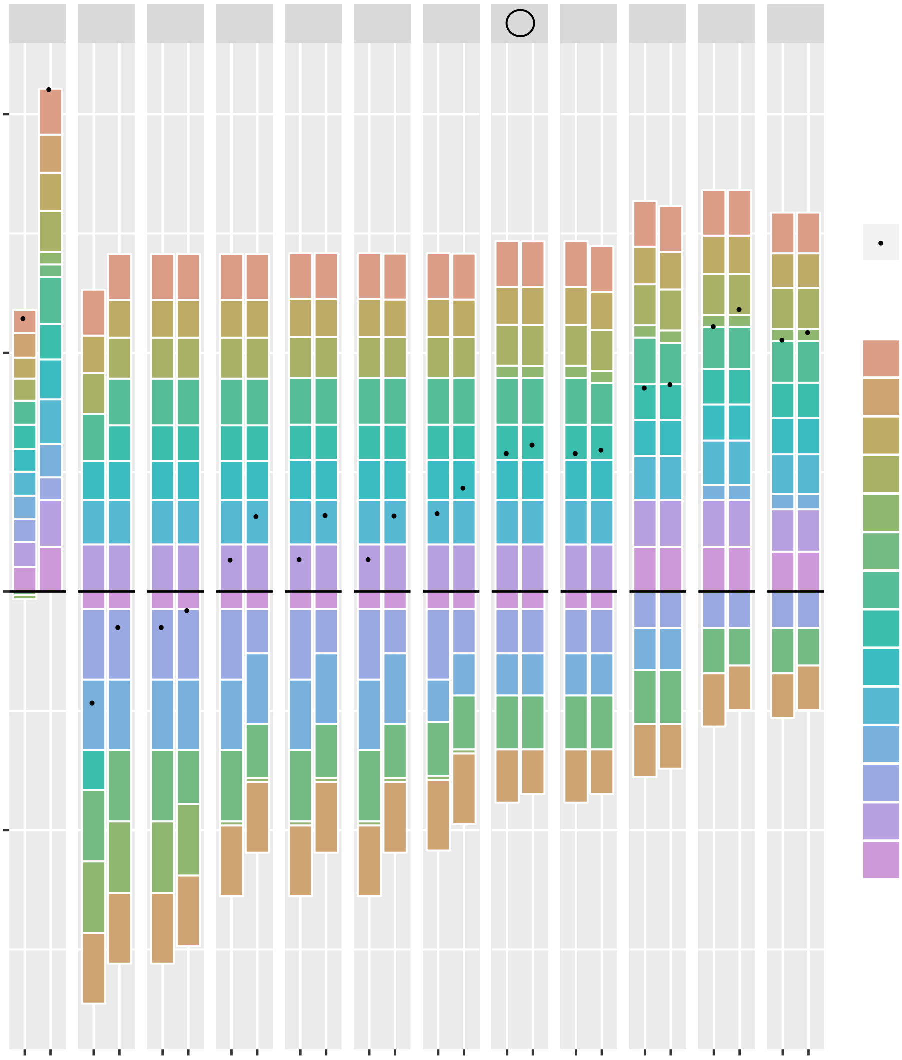


Figure 3-6. Total benefit for decisions informed by reservoir level alone (R) and with the addition of snow information (S) for the 10 sets of thresholds and the optimized thresholds (labelled as 62). The total benefit for uninformed decisions (A) and perfect information (P) is included as a reference. The colours indicate the yearly benefit while the points represent the total benefit for the period (total gains – total losses).

Figure 3-7 presents the relative value of the decisions using each of the two tested sources of information with respect to the decisions informed by perfect information and the uninformed decisions (Eq. 1). This shows that the relative values for the total benefits are negative for almost all thresholds, both when using only reservoir levels as well as when also using additional information on snow cover. This means that, for the period as a whole, selecting a course of action based on the expected availability informed by these datasets does not result in higher benefits than when following the path that performs best on average every year. The reason for this lies in the large losses incurred when failing to recognise a poor-availability year and as a consequence planting more than what can be irrigated. This is the case for the years with a negative benefit represented in Figure 3-6. These high losses also result in higher thresholds showing a better relative value, since these thresholds lead to more years being regarded as poor-availability years, thus leading to lower areas being planted.

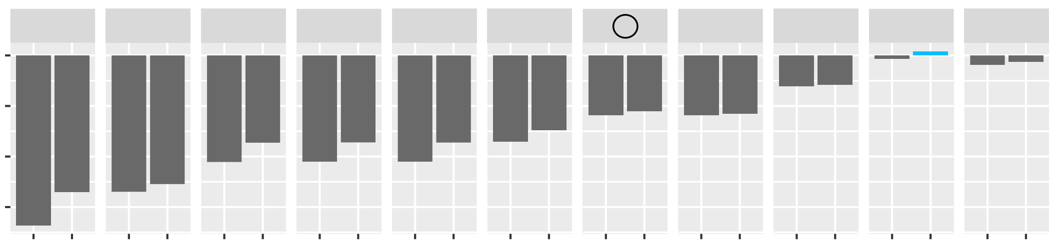


Figure 3-7. Total Relative Value for the period 2001–2014 for decisions informed by reservoir level alone (R) and with the addition of snow information (S) for the 10 sets of thresholds and the optimized thresholds (labelled as 62).

Still, the results show that the additional information does help to reduce the losses in some of the years and for all thresholds a better relative value is obtained when using the additional dataset on snow cover. This can be seen by the net benefit for the period 2001–2014 (represented by black dots in Figure 3-6) being higher for all thresholds when the snow-cover information is used.

3.6.2 Quantifying the effect of additional information

The high losses in some of the years are the result of the limited profit margin between the cost of planting and the selling price of the products. To illustrate further the effect of the profit margin in the decision and the value of information, we have run a series of additional simulations where the costs of planting are reduced by 50 %, 75 % and 100 % (which is the same as zero cost). The relative value of information for these simulations (shown in Figure 3-8) indicates there is a gradual increase in the relative value of the informed decisions as the ratio of the benefits from the crop yield to the cost of planting increases. The fully detailed gains and losses for these simulations can be found in Annex B1.

Relative values are still low, however, even when there is no cost for planting. This is because the uninformed decision used as a reference also improves with the reduction in the cost of planting. The course of action that performs better on average, in which the uninformed decision is based, is path 3 for the full reported cost, path 4 for the reduced costs and path 5 when no cost is considered. This means that with lower or no investment costs for planting it is better on average to plant the more water-demanding crops. These results also show that as the ratio between the profit made from the crop yield and the costs of planting increases, the relative value of the informed decisions for the years in which the optimal path is followed is also reduced.

At the reduced costs it also appears that the added value of the information from snow cover reduces and in some cases is even detrimental, particularly at the higher reservoir level thresholds. This is likely caused by the uncertainty in the relationship between snow cover and available water resources, which will be elaborated further in the discussion.

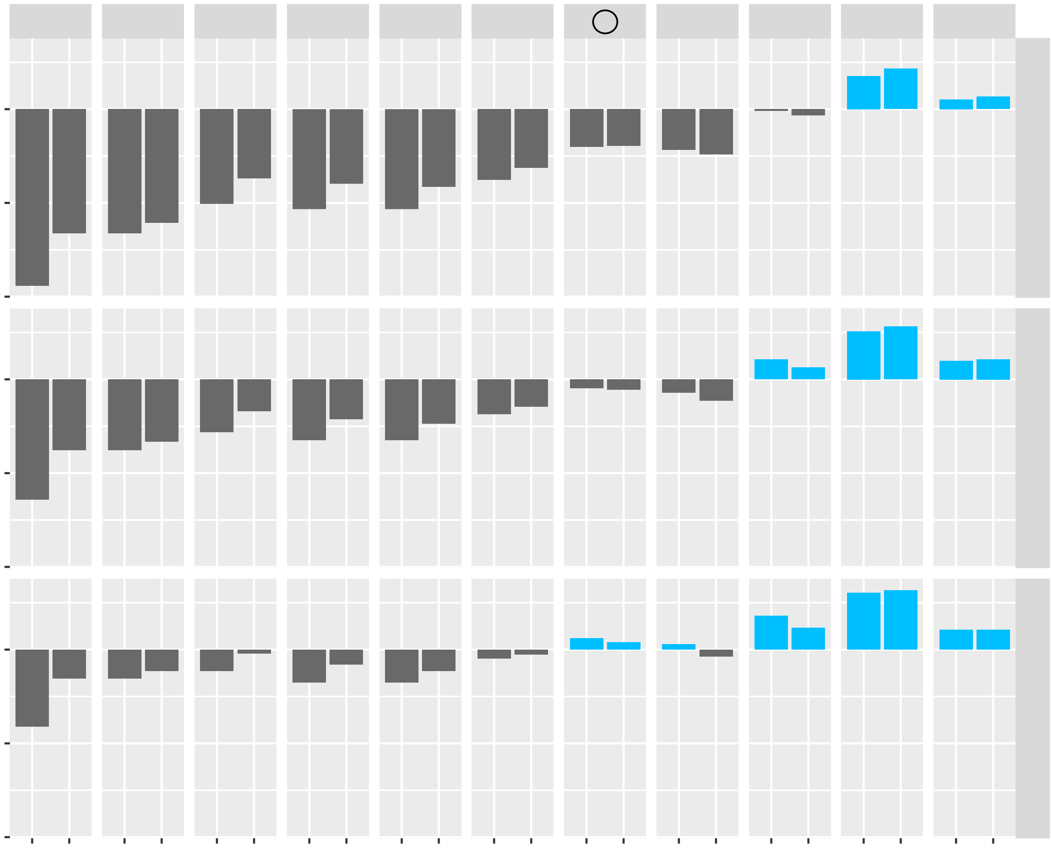


Figure 3-8. Relative value (RV) with different levels of cost for planting for decisions informed by reservoir level alone (R) and with the addition of snow information (S) for the 10 sets of thresholds and the optimized thresholds (labelled as 62).

3.7 DISCUSSION

To answer the question posed in the title on whether users would benefit from additional information on available water resources in drought conditions, we adopt an approach that starts with a stakeholder consultation to be able to understand the decisions users make and how they use information to support those decisions. This is followed by a model of the decisions to quantify how additional information can be used to inform and influence the decision process.

The consultation was performed by semi-structured interviews with key stakeholders. The advantage of this method is that it encourages discussion (Iglesias et al., 2017), although the main limitations are the small sample size, which means that only a partial view is obtained of the plurality of the stakeholders that make these decisions. Despite this limitation, the responses of the interviews provided a detailed description of the possible choices to deal with water shortages in the Ebro basin, and the interaction and feedbacks between water management strategies at basin, irrigation district and local farmer scales. This knowledge was used to build a model of the interrelated decisions of farmers and water managers at the irrigation district scale. The decisions modelled are informed by the expected water availability during the irrigation season, which is currently derived mainly from the reservoir levels. In this case we test the use of additional information of remotely sensed snow cover, as this is information users currently may consider, but further research on the value of different datasets that inform the expectation of the available water resource could be conducted using the model.

3.7.1 Potential value of additional information

Decisions made with perfect or no information were used as reference cases. The difference in the net benefit between these two cases reveals the potential improvements that information can bring with respect to the uninformed decisions. With perfect information, losses can be avoided in seasons of water scarcity and benefits maximised when enough water is available. It should be noted that the paths for perfect information in the model maximise the benefit of the whole group of farmers, rather than that of individual farmers. In reality, the benefits and losses are not shared by the group, and individual farmers would try to optimise their individual benefit instead, though community collaboration in the form of the established user associations in the basin ensures that to an extent farmers do make decisions that contribute to a common good and the tragedy of the commons does not arise.

The uninformed case follows a conservative approach considering that for every year the available water will be limited. Although this results in high losses being avoided, the benefits are well below the potential. Using additional information to inform decisions is expected to help the decision-makers in characterising each season in terms of the water availability and selecting what and when to plant, and accordingly increasing their benefits. As additional information we test a medium-resolution snow cover product derived through remote sensing. Gascoin et al. (2015) show the value of this product in providing snow cover information at the Pyrenees range scale. Our analysis shows that the information from this product also has value at the basin headwater scale, showing improvements in the decisions made when compared to decisions informed by reservoir levels alone.

Detailed analysis of the years where there is benefit in using the additional information shows that this arises mainly from the reduction in the losses in those years in which the optimal decision to make is more uncertain. In these the years the classification of the water resource as being good or bad is difficult, and the additional information on the snow cover adds value by making it more difficult for a bad year to look good. Losses occur in 2002, 2006, 2011 and 2012 (see Annex B2 for yearly relative value plots), which match the years for which drought impacts in irrigation agriculture have been reported (Linés et al., 2017). They are the consequence of an inappropriate course of action being chosen, as a result of the expected availability of water being too high, compounded by the high cost of planting relative to the return on investment of the crops planted.

To test the robustness of the observed effect of the additional information, the model was run 10 times with randomly sampled values of snow cover at each of the decision points. The results of these runs (included in Annex B3) show that the improvement then also follows a more random pattern and, in some cases, the additional information is detrimental, thus supporting the hypothesis that the improvements in the decisions are indeed caused by the additional information on snow cover.

However, the results of the model indicate that selecting the option that performs better on average, as is done in the uninformed case, leads to higher benefits than when using the information on reservoir levels (either alone or supported by the MODIS snow cover information). This is in contradiction with the current practice, in which the reservoir-level information is used to support the decision and different choices are made each year. One reason that farmers do not follow this strategy may lie in the fact that not all the losses are assumed by the farmers, since there are subsidies for certain crops or for losses incurred in disastrous years. These subsidies are often based on planted surface and influence the ratio between the return from the crop yield and the investment costs incurred when planting. Additionally, the actual farmer decision on what to plant is influenced not only by water availability, but also by the market prices of the crops. Maize has a high cost of production and therefore, when its selling price is low, farmers tend to select other crops with lower production cost (Espluga Trenc, 2016). In the model, however, the planting costs and selling prices were kept constant for all the years to better observe the effect of information on the selection of the crops.

3.7.2 Effect of the cost of planting on the value of information

The effect of the cost of planting and the profit margins on the usefulness of the information was explored by running the model for different planting costs. Changing the cost of planting modified the course of action both for the informed and uninformed decisions. The reduction in the costs results in higher relative values for the informed decisions for the period as a whole, caused again by the reduction in the net losses. The ratio between the cost of planting and the return on investment on the crop is similar to the cost–loss ratio used in evaluating the benefit of flood warnings (Verkade and Werner, 2011). Where the cost-loss ratio is high, the cost of taking an action in vain (false alarm) is also high, and significant losses may be incurred. This may even result in the information being detrimental, since it does contain uncertainty and may therefore lead to wrong choices being made. Larger losses than if that information is simply ignored and the business-as-usual action is taken may then be incurred. For users with a lower cost-loss ratio, explored here by lowering the cost of planting, additional (uncertain) information becomes increasingly valuable as these users become more tolerant of making a wrong decision. The role of uncertainty in the link between the information used (reservoirs levels and snow) and the realisation of the available water resource is not directly explored in this study through for example a hydrological model, though explicitly considering the uncertainty can add further value to the information. Several authors (e.g. Roulin, 2007; Verkade and Werner, 2011) have shown that the value of information from forecasts is always higher when these are probabilistic. In the application presented here, the relation between the reservoir levels and the available water resources is more certain than the relation between the snow cover and the available water. This may also explain the poorer performance when using snow cover information than when using only reservoir levels. This occurs in 2006. In this year the snow cover at the start of the year (February) was exceptionally high, leading to an expectation of good water resource conditions. However, this was due to widespread snowfall at the end of January just before the decision point in February. This snow melted rapidly and the snow cover in April was anomalously low, with low water resource availability for the rest of the season.

3.7.3 Value of the information for the different types of farmers

The value of the additional information is not equal to each of the different types of farmers identified. The additional information on the expected water resource provided by the snow cover is found to be relevant only to the decisions that are made in February.

For the technified farmers the information is therefore of little value, as the main decisions made by them fall in November and in May, respectively, before the snow accumulation period and after the snowmelt period.

For the small-scale farmers, the additional information can be relevant for the decisions that are made when there is snow cover, primarily those made in February, but also those made in April. These small-scale farmers have only one crop. Once a decision is made to plant a crop, there is no further value to information as there is no further decision to be made. However, the benefit is again not evenly distributed. Small-scale farmers were divided here into three groups of decreasing risk averseness (R1, R2 and R3). We find that the additional information benefits the group of farmers that is willing to take more risk most. These are the farmers that decide to take the risk to wait for a possible improvement when the water availability is classified as not being good at the decision point, instead of taking the safe bet and securing a crop by planting a barley crop, which does not depend on irrigation and possible curtailments. The most risk-averse small-scale farmers (R1) do not even wait for any information on water availability and already plant barley in November. For them there is no value in the additional information. For the slightly less risk-averse farmers (R2) there is limited value in the additional information. If in January the water resource situation is expected to be good, then they will choose to plant maize, but at the first sign of it being bad they will forfeit the possible higher profits from maize and opt to take the safe bet by planting barley. The most risk-acceptant small-scale farmers benefit the most from the additional information, as it will help them make the choice between taking the gamble of waiting for the water resource availability to become better so that they can plant maize, or plant a cereal to avoid the risk of having to leave the land fallow if it does not. In this case these results show that the additional information may be beneficial to improved equity across the farmers in the irrigation district as it is most beneficial to small-scale farmers, provided they are willing to take a gamble to improve their benefits.

In this paper we model the distribution of risk averseness using only a simple percentile distribution. A more realistic distribution of risk averseness can be developed using for example the constant absolute risk aversion utility function (Matte et al., 2017; Quiroga et al., 2011), though this will require extensive survey data to determine how risk averseness is distributed among farmers.

3.8 CONCLUSIONS

An approach that combines stakeholder consultation and decision modelling was followed, allowing a comprehensive analysis of the role of information on drought management decisions in the area. Consultation with the different decision-makers in the

Ebro basin provided useful insight into the operational decisions they make in managing water resources when scarce, and their information needs and use. This allowed us to identify the courses of action available to the farmers and water managers, and to analyse their choices as a function of the information they have available to them. Feedbacks between the decisions made by farmers and the reservoir operators at irrigation district level were identified: curtailments imposed at irrigation district level as a result of water scarcity influences the decision farmers make on the planting of crops, which in turn influence demand and consequently water scarcity.

Based on the findings of the consultation, a decision model representing these interrelated decisions was built with the aim of quantifying the effect of additional information on the decisions. The modelled decisions, which consider the allocation of water, are taken based on the expected availability of water during the irrigation season. This is currently informed primarily by observed reservoir-level data. When levels are above a defined threshold at the time of the decision, water resources availability is classified as good, whereas when levels are below the threshold and expected demand is high it is classified as poor and curtailments to water allocations are applied. Farmers decide on the crop to be planted based on their expectation of water resources availability, and whether curtailments are in force. The decision model was then extended from considering only reservoir levels to include additional information on snow cover in the basin headwaters obtained from MODIS remote sensing data to inform the expectation of water resources availability.

Our simulations with the decision model show the additional information can contribute to better decisions and ultimately to higher benefits for the farmers. However, the ratio between the cost of planting and the market value of the crop proved to be a critical aspect in determining the best course of action to be taken and the value of the (additional) information. When there is little room for error due to small margins, then any information used to inform the decision may even be detrimental to any benefits being made. However, even in this case the additional information on snow cover can provide benefit over using the reservoir levels alone. Tests with reduced planting costs, and thus increasing margins, does lead to a higher benefit when using the additional information from snow cover. Nevertheless, uncertainty in the relationship between good snow cover and water resource availability may lead to overestimation of the expected resources and consequent losses.

A key finding of our research is that farmers can benefit when the operational decisions they make consider the additional information. To what extent they benefit does, however, depend to a great extent to their level of risk averseness. Risk-averse farmers will decide to take the safe option early on, with information on the available water resource then having no value. Farmers that are less risk averse do benefit as the information helps them weigh the options between planting a crop with a higher return or having to leave the land fallow.

4

How useful are seasonal forecasts for farmers facing drought? A user-based modelling approach

This chapter is based on:

Linés, C. and Werner, M.: How useful are seasonal forecasts for farmers facing drought? A user-based modelling approach. Climate Services (submitted for publication, 2023).

Abstract

Seasonal forecasts of water availability have clear potential benefit for decisions in irrigated agriculture. This potential depends in part on how accurate the information provided is. The actual benefit, however, depends on how the information is used in the decisions, by whom, and the outcome of those decisions. In this paper we assess how useful seasonal forecasts are in supporting drought management decisions by farmers at the irrigation district level. We model the decisions irrigated farmers make on what and when to plant in the Ebro basin (Spain), and the interconnected decisions reservoir operators make on whether to apply curtailments to the water allocated to farmers. The modelled farmers are supplied from a reservoir with capacity for a single irrigation season and therefore their decisions are conditioned by the expected water availability through to the end of the season. Different farmer behaviours are considered as a function of their risk averseness and their technical capacity. The value of seasonal streamflow forecasts to inform these decisions is compared against that of current practice using extrapolated historical records, as well as against a reference forecast based on climatology. Results show that seasonal forecasts of water availability have skill, albeit limited. How salient information is to the decisions that farmers make, however, differs for each type of farmer as they take key decisions at different points in the season. As a consequence, seasonal

forecast information is found to not serve the various farmer types considered equally. Our results illustrate how assessing the usefulness of information to servicing a decision can be approached from a combined technical and user-centric perspective.

4.1 INTRODUCTION

Early information of water availability during the hydrological year is critical for supporting water management decisions, but difficult to predict due to the variability of the climate, as well as the uncertainty of demand through the season and from year to year. Information on expected water availability is often derived from climatology using historical observed flow data (Lopez and Haines, 2017; McMillan et al., 2017). Though this is a practical approach, it risks not capturing the full variability due to the limited length of records, or due to changes in climate and in the catchment (Hall et al., 2012).

An alternative source of information to partially overcome these issues, is to establish seasonal water availability through seasonal streamflow forecasting, though the skill with which seasonal water availability can be forecast varies (Arnal et al., 2018; Pechlivanidis et al., 2020).

Several studies have addressed the potential contribution of seasonal forecasts to inform water management decisions in a broad range of sectors including hydropower planning (Alexander et al., 2021; Beckers et al., 2016; Graham et al., 2022), food security early warning (Shukla et al., 2020), rain-fed agriculture (Winsemius et al., 2014), and irrigation planning and crop selection (Kaune et al., 2020; Steinemann, 2006). However, despite the apparent advantage of skilful seasonal forecasts demonstrated in research, the uptake by water managers and farmers faces multiple barriers (Antwi-Agyei et al., 2021; Bruno Soares and Dessai, 2016; Hansen, 2002; Lemos et al., 2012). Barriers include perceived lack of reliability, lack of relevance or awareness (Bruno Soares and Dessai, 2016), difficulty to interpret probabilistic seasonal forecasts (Crochemore et al., 2016), as well as risk perception (Kirchhoff et al., 2013). Lemos et al. (2012) classify these barriers in three categories: the user's perception of the information (e.g. accuracy, reliability, timeliness), the interplay of the information and the user's context (e.g. existing practices, technical capacity, risk aversion), and the interaction between the information producers and users.

Studies on the value of seasonal forecasts for water management tend to focus on the skill of predictions of climate variables required by decision makers, such as precipitation and streamflow. However, as a result of the barriers to the uptake and usage of seasonal forecast, it is increasingly recognised that better skill alone does not necessarily lead to added value and there is a need to consider the context in which the information is used (Findlater et al., 2021; Ritchie et al., 2004; Turner et al., 2017). Crochemore et al. (2016, 2021) set up participatory games to explore how seasonal forecasts are used to support reservoir operation decisions and assess the perceived value of this information, observing that improved seasonal forecasts led to better decisions. Golembesky et al.

(2009) assess the utility of a 3-month lead-time streamflow forecast product in combination with a reservoir operation model to improve management decisions, and Kaune et al. (2020) evaluate integrating a seasonal forecast product into the complex water allocation policy in an irrigation district in Australia, finding that this allows decisions on water allocation to annual crops to be established 1-2 months earlier than when based on climatological information, which is useful to farmers.

Findlater et al. (2021) call for considering social aspects when assessing climate services, such as seasonal forecasts. Examples of such integration in climate services assessment can be found in the field of disaster adaptation decisions, in which socio-hydrologic approaches such as agent-based models are increasingly being used to account for the behaviour of individuals or groups in decision processes (Aerts et al., 2018; Schrieks et al., 2021; Wens, 2022).

Considering the behaviour of users in response to the provision of seasonal forecast information is limited among studies that assess the value of climate services that support operational water management decisions. Li et al. (2017) apply a process-based agricultural model coupled with a farmers' decision model over a period of 5 years to assess the value of different seasonal forecast products, showing that farmers attitudes to risk have an impact on the operational value of the products. Giuliani et al. (2020) explore the impact of forecast system setup and operator risk averseness on the value of seasonal forecasts for the operation of a lake with irrigation and flood control objectives, though their focus is on the behaviour of the operator in allocating water, rather than the farmers and the decisions they make, which influence demand. They suggest further research in different locations and decision contexts is required to develop general conclusions on the value of seasonal forecasts and their potential to improve decisions. These two studies do show that the attitudes users, such as farmers and reservoir operators, have to risk can have an impact on the operational value of the seasonal forecast products.

In this paper, we extend this work on assessing the potential value of climate services as a function of the behavioural response of users to seasonal forecast. We apply a user-based model of the decisions on what and when to plant in an irrigation district in a drought-prone area to assess how useful seasonal streamflow forecasts are in supporting farmers in making these decisions. The model also considers the interlinked reservoir operator decision on whether to apply curtailments to water allocations so as to preserve water and ensure supply through to the end of the season. In addition to three levels of risk averseness, our decision model considers two types of farmers, each with different levels of technical capacity. This determines whether they can plant a single or a double crop and influences the multiple paths they can follow to adapt their decision to the available information on water availability as the season evolves. This allows us to look at the role of the timing of the decision and available options, as well as how the usefulness and value of the seasonal forecasts changes during the season and from year to year.

4.2 METHODS

4.2.1 Study area

We select an irrigation district located in the northeast of the Ebro basin. The Ebro basin is a large (85,600 km^2) and highly regulated (over 7,900 hm^3 of total storage capacity) Mediterranean basin in the northeast of Spain. The basin has a long tradition of hydraulic infrastructure to store and distribute water resources for agriculture (Pinilla, 2006), with a good and accessible data record. This tradition originates from the mismatch between crop water requirements (which are high in the summer) and the seasonality of rainfall (which peaks in spring and autumn and has lows during the summer, typical of a Mediterranean climate). The issue is exacerbated by high interannual variability of rainfall, which ranges between 430 and 830 mm (CHE, 2022).

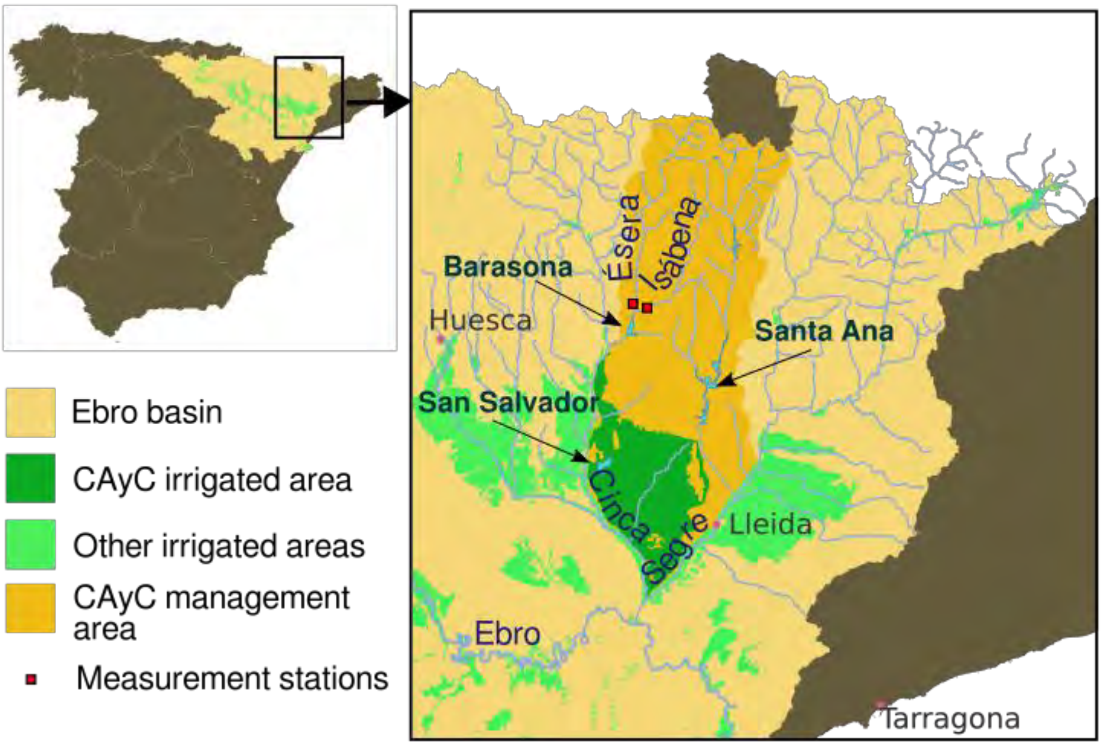


Figure 4-1. Study area: Canal de Aragón y Cataluña (CAyC) irrigation district in the Ebro basin.

The selected irrigation district is supplied by the Aragón and Cataluña Canal (Canal de Aragón y Cataluña, CAyC, Figure 4-1. Study area: Canal de Aragón y Cataluña (CAyC) irrigation district in the Ebro basin.) and is mainly supplied from Barasona reservoir (92 hm^3), fed by the Ésera and Isábena rivers. These have a combined catchment of 1511 km^2. Supplying the irrigation district is the main use of Barasona reservoir. Groundwater use in the irrigation district is limited (CHE, 2022).

The period 1984-2016 was selected for the analysis due to data availability. This includes several drought episodes of different length (Linés et al., 2017), as well as wet years. The study area was the most affected in the basin by the drought episode in 2004-2005 (CHE, 2018).

Observed data

Streamflow:

The water available for irrigation is determined by the accumulated inflow into Barasona reservoir from 1st of October (after the end of the previous irrigation season). The total inflow into the reservoir is established by summing the flow of the two tributaries. We use streamflow data from two gauging stations, Graus (Ésera River) and Capella (Isábena River), from the national gauging stations network (ROEA). The data record starts in 1931 but there are several gaps before 1984.

Precipitation:

Daily precipitation data (liquid and solid) was obtained from the SAFRAN dataset over Spain (Quintana Seguí, 2015; Quintana Seguí et al., 2016; Quintana-Seguí et al., 2017), which is based on interpolated station data from the Spanish State Meteorological Agency (AEMET), combined with ERA-Interim and available for the 1979-2016 period at a resolution 5x5km.

The daily data was aggregated to monthly (sum per pixel), and spatially weighted (mean for the catchment). This dataset was also used to derive the three-month Standardised Precipitation Index (SPI-3) using the SPEI package in R (Beguería and Vicente-Serrano, 2013).

4.2.2 Seasonal forecasting of precipitation and streamflow

Seasonal precipitation forecasts for the 1984-2016 period are obtained from the ECWMF SEAS5 ensemble seasonal forecast model (Johnson et al., 2019), with an ensemble size of 25 and horizontal resolution of approximately 36 km (Johnson et al., 2019). Forecasts, with a 7-month lead time are initiated on the first day of each calendar month. Monthly forecast precipitation is spatially weighted over the catchment upstream of the Barasona reservoir, and bias corrected against the catchment averaged SAFRAN data through a parametric quantile-mapping approach (Yuan et al., 2015), using the gamma distribution for both observed and forecast precipitation (Annex C, Table C1-1, Piani et al., 2010; Zhao et al., 2017). We assess the skill of the bias-corrected forecasts through the correlation of the ensemble mean to observed monthly precipitation and the continuous ranked probability skill score (CRPSS; Hersbach, 2000), using leave-one-year-out cross validation (Schepen et al., 2018). A climatological reference forecast is obtained through randomly sampling the gamma distribution fitted to the observed precipitation for each month.

Streamflow in the basin is bi-modal, with high flows in October-December due to excess precipitation, and in spring (April-May) due to precipitation and snowmelt (Annex C, Figure C1-2). To forecast monthly inflows to the Barasona reservoir, we develop a simple stochastic model forced by the bias-corrected seasonal precipitation forecasts. As baseflow has a longer memory (good autocorrelation, see Annex C, Figure C1-3), we separate this from the observed flow using a Lyne & Hollick baseflow separation procedure (Ladson et al., 2013; parameter alpha=0.8). This is then transformed into the standardised form using a gamma distribution to account for seasonality (Stagge et al., 2015), and an auto-regressive time series ARIMAX model (Wilks, 2011; Mishra et al., 2007; Valipour et al., 2013) is applied to model the transformed baseflow. The three-monthly Standardised Precipitation Index (SPI-3) is used as exogenous variable, established using observed and then forecast precipitation out to the seven-month lead time. The shorter memory (low autocorrelation, Annex 3, Figure C1-3) quickflow, is modelled using a simple linear regression model against (forecast) precipitation. A separate regression model is established for each calendar month to account for seasonality (Annex C, Table C1-2), and added to the forecast baseflow. Inputs to the decision model are then derived by accumulating monthly streamflow forecasts from the forecast initiation date to the end of season. Where the accumulation window is longer than seven months, flows are extrapolated for each ensemble member using the currently used forecast procedure (decision model and extrapolation approach described in next section). The skill of monthly and accumulated end-of-season forecasts is assessed using the same approach as for the precipitation forecast, again using a leave-one-year-out cross validation strategy.

4.2.3 Modelling the cropping decisions of the farmers

The decisions farmers in the CAyC make on which annual crop to plant in each season are modelled with a simplified version of the decision model that is described in full in Linés et al. (2018), which is based on interviews with stakeholders in the area. Decisions are made to maximise economic benefits, depending on the expected availability of water, but farmers may select different options depending on the risk they are willing to take. Planting later in the season helps reduce the uncertainty of expected water availability to the end of season, and therefore reduces the risk of losing the crop due to water shortage. However, the available options to the farmer reduce as the season progresses, increasing the risk of having to leave the land fallow if conditions turn out to be unfavourable, rather than planting a "safe" rain-fed crop.

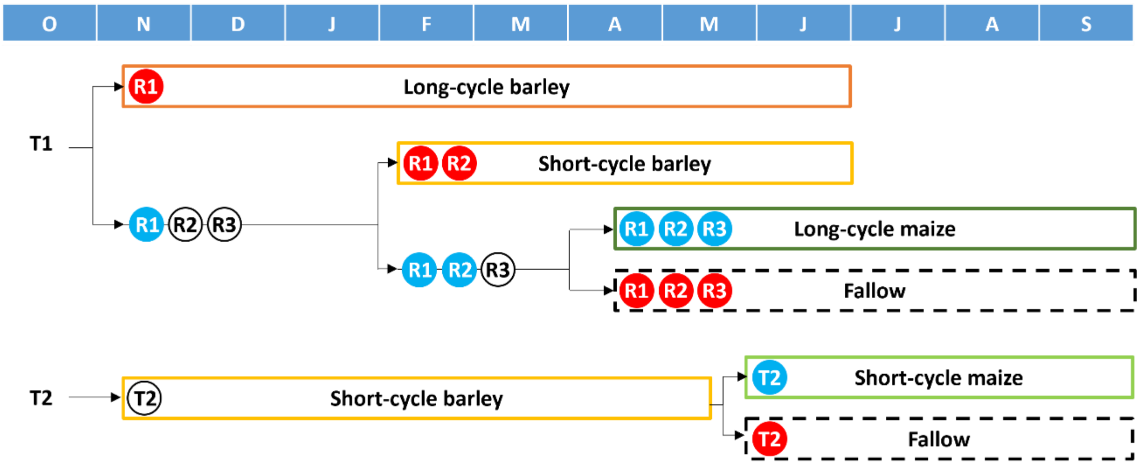


Figure 4-2. Crop options for the different types of farmers: single-crop farmers (T1) and double-crop farmers (T2). For single-crop farmers three levels of risk aversion are considered, with R1 being the most risk averse and R3 the least risk averse. The arrows mark the decision path each type of farmer follows, which depends on the expected water balance at the end of the season. Blue (red) circles indicate the path that is followed if a positive (negative) balance at the end of the season is expected. White circles indicate that the path is followed irrespective of water availability.

Figure 4-2 shows the different decision paths farmers can follow. We consider two types of farmers with different technical capabilities: farmers who can only plant a single crop each season (T1) and farmers who have the technical capacity to plant a second crop after the first one is harvested (T2). This double-crop is invariably short-cycle rainfed barley (SCB) during the winter, followed by a short-cycle irrigated maize (SCM) crop planted in May if water availability is considered sufficient. If availability is considered insufficient in May, the land is left fallow.

For the single crop farmers there are different options, depending on the level of risk the farmer is willing to take. Three levels of risk aversion are considered (R1-R3). The single crop can be either long-cycle rainfed barley (LCB) planted in November, short-cycle rainfed barley (SCB) planted in February, or long-cycle irrigated maize (LCM) planted in April. Maize is more productive than barley and therefore preferred, but it is more expensive to plant and can result in higher losses if the crop is lost due to drought conditions and subsequent shortage of water. LCB is more productive than SCB, but needs be planted earlier in the season. This poses a lock-in as the decision to plant barley prevents the farmer to plant the more productive maize crop if conditions improve. Risk averse farmers prefer to secure a crop, even if it is less profitable, rather than waiting to see if conditions improve and risking having to leave the land fallow if the expected water availability is not enough to irrigate the maize crop. More risk averse farmers (R1) therefore go for the safe option and plant LCB in November if the expected availability is not good at that time. Medium risk averse farmers (R2) in contrast wait until February to decide, and then plant SCB if expected water availability is insufficient to support the preferred LCM crop. The least risk averse farmers (R3) wait until April and then choose either to plant LCM or leave the land fallow. If during the irrigating season water is considered insufficient to support the demand of the irrigated crops planted following decisions made, allocated water is curtailed by the operator, with all irrigated annual crops receiving the same reduction.

Table 4-1. Model parameterspresents the proportions for each type of farmer in the area, with 35 % of the farmers planting one crop per season (T1), and 65 % two crops (T2). Annual crops cover a third of the total area, while the other two thirds are predominantly covered in equal parts by two permanent irrigated crops, alfalfa, and peaches. These permanent crops have priority to be irrigated over maize when water is scarce (Linés et al., 2018).

Table 4-1. Model parameters

Parameter	**Value**
Proportion farmer types	0.35 (T1), 0.65 (T2)
Proportion risk aversion levels	1/3 (R1), 1/3 (R2), 1/3 (R3)
Proportion crops	1/3 (alfalfa), 1/3 (fruit), 1/3 (variable)

Farmers base their decision on their perception of sufficient water availability during the season to grow irrigated maize, which is calculated as the balance between the expected availability of water and the expected demand of irrigated crops through to the end of the season. This balance is also used by the reservoir operators to decide whether to apply curtailments to water allocations. Farmer's decisions that occur before the start of the irrigation season (November, February and April, see Figure 4-2) consider the total demand if LCM and SCM are planted by T1 and T2 farmers respectively (D1 demand), while decisions made in May, consider the total demand since the start of the irrigation season plus the additional demand if SCM is then planted by T2 farmers (D2 demand). Both D1 and D2 include the demand of the permanent crops (alfalfa and peach). A positive balance indicates the expected availability is enough to plant the maize crop. We consider four scenarios to inform expected availability to the end of the season:

i. Historic extrapolation (HE): Water availability is based on percentiles of the historic record. The climatological percentile of the inflow at the decision moment is used to extrapolate the inflow to the end of the season. This is the current approach used by the irrigation association.

ii. Seasonal streamflow forecast (F#): Water availability is based on the ensemble streamflow forecast. The numeral indicates the non-exceedance decile of the ensemble (F10-F90), or the ensemble mean (FM).

iii. Perfect streamflow forecast (Fp): Water availability is based on streamflow model driven by observed precipitation from SAFRAN.

iv. Perfect information (P): Water availability is based on the observed streamflow.

As the available reservoir storage is expected to be depleted during each irrigation season, the annual availability of water is determined by the variable inflow to the reservoir during the hydrological year.

Perfect information of crop water requirements over the season is used in all scenarios, so the differences come from the estimation of the future availability alone. Yield estimations and monthly water requirements of the crops planted are obtained through simulation with the AquaCrop-OS (Foster et al., 2017) and Cropwat 8.0 (FAO, 2000) models. Default parameters for each of the crops are used, adapted to the Ebro basin calendar and the two different types of maize considered (Foster et al., 2017). The monthly water requirement values obtained are assigned to the first day of each month in the decision model.

In the decision model, the yield obtained from the crop models is multiplied by the number of hectares planted. If curtailments are applied in the decision model, irrigated areas are reduced proportional to the curtailment as the crops are considered to be lost. Curtailments applied by the reservoir operator are determined proportional to the availability such that the conservation storage of the reservoir is depleted and applied to the variable crops.

4.2.4 Evaluating the benefit of decisions

Selected forecast verification scores are calculated to evaluate the outcomes of the decision model informed by each of the scenarios (HE, Fp, F#). The scores considered are summarised in Table 4-2 and are calculated through a confusion matrix, comparing the outcome (i.e. the crop selected) of the crop model in each of the scenarios against the outcome of the decisions made using the perfect information scenario. The decisions made under perfect information are either planting maize (LCM for T1 farmers or SCM for T2 farmers), if there is sufficient water to irrigate during the season, or selecting the preferred non-irrigated option in the case of insufficient water. The preferred non-irrigated option corresponds to LCB for R1, SCB for R2, and leaving the land fallow for R3 and T2. If the outcome in the tested scenario matches the outcome in the perfect information scenario, then we classify the result as a true-positive if the farmers opt to plant maize, as this is the preferred option, or a true-negative if they opt for the preferred non-irrigated option. Otherwise, if the outcome in the perfect information scenario is maize and in the selected scenario it is not, then we classify the result as a false-negative, while if the outcome in the perfect information scenario is the preferred non-irrigated option and in the other scenario it is something else, then the result is classified as a false-positive.

Table 4-2. Definition and formula for the selected scores.

Score	Formula*
Accuracy: fraction of the years in which the crop planted using imperfect information corresponded to the crop planted using perfect information.	$\frac{tp + tn}{n}$
Precision: fraction of the years in which the preferred crop was planted when using imperfect information that corresponded to the preferred crop being planted using perfect information. Same as 1-*false alarm rate.*	$\frac{tp}{tp + fp}$
Recall: fraction of the years in which the preferred crop was planted when using perfect information that corresponded to the preferred crop being planted using imperfect information. Also referred to as the *hit rate*.	$\frac{tp}{tp + fn}$
F1-score: harmonic mean of precision and recall, indicating balance between these two. F-score is zero when either precision or recall are zero, and one when both underlying scores are one (perfect prediction).	$\frac{2tp}{2tp + fn + fp}$

*tp: true positive; tn: true negative; fp: false positive; fn: true negative; n: number of years

The scores above do not consider the application of curtailments, but only evaluate the decision made as a function of the information scenario used. If curtailments are applied, then these may reduce the yield and consequent profits due to the crop options selected.

We determine the relative economic value (Zhu et al., 2002) of the decisions made as the total benefit obtained from the crops with decision based on each of the scenarios (F#) for forecasting water availability to the end of season, compared to the benefit obtained using the current (HE) forecast applying a skill score function (Stanski et al., 1989):

$$\mathrm{RV} = \frac{Benefit_F - Benefit_{HE}}{Benefit_P - Benefit_{HE}} \tag{4.1}$$

The relative economic value (RV) ranges between $-\infty$ and 1. RV =1 corresponds to perfect information. RV = 0 means that the information does not contribute to improving the decisions made over the reference (HE), while a negative RV implies that it is of more value to base decisions on the reference (HE).

We establish the economic benefit of decisions made using a selling price of 191 euro/1000 kg for barley and 181 euro/1000 kg for maize. The costs of planting are 400 euro/ha for barley and 1438 euro/ha for maize (MAPA, 2020). The impact of these parameters is then assessed through a sensitivity test. Note that while the selling price for barley and maize are comparable, the yield per hectare is higher for maize (Annex C, Table C2-1), thus explaining the preference for that crop. Crop yields vary with the actual weather conditions, and the ranges obtained in the crop model for each of the crops are 16,770-18,640 kg/ha for LCM, 14,210-15,970 kg/ha for SCM, 9,790-11,590 kg/ha for LCB and 3.890-4,670 kg/ha for SCB.

4.3 RESULTS

4.3.1 Seasonal forecast of water availability to end of season

The model was run for each information scenario for the period 01/10/1984 to 30/09/2016 with the farmer proportions indicated in Table 4-1. Figure 4-3 illustrates the water balance to the end of season at each decision point. Light blue bars indicate the expected accumulated inflow to the end of the season as derived from historic data (HE), while black dots and whiskers show the ensemble median (FM) and the 10 and 90 percentiles (F10 and F90) of expected water availability based on the streamflow forecast. Dashed lines indicate the expected demand (D1 for the November, February and April decisions, and D2 for the May decisions). If the expected accumulated inflow at the end of the season (30th September, labelled O in Figure 4-3) is greater than the expected demand, water availability is considered sufficient for an irrigated maize crop (i.e. the option marked in blue in Figure 4-2 is selected). If the accumulated inflow to the end of season is less than expected demand, availability is considered poor as curtailments may then be necessary, and the options commensurate with poor availability are selected (marked in red in Figure 4-2).

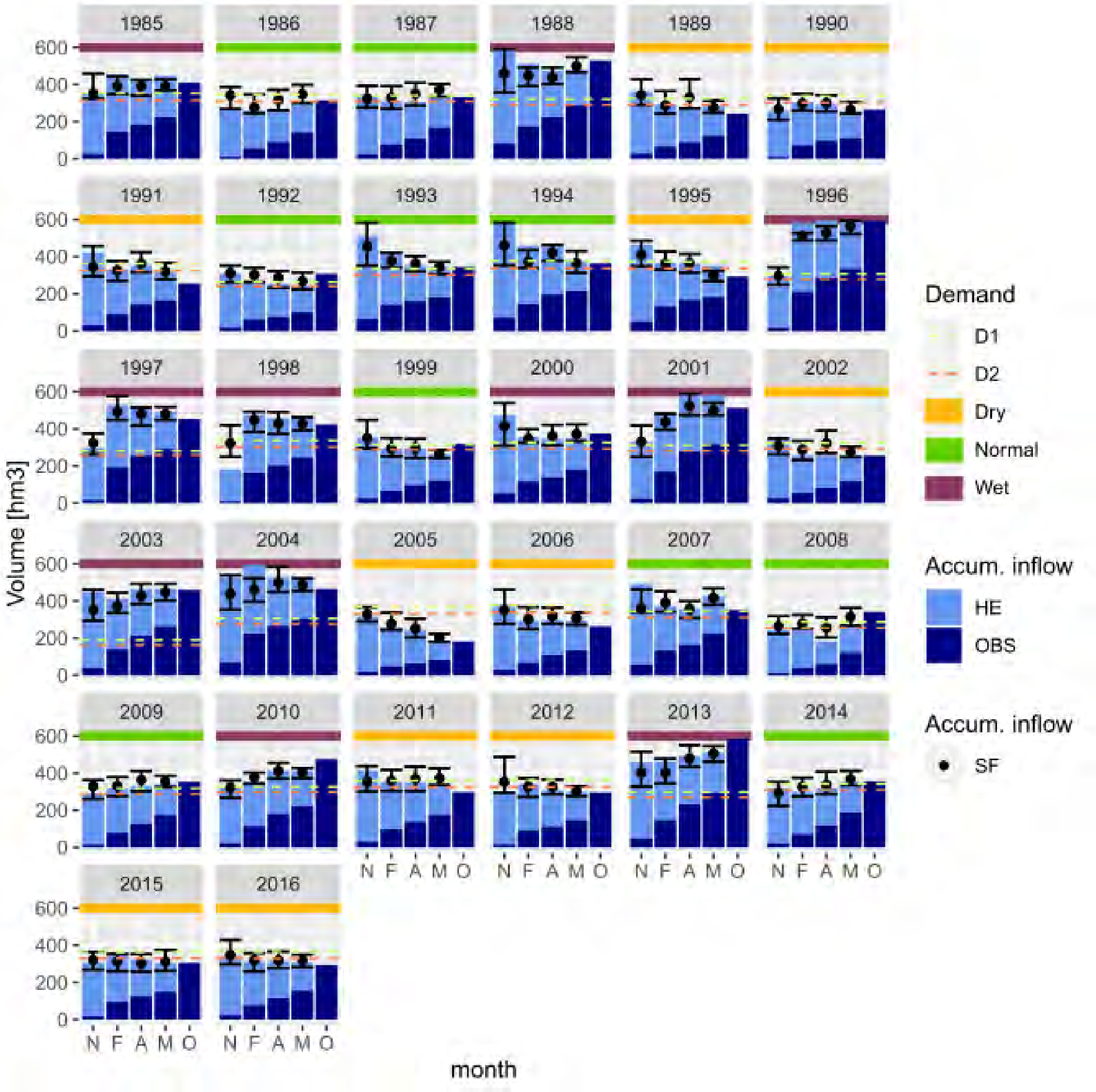


Figure 4-3. Accumulated inflow to the end of season estimated at each of the decision points in November (N), February (F), April (A), May (M) and observed at the end of the season on 30th September (O). The dashed green horizontal line corresponds to D1 demand; the dashed red horizontal line corresponds to D2 demand. Years are marked as wet (purple), normal (green) or dry (yellow) based on the terciles of accumulated observed inflow to the end of season.

The observed accumulated inflow at each step is shown by the dark blue bars for comparison. This shows that the skill of the predicted availability is low in November, with accumulated inflow to the end of season derived from the seasonal streamflow forecast (SF) showing little improvement to predictions based on historic extrapolation (HE). Selected years do, however, show the added value of including the indication of uncertainty (e.g. 1988, 2004), though in the more extreme drought years (e.g. 2005) the final availability is well below this range. Predicted water availability for both methods improves markedly by February.

4.3.2 Comparison of decisions made under the different information scenarios

Figure 4-4 shows the expected water balance to the end of season at each decision point, depending on the information used. Red squares indicate a negative water balance (availability < demand) and blue squares a positive water balance. These balances are used to determine the decision path followed (corresponding to red and blue circles in Figure 4-2) and consequently the crops planted. The figure also shows whether water curtailments are applied by the operator because of available water deemed insufficient to meet demand. This is indicated by a cross or a circle for curtailments applied to LCM or SCM respectively. The size of the symbol represents the proportion of the planted crop that cannot be irrigated. For decisions made using the ensemble streamflow forecast, the ensemble mean (FM) is explored as well as five non-exceedance deciles (10 %, 30 %, 50 %, 70 %, 90 %, labelled F10 to F90). A non-exceedance of 10 % (90 %) represents a conservative (confident) expectation of water availability.

As expected, the streamflow forecast based on perfect rainfall information (Fp) produces a decision pattern that resembles that of the perfect streamflow information (P) most, as the uncertainty derives only from errors of the streamflow model.

Curtailments are applied mostly when the higher deciles of the forecast are used (F70, F90), which is also expected as these are overconfident in predicting the availability of water, particularly for dry years (1989, 1991, 1995, 2002, 2011). Crop choices commensurate to good water availability are then too often made, leading to expected shortfalls. Interestingly, for the more extreme drought years (1990, 2005, 2006, 2015, 2016) few curtailments are applied for all scenarios (except for the most overconfident F90 forecast). This is due to the expected availability being low from the start in these years, with farmers then taking the non-irrigated options related to poor water availability, resulting in low demand. 2011 is the year in which curtailments are applied most as all scenarios except perfect information fail to predict the exceptionally dry summer, with the start to the hydrological year looking normal (Figure 4-3). Curtailments for the HE scenario tend to happen when there is a wet start to the hydrological year that ends to be average (1994) or very dry (1995, 2011).

The final economic benefit obtained for the harvested crops each year depending on the information used is shown in Figure 4-5. For most years, the decision made using the forecast mean (FM) provides the same or slightly higher benefit than when using the current (HE) scenario. Informing the decisions using the higher deciles (F70, F90) sometimes results in significant curtailments (1989, 1991, 1995, 2002, 2011, 2012, 2015, 2016). Losses in 2011 are particularly high as curtailments affect both types of crops (LCM and SCM). Curtailments of smaller proportion only result in a small loss of value (1986, 1987, 1994).

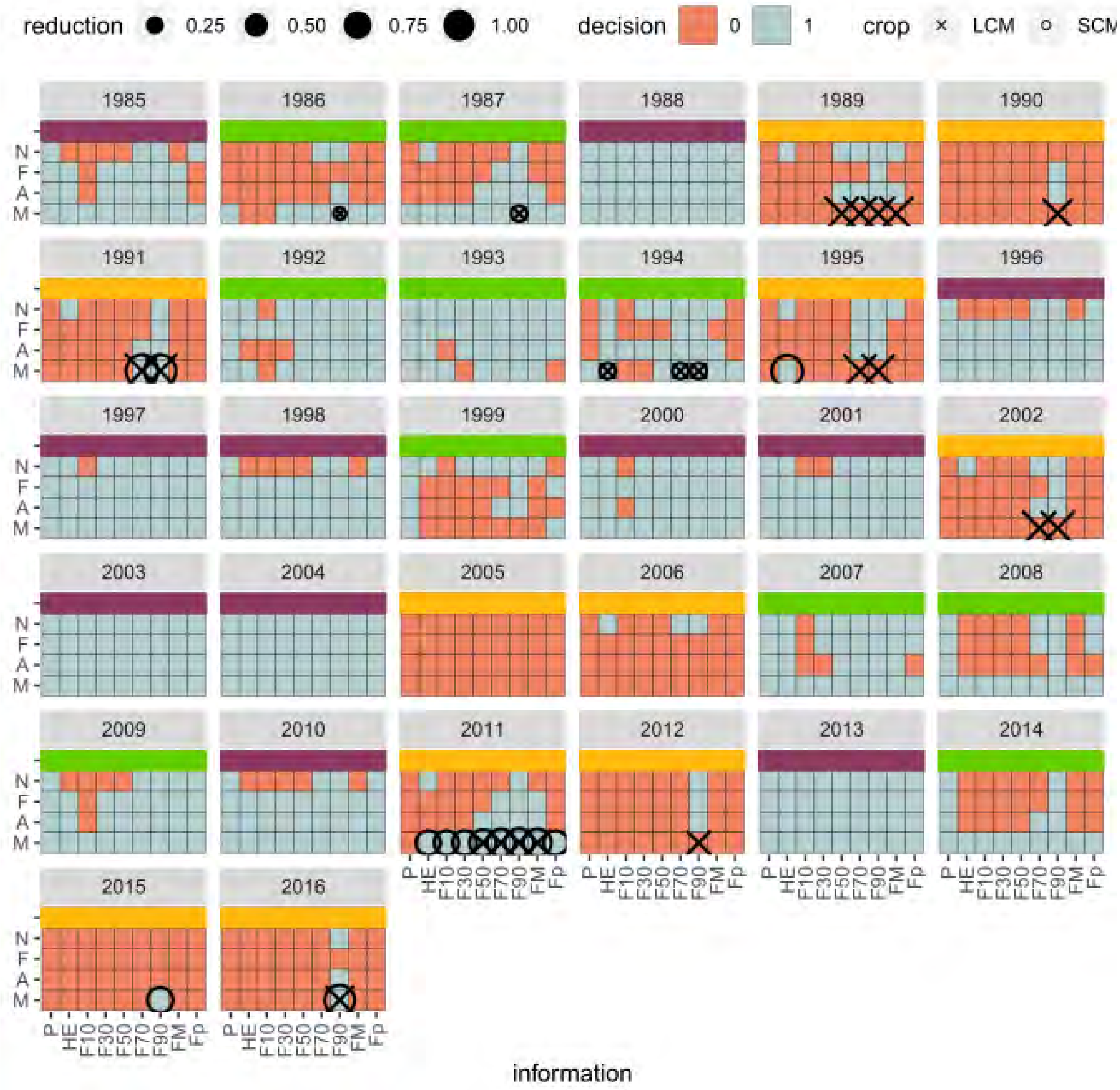


Figure 4-4. Decisions taken at each decision point based on the expected water balance to end of season. Blue (red) squares indicate positive (negative) water balance at the end of season if the preferred option is selected for each decision point (vertical axis) and information source (horizontal axis). Circles in the lower row indicate the need for curtailments for SCM (black circle) and LCM (crosses). The size represents the proportion of the crop that cannot be irrigated.

For wet years, the information used does not make a difference to the benefits achieved. These are years in which there is plenty of water (e.g. 1988, 2003, 2004, 2013). This is also the case when water is abundant after a relatively dry start of the season (low accumulated inflow values in November, e.g. 1996, 1997, 1998, 2001, 2010).

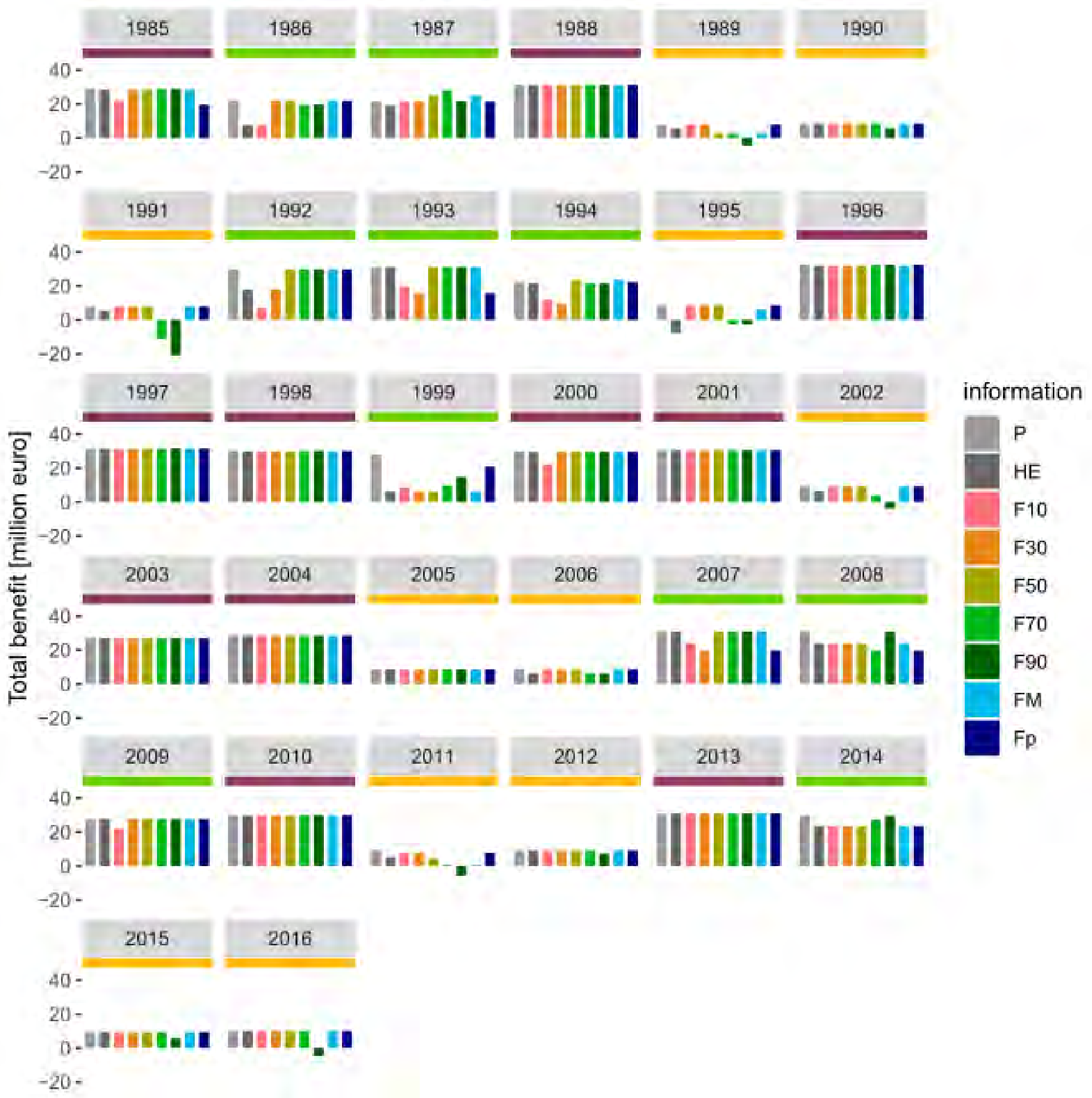


Figure 4-5. Benefit obtained each year from the variable crops depending on the information used to decide what to plant.

4.3.3 Influence of farmer type on forecast value

Figure 4-6 shows the verification scores based on the outcomes of the decision model for all farmer types and information scenarios considered. For all scores, the outcomes of the decision model established with perfect knowledge the reference. For the risk averse farmers (R1), recall is low for the conservative scenarios (F10 to F30). This is due to them readily making the choice for the safer LCB crop, despite water availability in many years being sufficient for the more desirable LCM crop.

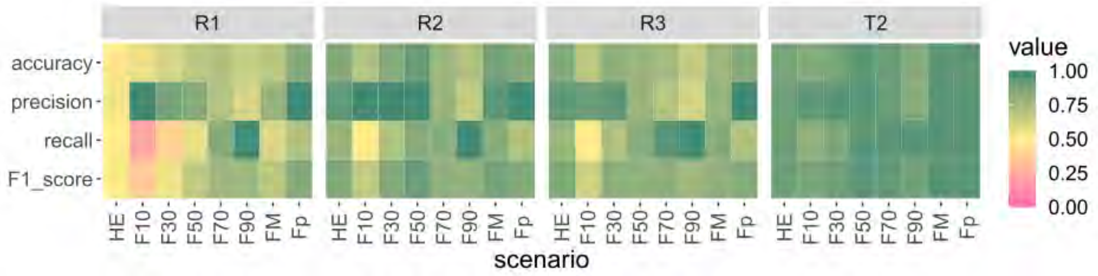


Figure 4-6. Scores for the outcomes of the decision model as a function of information scenario used, separated per farmer type.

Precision is high, however, as when the LCM crop is selected, it is indeed a good choice. For the more confident scenarios, recall increases while precision drops, as the more desirable crop is selected more often though it is equally not always the correct choice. As a consequence, the F1-score, the geometric mean of precision and recall, is low for all scenarios for the R1 farmers (with the exception of the forecast based on perfect precipitation). The overall accuracy, which considers the correspondence of all outcomes for the selected information scenario to those found using perfect information, is also low. For the less risk averse R2 and R3 farmers, a broadly similar pattern is found, though all scores are marginally better, with improved F1-score and accuracy. This is likely due to these farmers taking decisions later in the season, when forecast skill improves. The scores for T2 farmers, who take the decision on the second crop only in May, are almost perfect, with only the most conservative or most confident scenarios showing lower performance. Though the scores of the different farmer types may be modulated due to the different number of possible outcomes, the results suggest that the T2 farmers can rely most on the information provided being accurate for the decision they make, while this is least so for the R1 farmers. Moreover, the latter are more sensitive to forecast uncertainty, as selection of the crop to be planted based on a different non-exceedance probability (F#) influences the outcomes more than it does for the T2 farmers.

Figure 4-7 shows the total benefit each type of farmer obtains over the period analysed (1985-2016). To calculate the benefit, we consider that all single crop farmers (T1, Figure 4-2) have the same benefit when making decisions based on scenarios P and Fp as they would all select the same crops if they knew from the start of the season how water availability would evolve. They would then either plant LCM later in the season, if there is sufficient water, or LCB early in the season if there is not.

Risk averse farmers (R1) have the highest overall benefit as they rarely end up leaving the land fallow (this only happens in 1992 and 1993 for F30, 2007 for F50 and Fp and 2008 for F70 and Fp), because, together with R2 farmers, they then get the least curtailments, and especially because they have the most productive alternative option (LCB) for years with limited water availability. Despite the potential higher gain obtained from planting a double crop, T2 farmers have a lower overall benefit per hectare than R1 farmers. This is due to the losses of leaving the land fallow in some years not being compensated by the higher gain in the good years in the long run. For the T2 farmers benefits for the ensemble mean (FM) and F50 scenarios are the highest, balancing between the more conservative F10 scenario where the land is left fallow in more years, and the F70 and F90 scenarios where SCM is planted in dry years (e.g. 1991, 2002, 2011, 2015, 2016), thus increasing demand and requiring curtailments to be applied, leading to losses.

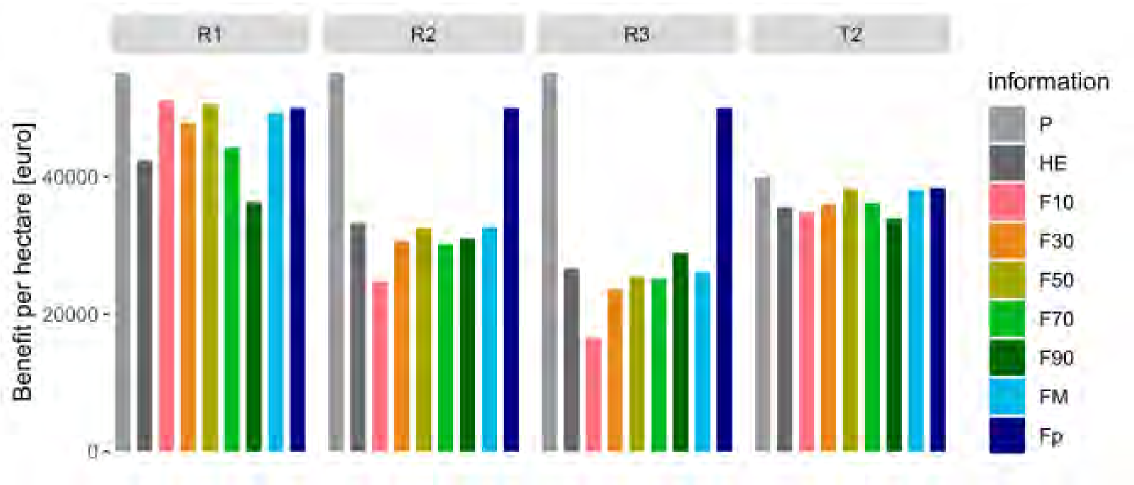


Figure 4-7. Benefit per hectare over the whole period by farmer types, with R1 the most risk averse single crop farmers, R3 the least risk averse single crop farmers and T2 the double crop farmers.

In Figure 4-8, we explore the relative value of each information scenario, scaling the values between those of the perfect information (P) and the reference hydrological extrapolation (HE) scenarios, which is current practice. The central bars (solid colour) show the relative value of information for each type of farmers. The forecast based on perfect rainfall information (Fp), which has the closest decision pattern to that of the scenario using perfect information in Figure 4-3, performs well for all types of farmers. For other information scenarios there is a difference between R1 farmers who favour a conservative estimate of water availability, and R2 and R3 farmers, for whom the opposite is true. This is because in the decision model the risk averse R1 farmers can best avoid the risk of leaving the land fallow by being overly cautious and always planting barley early in the season while R2, R3, as well as T2 farmers, can best avoid that risk by being more confident in the prediction, and planting maize instead of leaving the land fallow. The risk of curtailments is higher for T2 farmers as they represent a larger total area in the irrigation district and therefore require more water, given that in the model they all follow the same behaviour. This results in a higher risk of losses, which makes being overconfident a less profitable option.

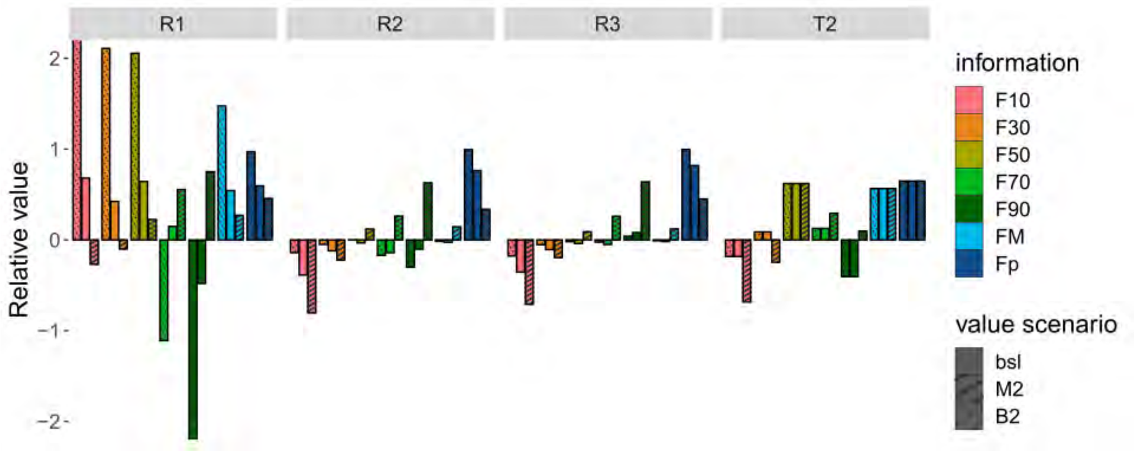


Figure 4-8. Relative value of information over the period of study (baseline, bsl – solid colour bars) and sensitivity to crop value variation for each farmer type: Relative value with either the value of maize (M2 – striped bars) or barley (B2 – dotted bars) doubled.

However, the relative values of the different information scenarios in our results are highly dependent on the ratio of benefits obtained from each of the two crops considered. When this ratio is altered by for example doubling the value of maize (striped bars, M2, in Figure 4-8) or doubling the value of barley (dotted bars, B2) the picture changes significantly, especially for single crop farmers. With a higher benefit for maize, overconfident scenarios improve in relative value for all types of farmers, as the increased profit of maize weighs up against the lower profits of barley, despite more frequent losses due to curtailments. With a higher crop value for barley (B2), the simplified decision model is stretched beyond its initial assumptions, in which maize is the preferred option because of its higher value. As the value per hectare for LCB is now higher than maize this assumption no longer holds. This results in the more conservative scenarios having a higher value than the perfect information scenarios and the relative values being >1 for R1 farmers. Information provided by the seasonal forecast has no value as planting LCB in November is then always the best choice. Changes in the benefit ratio of the two crops have less impact on the relative value of information for T2 farmers as they always plant SCB, and the only decision modelled is whether they plant SCM afterwards. With a higher value for maize, it again pays to be overconfident as the opportunity cost of leaving the land fallow is compensated by the higher gain obtained from maize in good years, compared to the lower losses incurred due to curtailments imposed in the not so good years.

4.4 Discussion

4.4.1 Is the forecast information good enough to be useful?

Quality, or skill, of a forecast in predicting the variables of interest to decision makers is an important aspect to credibility (Bojovic et al., 2022; Peñuela et al., 2020), and pre-requisite to usefulness (see e.g. Bennett et al., 2016; Shukla et al., 2020; Winsemius et al., 2014; Anghileri et al., 2016). Our assessment of the skill of the bias corrected precipitation seasonal forecasts over the Barasona catchment, shows that though correlation of the ensemble mean is positive for all forecast lead times (see Annex C, Figure C1-5), skill reduces substantially beyond the one-month lead-time. CRPSS also shows positive skill compared to the climatological reference for one-month lead time but decreases to zero or marginally negative skill at longer lead times. This reflects the poor seasonal predictability of precipitation in this region of Europe (Crespi et al., 2021). Although a more elaborate bias correction method may result in a slightly increased skill, this is expected to be minor given the positive correlation of the ensemble mean to the observed precipitation at all lead times (Zhao et al., 2017). For streamflow, forecast skill is better than for precipitation (Annex C, Figure C1-6), with a correlation of > 0.6 of the ensemble-mean to observed flows. This is attributed primarily to the skill in predicting the longer memory baseflow component, with the skill of the fast response (quickflow) component poor. We also assess skill of the accumulated streamflow forecasts to end of season (Annex C, Figure C1-7), as this is the variable that is used in the decision. This indicates good correlation for most months, except in November and in the spring snowmelt season, where the simple regression-based quickflow model performs worst due to the absence of snow accumulation and melt. The low CRPSS values, with the forecast being reliable for most months (except November), tested using the Probability Integral Transform (Zhao et al., 2017) (Annex C, Figure C1-8) suggests that the ensemble spread is too wide (underconfident). The strong correlation of the streamflow forecast model forced with perfect precipitation indicates that loss of skill with lead time can primarily be attributed to the uncertainty in the forecast precipitation, as well as the poor performance of the quickflow model. The skill of the streamflow forecasts we find compares to those found by Pechlivanidis et al. (2020) in the Northeastern part of the Iberian Peninsula using a conceptual hydrological model, which includes snow accumulation and melt. Though a more complex model could improve skill here, the good skill of the baseflow forecast, which accounts for 73 % of the annual flow suggests this may only provide marginal improvement to the skill of the forecast of the volumetric decision variable.

4.4.2 In what context is the forecast information useful?

Although there is (limited) skill in the streamflow forecasts, whether the information provided is useful depends on the context in which the forecast is used as well as on the users themselves (White et al., 2022). To be of value, information not only needs to be credible through being scientifically sound, but also salient to the decision in which it is intended to be used (Bremer et al., 2022; Cash et al., 2003) so that users can act on it (Hansen, 2002; Macauley, 2006). The decision model we develop here for the different types of farmers in the selected irrigation district in the Ebro basin, maps out the decision points they make. This is, however, clearly a simplification of the true diversity of farmers in the region and their behavioural choices. Indeed, the model used here is simplified compared to the more elaborate model used to evaluate farmer decisions in the same irrigation district in Linés et al. (2018). Despite its simplicity, the decision points identified through the cropping season are the points when farmers may act on seasonal forecasts of water availability through their crop choice. Similar approaches to mapping out decision points of corn farmers in the US (Haigh et al., 2015) and Argentina (Bert et al., 2006), or livelihood calendars for maize farmers in Malawi (Calvel et al., 2020) have been used to support a qualitative assessment of the usefulness of climate information. Here we extend these through a quantitative modelling of the interconnected decisions of irrigated farmers and reservoir operators. This shows that information is more relevant at the beginning of the season when water availability is more uncertain, though this is primarily so for the T1 type farmers who need to take a decision early in the cropping season, in particular the more risk averse farmers (R1). High uncertainty early in the season results in a lower overall accuracy of the forecasts to the R1 farmers, as well as lower precision and recall when compared to decision made using perfect forecast information. For farmers that have the option of two crops (T2), the uncertain early season information is less relevant than the forecast information in May, when most of the seasons' accumulated inflows are already in the reservoir, though the streamflow forecast in May is also uncertain due to the poor snowmelt prediction of the model used. The forecast then supports T2 farmers' choice between cropping an irrigated crop or leaving the land fallow in dry years, which is the action taken when considering the more conservative inflow scenario.

Whether information provided is salient to the decisions farmers make also depends on water availability. In wet years, when there is plenty of water, the seasonal climate information does not make a difference, as all information scenarios indicate sufficient water to support the crops. Similar results by Kaune et al. (2020), show that seasonal forecast information is most relevant when it provides resolution to the decision being made. This is also found by (Golembesky et al., 2009), who conclude that when the reservoir capacity is much larger than the maximum potential seasonal demand, then information on water availability is of lesser value. Interestingly our results also show that information is less useful in the more extreme dry years. This insight is gained through the modelling of the interlinked decisions of the farmers in their choice of crop, and of the reservoir operators in applying curtailments when demand due to the farmer decisions exceeds available water. Our results suggest that in years with more extreme droughts (e.g. 2005, 2006, 2015, 2016), water scarcity to irrigated agriculture may be less an issue if most farmers choose to leave the land fallow or choose the rain-fed crop to avoid the losses as assumed in the model, thus reducing demand for irrigated water.

4.4.3 To whom is the information useful?

The decision analysed shows that information provided by the seasonal forecast is not equally useful to all types of farmers at each of the decision points. The four types of farmers we consider here have different options available to them. The options available, and as described in the previous section, the timing associated with each of those options, play a key role both in the benefit they obtain, and the usefulness of the information provided by the forecast. Farmers who have the option to make their crop choices later in the season can rely more on information being more accurate. This is the case for the T2 farmers who only use the forecast in May to select whether to plant a second crop. The decisions made at this stage in the season are also less sensitive to the uncertainty in the forecast, though this also means that the seasonal forecast is less salient than to farmers who are taking the highest risk, such as R2 and R3 as for them selecting the wrong option has a higher cost. The results therefore imply that the farmers with a higher technical capacity (T2), whose available options are less affected by the uncertainty of the forecast, benefit from the forecast being more accurate when they need it. This raises questions on the equity of climate services provision (Greene and Ferguson, 2023), as the more advantaged farmers stand to benefit most. The more risk averse R1 farmers are also more sensitive to uncertainty in the forecast, and so may be less inclined to using the information provided to their benefit.

The different types of farmers favour different information scenarios depending on their options and their attitude to risk. R1 farmers benefit from conservative scenarios, while R2 and R3 prefer overconfident scenarios, as those are the scenarios in which leaving the land fallow is less likely. T2 farmers, being a larger group, have a higher risk of curtailments when they all plant an irrigated crop and therefore, they do not benefit as much from the overconfident scenarios. These preferences depend, however, on the cost-benefit ratio between the different options and changes when these ratios change. The decision model applied here uses the assumptions that maize has better value than barley and that the value for both crops over the whole period is constant. In reality, prices change every year and may also be subject to (European) subsidies (Gil et al., 2013; Linés et al., 2018). This adds uncertainty and complexity to the actual decision of farmers. The simple decision used here also includes other assumptions, with limited and fixed options for each type of farmer, and all farmers of a given type making the same decisions. The latter has some impact on the results as when the water availability is not enough for all of them to plant an irrigated crop, they will all choose the alternative option, despite water availability being sufficient for some to plant the irrigated crop. Allowing for more heterogenous decisions per farmer type may then result in a higher value for the group. We also assume that all farmers have the same access to information and capacity to understand it, which are also factors that influence the use of information and may introduce inequalities (Lemos et al., 2010).

Developing a full agent based model, with agents formed by groups of farmers and their behaviour defined by decision rules (Helbing, 2012; Huber et al., 2018) would allow for more individual and heterogenous behaviour, and agent-based models have previously been applied to understand drought adaptation behaviours (Schrieks et al., 2021; Wens et al., 2019) and farmer's crop choices (Yuan et al., 2021). Although the model we use here has some characteristics of an agent-based model, more simple models or game scenarios (see also Giuliani et al., 2020, and Crochemore et al., 2021) are helpful to isolate the impacts on the usefulness of the information provided to the four types of user considered, and contribute to increase the understanding of different decision maker's needs. This can inform the design of climate services to meet those needs, thus improving usability (Lemos, 2015).

4.5 Conclusions

This paper aims to bridge the gap between technical evaluations of the usefulness of seasonal forecasts, and human-centred approaches that evaluate how useful forecasts are to actual decisions users make. We assess the usefulness of seasonal forecasting in supporting decisions in irrigated agriculture in the Ebro Basin in Spain through a user-based model of farmer decisions on what and when to plant, which is conditioned by water availability and the interrelated decision of water managers on when to apply curtailments should shortages occur during droughts. We consider two types of farmers with different available options depending on their technical capabilities, as well as differing levels of risk aversity. This allows the usefulness of information to be illustrated through three key angles:

i. Credibility: We show that seasonal forecasts of water availability to the end of the season have positive skill, even using a simple streamflow prediction model.

Though seasonal precipitation forecasts have only limited skill, the memory of the baseflow response contributes to improved skill of streamflow predictions. Accuracy of the information on which decisions are based is important to this being considered credible by users.

ii. Salience: How useful the seasonal forecast information is, depends on how relevant it is to the decisions informed. The different types of farmers considered take key decisions at different times in the season, depending on their options. Forecasts are most relevant to the farmers that are more risk averse and have fewer technical capacities, as these need to take decisions early in the season, when water availability to the end of season is most uncertain. The relevance of the seasonal forecasts also varies between years and is low for years that are clearly wet from the outset. Interestingly, we find that forecasts are also less relevant in years that are clearly dry from the start, as then demand for irrigation is lower due to farmers opting choosing a rainfed option. Seasonal forecasts are most relevant in years that are changeable, such as those starting wet and then following a drier path, or vice versa.

iii. Equity: The results also show that how useful the forecast is to a user depends on their individual behaviour. This means forecast information does not serve all the farmers equally. Farmers with higher technical capacity have more flexibility to design their crop pattern in a way that decisions are made later in the season when there is less uncertainty on seasonal water availability and information from the forecast. Although the added value of the forecast is not high to them, it is useful when they do as accuracy is then high. More risk averse farmers with less options available stand to obtain a higher added value from using the forecast. However, as they need to make key decisions earlier in the season due to their limited technical capacities, they also then make use of forecast information that is less accurate.

Overall, we show that seasonal streamflow forecasts are useful and there is benefit over the currently used approach in using seasonal forecast information to support the decisions farmers in the Ebro basin make. However, how useful forecast information is, depends very much on the context in which decisions are made, by whom, and the options they have available to them. This also means that the usefulness of forecast information is not equal among different users, highlighting the importance of not only considering usefulness of information provided through a service such as a seasonal forecast from the perspective of the information itself, but also from the perspectives of the various users, and the decisions they make.

5
SYNTHESIS

This chapter summarises the main results of the thesis, offers the conclusions to the research questions introduced in Chapter 1, and highlights the limitations and opportunities for further work.

5.1 MAIN RESULTS: INSIGHTS FROM THE DIFFERENT PERSPECTIVES

This thesis investigates the usefulness of information for drought management decisions at the basin scale, as described in the research objectives in Section 1.3. The multifaceted nature of the question is explored by approaching the same case study in the Ebro basin from three complementary perspectives to assess the usefulness of information.

First the question is approached from the perspective of data; assessing the extent to which data that is available provides the information required to support the decision. More specifically, the case presented in Chapter 2 shows how good the data is at detecting early stages of drought at the river basin scale. The study focusses on assessing the predictive power of different types of data (i.e. global remote sensing data products) in detecting emerging drought conditions that will lead to impacts with sufficient anticipation for drought managers to implement necessary mitigation measures. Newspaper reports and crop yields are used in the study as a benchmark of drought impacts. Data-centred perspectives such as the one presented in Chapter 2, are a helpful approach for data developers or data providers to demonstrate the usefulness of information to drought management decisions, as the results in that chapter prove. The analysis shows that early signs of drought impacts can be detected up to six months before these impacts are reported in newspapers. The remotely sensed datasets that are shown to provide the best correlation–anticipation relationships in the context of the Ebro basin are the standard precipitation index (SPI), the normalised difference vegetation index (NDVI) and evapotranspiration (ET).

The focus then shifts to the perspective of the decision maker in Chapter 3, looking into how information supports specific decision processes and how those decisions could benefit from additional information identified as being useful by the decision makers. The options available to water managers and farmers in the area and the information use and needs they have to support these decisions was explored through semi-structured interviews. The interrelated decisions of the irrigation association responsible for the allocation of water to meet demands, and the farmers were modelled to assess the benefit of additional information on the decision. In addition to the information on currently used reservoir levels, on which decisions are currently taken on, snow cover in the headwater catchments was added. This information was identified by users to be potentially useful in the interviews. Through simulation of the interrelated decisions that incorporated information on snow cover, obtained from remote sensing, it was shown that better decisions and ultimately higher benefits for the farmers could be obtained. The most risk averse small-scale farmers benefited the most, due to the snow cover information adding the most value around the time that they make their decisions (February and April). However, the ratio between the cost of planting and the market value of the crop proved to be a critical aspect in determining the best course of action to be taken and the value of the (additional) information, i.e., when the cost of making a wrong decision is high due to higher planting costs, there is less need for information as the default safer course of action is then always chosen.

Combining the two perspectives, in Chapter 4 the user-based model from the previous chapter is adapted to assess the usefulness of seasonal forecasts as an alternative source of data to inform the decision. While seasonal forecasts were not seen as useful in their current state by the stakeholders interviewed, numerous examples of analyses showing the potential of seasonal forecasts to benefit water management decisions are available in the literature. In addition to exploring the potential benefit of using seasonal forecasts to inform decisions made, the analysis in Chapter 4 also aimed at identifying the factors that influence the usefulness of the information for those decisions. To that end, farmers with different levels of technical capacity, which determine the crop options available to them, and different level of risk averseness were considered in the analysis. The results show that there is clear benefit in using seasonal forecasts over the current approach, which is based on historical data. However, these also demonstrate that the extent to which seasonal forecasts are useful depends on the context in which the decisions are made, by whom, and the options that are available to them. The usefulness depends not only on the credibility, expressed here as the skill of the forecast, but also on the salience of the information, or in other words how relevant the information is to the decisions made. The variability of the season and the timing of the decision are shown to impact the usefulness of the forecast. Forecast information was found to be more relevant in seasons when the availability of water was most unclear, such as in seasons that initially looked wet and then flipped to dry due to the onset of drought conditions, or vice-versa. In other years, either clear wet or clear drought years, seasonal forecast information was of lesser value compared to the approach that is currently used, as it had little impact on decisions made. Additionally, farmers that can make their decisions later in the season were found to benefit from higher forecast accuracy, while the information was more salient to farmers taking decisions early in the season. This has implications for the equity of information, as it is usually the farmers with higher technical capacity that have the flexibility to select a crop pattern that allows them to make decisions later in the season when the information is more accurate. Farmers that have less technical options available to them, and that are more risk averse, tend to take decisions early in the season when uncertainty is highest.

Overall, these results highlight that the usefulness of information depends not just on the information itself, but also on the decision that is being informed, the context within which the decision is taken, and by whom. This underpins the importance of integrated approaches to conduct these types of analysis. The following three sections discuss insights the different approaches followed in this thesis can provide to that integrated approach, and the implications for the assessment of the usefulness of information.

5.2 HOW TO ASSESS THE USEFULNESS OF INFORMATION

The semi-structured interviews with the basin water resources managers, one of the irrigation associations, and one of the farmers to learn about their decision processes and the role of information in them (conducted for Chapter 3) confirmed there is a need for (additional) information by decision makers. The user-centred perspective was helpful to comprehend the details of the decision, especially the courses of action available and the conditions that determine the selection of a specific course of action. Indeed, it is essential for the assessment of the usefulness of the information to those decisions, since for the information to be useful, it needs to be able to provoke a change in the decision outcome. Although this may be less critical for decisions that appear well defined and documented, such as in drought management plans or reservoir operation rules, there is still plenty to learn about the actual decision process in those cases. For example, alternative sources of information, such as information on the snow cover identified in Chapter 3, may be used to complement the official indicators to reinforce the decision. Additionally, understanding the actual decision process can provide insights on the time limits to making critical decisions, which determines how much delay there can be between the event and the reception of the information by the decision maker for it to still be useful.

Although this shows the importance of assessing the usefulness of information from the decision maker's perspective, assessments of the usefulness or value of information to support a decision from the side of the data, such as shown in Chapter 2, are relevant in identifying the type of information that is potentially useful to support a decision. Still, to demonstrate whether that information has the capacity to change the outcome, and therefore is indeed useful for the decision, a decision model or trial is required. As shown in Chapter 4, several aspects of the decision, such its timing, the technical capacity and risk attitude of the decision maker, and the uncertainty of water availability during the season influence the usefulness of information and the benefit it brings to the user.

5.3 BRIDGING THE GAP BETWEEN TECHNICAL AND HUMAN-CENTRED APPROACHES

The three perspectives taken in this thesis show that the assessment of the usefulness of information for a decision requires combining the perspectives of both usefulness to the decision makers, as well as usefulness of the data itself. However, assessments are often approached from disciplines that focus on either a technical or socio-economic perspective. This thesis explores, and ultimately combines, these perspectives to contribute to filling the gap between technical and human-centred approaches to assess the usefulness of information for drought management decisions.

At a smaller scale, these two perspectives are also brought together in Chapter 2. There the question of the usefulness of information is approached from a data analysis perspective to assess whether selected information products have the capacity to detect emerging drought with enough anticipation to allow the implementation of measures by the basin managers. One of the obstacles to determining the ability of information products or drought indicators to inform decision makers about the occurrence of drought, is the lack of a benchmark for drought. The innovative solution applied in Chapter 2 to build that missing benchmark consists in using drought impacts reported in (regional) newspapers, thus incorporating a connection to drought impacts into the evaluation of drought indicators. This is critical, but often disregarded.

5.4 INTERPLAY BETWEEN INFORMATION AND DECISIONS

As expressed throughout the thesis, there are two main conditions for information to be useful to a decision: (1) the capacity of the information to provide the facts or indicators required by the decision maker in a timely manner; and (2) the capacity of the decision maker to change the course of action as a result of that information. The first point is explored in Chapter 2, while Chapters 3 focuses on the second point and Chapter 4 aims to combine both points. The three chapters show that each of the points has multiple factors that determine that capacity and which need to be considered to assess the usefulness of information.

The first condition is connected to the quality of the information and its ability to provide accurate observations or predictions, but also to provide information that is salient to the decision. Information provided must inform on something that the decision maker needs to know to select one of the available courses of action and it needs to provide that information both early enough to be available at the time of making the decision (as happens with the early detection of drought in Chapter 2), and at the time of the year or season in which the decision is made (as happens with crop selection decisions in Chapters 3 and 4).

The capacity of the decision maker to change course of action as a result of information, i.e. the second condition for the usefulness of information, is not a constant but may vary with the context. For example, as shown in Chapters 3 and 4 in clearly wet or dry years the information is less useful than in changeable years as the information helps clarify what the best course of action is. The cost of planting and the reduced profit margins were also shown to have clear impact on the usefulness of information. When the risk of losses is too high, a conservative approach tends to be the best path to follow and therefore information is less useful (as the course of action does not need to be changed as that typically implies the taking of more risk).

It is implicit in the second condition that the capacity to make use of the information depends on the users and the options available to them, as is shown by the decision models and the different users considered in Chapters 3 and 4. The cases analysed in those chapters show that the time of the season in which the decision is made has a strong influence in the usefulness of the information, and therefore users making decisions at different times would not benefit from the same type of information equally. This is shown for forecast data, which has varying levels of accuracy over the season, but also for observed data, as the relevance of hydrological variables can also change over the season. The case of snow cover information analysed in Chapter 3 is a clear example of that change in relevance over the season.

5.5 OPPORTUNITIES FOR FURTHER INVESTIGATION

As summarised in the previous three sections, this thesis shows the contribution of data and user-centric approaches to assess the usefulness of information and explores their integration to fill the existing gap between the technical and human disciplines that are interested in assessing this usefulness. The results show that the usefulness of information depends on multiple aspects of the decision that is being informed, confirming the necessity of considering both the data and the user aspects when assessing the usefulness of information. The thesis presents a combined approach for the case study of an irrigation district in the Ebro Basin and water management decisions. Other irrigation districts in the Ebro Basin and in other Spanish basins share similar decision processes as they all follow a common national framework for river basin and drought management plans. This facilitates the transferability of the methods and the results of this research to other areas in the country, although local variations in for example the crop options or the level of cooperation between farmers would need to be considered and incorporated as required. Basins beyond Spain may also share similarities in water allocation decisions, climate conditions and crop patterns, which could facilitate some extrapolation of the methods and results, though tailoring would again be needed to suit the specific characteristics of the local context. Broader research on the integration of social sciences methods, modelling of decisions, and hydro-climatological modelling is nevertheless necessary to identify more general applicable guidance to the assessment of the usefulness of information.

In the analyses presented in this thesis, simpler models were preferred to help isolate the impact of different factors on the usefulness of information. However, having all farmers in each type of the four farmer groups making the same decision is shown to have an impact on the decision made by the group. For example, in some cases there was not enough available water for all of them to plant an irrigated crop, and as a result none of them planted that crop. This opens an opportunity for more complex modelling, such as that offered by agent-based models. Agent-based models could allow for more heterogeneity among the farmers and help identify additional detail in the usefulness of information among the different users. Additional aspects, such as the variable prices of crops or subsidies, that were not considered in the model used in this thesis for simplicity, could also be incorporated into the model to assess their impact on the usefulness of information.

The results in Chapter 4 show that how useful information is depends on the behaviour of the decision maker (defined here by their technical capacity and attitude to risk). This has implications on the equity of information, as different users benefit differently, depending on when the decision is taken, the uncertainty of the information at the time of the taking of the decision, and the options available to them. The question of how equitable information provided through climate services is has as yet been little researched, and further research in other contexts is recommended to develop a more complete insight. This also underlines the importance of a trans-disciplinary approach, where the usefulness of information is explored from the perspective of the data itself as well as from the perspective of the users and decision makers.

References

Aerts, J. C. J. H., Botzen, W. J., Clarke, K. C., Cutter, S. L., Hall, J. W., Merz, B., Michel-Kerjan, E., Mysiak, J., Surminski, S., and Kunreuther, H.: Integrating human behaviour dynamics into flood disaster risk assessment, Nat. Clim. Change, 8, 193–199, https://doi.org/10.1038/s41558-018-0085-1, 2018.

Alahacoon, N. and Edirisinghe, M.: A comprehensive assessment of remote sensing and traditional based drought monitoring indices at global and regional scale, Geomat. Nat. Hazards Risk, 13, 762–799, https://doi.org/10.1080/19475705.2022.2044394, 2022.

Alexander, S., Yang, G., Addisu, G., and Block, P.: Forecast-informed reservoir operations to guide hydropower and agriculture allocations in the Blue Nile basin, Ethiopia, Int. J. Water Resour. Dev., 37, 208–233, https://doi.org/10.1080/07900627.2020.1745159, 2021.

Alexandridis, T. K., Cherif, I., Bilas, G., Almeida, W. G., Hartanto, I. M., Van Andel, S. J., and Araujo, A.: Spatial and Temporal Distribution of Soil Moisture at the Catchment Scale Using Remotely-Sensed Energy Fluxes, Water, 8, 32, https://doi.org/10.3390/w8010032, 2016.

Allen, R. G., Pereira, L. S., Raes, D., and Smith, M.: Crop evaporation: guidelines for computing crop water requirements, Rome, Italy, 1998.

Anderson, M. C., Norman, J. M., Diak, G. R., Kustas, W. P., and Mecikalski, J. R.: A Two-Source Time-Integrated Model for Estimating Surface Fluxes Using Thermal Infrared Remote Sensing, Remote Sens. Environ., 60, 195–216, 1997.

Anderson, M. C., Hain, C., Wardlow, B., Pimstein, A., Mecikalski, J. R., and Kustas, W. P.: Evaluation of Drought Indices Based on Thermal Remote Sensing of Evapotranspiration over the Continental United States, J. Clim., 24, 2025–2044, https://doi.org/10.1175/2010JCLI3812.1, 2011.

Anghileri, D., Voisin, N., Castelletti, A., Pianosi, F., Nijssen, B., and Lettenmaier, D. P.: Value of long-term streamflow forecasts to reservoir operations for water supply in snow-dominated river catchments, Water Resour. Res., 52, 4209–4225, https://doi.org/10.1002/2015WR017864, 2016.

Antwi-Agyei, P., Dougill, A. J., and Abaidoo, R. C.: Opportunities and barriers for using climate information for building resilient agricultural systems in Sudan savannah agro-ecological zone of north-eastern Ghana, Clim. Serv., 22, 100226, https://doi.org/10.1016/j.cliser.2021.100226, 2021.

Aragon Statistics Institute: Precios anuales promedio percibidos en la venta de productos agrarios, por los agricultores y ganaderos. C.A. Aragón. Años 1990-2013 Mean annual prices received for the sale of agricultural products by farmers. Aragon 1990-2013), Aragón, 2015.

Arnal, L., Cloke, H. L., Stephens, E., Wetterhall, F., Prudhomme, C., Neumann, J., Krzeminski, B., and Pappenberger, F.: Skilful seasonal forecasts of streamflow over Europe?, Hydrol. Earth Syst. Sci., 22, 2057–2072, https://doi.org/10.5194/hess-22-2057-2018, 2018.

Bachmair, S., Kohn, I., and Stahl, K.: Exploring the link between drought indicators and impacts, Nat. Hazards Earth Syst. Sci., 15, 1381–1397, https://doi.org/10.5194/nhess-15-1381-2015, 2015.

Bachmair, S., Stahl, K., Collins, K., Hannaford, J., Acreman, M., Svoboda, M., Knutson, C., Smith, K. H., Wall, N., Fuchs, B., Crossman, N. D., and Overton, I. C.: Drought indicators revisited: the need for a wider consideration of environment and society, WIREs Water, 3, 516–536, https://doi.org/10.1002/wat2.1154, 2016.

Batalla, R. J., Gómez, C. M., and Kondolf, G. M.: Reservoir-induced hydrological changes in the Ebro River basin (NE Spain), J. Hydrol., 290, 117–136, https://doi.org/10.1016/j.jhydrol.2003.12.002, 2004.

Beckers, J. V. L., Weerts, A. H., Tijdeman, E., and Welles, E.: ENSO-conditioned weather resampling method for seasonal ensemble streamflow prediction, Hydrol. Earth Syst. Sci., 20, 3277–3287, https://doi.org/10.5194/hess-20-3277-2016, 2016.

Beguería, S. and Vicente-Serrano, S. M.: SPEI: calculation of the standardised precipitation-evapotranspiration index. R package version, 1(6)., 2013.

Bennett, J. C., Wang, Q. J., Li, M., Robertson, D. E., and Schepen, A.: Reliable long-range ensemble streamflow forecasts: Combining calibrated climate forecasts with a conceptual runoff model and a staged error model: LONG-RANGE ENSEMBLE STREAMFLOW FORECASTS, Water Resour. Res., 52, 8238–8259, https://doi.org/10.1002/2016WR019193, 2016.

Berg, A. and Sheffield, J.: Climate Change and Drought: the Soil Moisture Perspective, Curr. Clim. Change Rep., 4, 180–191, https://doi.org/10.1007/s40641-018-0095-0, 2018.

Bert, F. E., Satorre, E. H., Toranzo, F. R., and Podestá, G. P.: Climatic information and decision-making in maize crop production systems of the Argentinean Pampas, Agric. Syst., 88, 180–204, https://doi.org/10.1016/j.agsy.2005.03.007, 2006.

Blauhut, V., Gudmundsson, L., and Stahl, K.: Towards Pan-European drought risk maps: quantifying the link between drought indices and reported drought impacts, Environ. Res. Lett., 10, https://doi.org/10.1088/1748-9326/10/1/014008, 2015.

Bojovic, D., Nicodemou, A., St.Clair, A. L., Christel, I., and Doblas-Reyes, F. J.: Exploring the landscape of seasonal forecast provision by Global Producing Centres, Clim. Change, 172, 8, https://doi.org/10.1007/s10584-022-03350-x, 2022.

Bouma, J. A., van der Woerd, H. J., and Kuik, O. J.: Assessing the value of information for water quality management in the North Sea, J. Environ. Manage., 90, 1280–1288, https://doi.org/10.1016/j.jenvman.2008.07.016, 2009.

Bouma, J. A., Kuik, O., and Dekker, A. G.: Assessing the value of Earth Observation for managing coral reefs: An example from the Great Barrier Reef, Sci. Total Environ., 409, 4497–4503, https://doi.org/10.1016/j.scitotenv.2011.07.023, 2011.

Bremer, S., Wardekker, A., Baldissera Pacchetti, M., Bruno Soares, M., and van der Sluijs, J.: Editorial: High-Quality Knowledge for Climate Adaptation: Revisiting Criteria of Credibility, Legitimacy, Salience, and Usability, Front. Clim., 4, 2022.

Brown, B. G., Katz, R. W., and Murphy, A. H.: On the Economic Value of Seasonal-Precipitation Forecasts: The Fallowing/Planting Problem, Bull. Am. Meteorol. Soc., 67, 833–841, https://doi.org/10.1175/1520-0477(1986)067<0833:OTEVOS>2.0.CO;2, 1986.

Brown, J. F., Wardlow, B. D., Tadesse, T., Hayes, M. J., and Reed, B. C.: The Vegetation Drought Response Index (VegDRI): a new integrated approach for monitoring drought stress in vegetation, GIScience Remote Sens., 45, 16–46, 2008.

Bruno Soares, M. and Dessai, S.: Barriers and enablers to the use of seasonal climate forecasts amongst organisations in Europe, Clim. Change, 137, 89–103, https://doi.org/10.1007/s10584-016-1671-8, 2016.

Calvel, A., Werner, M., van den Homberg, M., Cabrera Flamini, A., Streefkerk, I., Mittal, N., Whitfield, S., Langton Vanya, C., and Boyce, C.: Communication Structures and Decision Making Cues and Criteria to Support Effective Drought Warning in Central Malawi, Front. Clim., 2, 2020.

Carr, G., Potter, R. B., and Nortcliff, S.: Water reuse for irrigation in Jordan: Perceptions of water quality among farmers, Agric. Water Manag., 98, 847–854, https://doi.org/10.1016/j.agwat.2010.12.011, 2011.

Cash, D. W., Clark, W. C., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., Jäger, J., and Mitchell, R. B.: Knowledge systems for sustainable development, Proc. Natl. Acad. Sci., 100, 8086–8091, https://doi.org/10.1073/pnas.1231332100, 2003.

Casterad Seral, M. A.: Aplicaciones basadas en tecnologías de la información geográfica para ayudar a gestionar el agua de riego en comunidades de regantes (Applications based on geographic information technologies to support irrigation water management by irrigation associations), in: Análisis espacial y representación geográfica: innovación y aplicación (Spatial analysis and geographic representation: innovation and application), edited by: de la Riva, J., Ibarra, P., Montorio, R., and Rodrigues, M., Universidad de Zaragoza-AGE, Zaragoza, Spain, 571–580, 2015.

Cerdá Tena, E. and Quiroga Gómez, S.: Cost-Loss Decision Models with Risk Aversion, Inst. Complut. Estud. Int., 2008.

Chatfield, C.: Time-series forecasting, Chapman and Hall/CRC, New York, 2004.

CHE: Plan Especial de Actuación en Situaciones de Alerta y Eventual Sequía en la Cuenca Hidrográfica del Ebro (Special plan for alert conditions and potential drought in the Ebro basin), Confederación Hidrográfica del Ebro, Zaragoza, Spain, 2007.

CHE: Plan Hidrológico de la parte española de la demarcación hidrográfica del Ebro 2015–2021 (Hidrological Plan for the Spanish part of the Ebro hydrographical demarcation 2015–2021), Confederación Hidrográfica del Ebro, Zaragoza, Spain, 2015.

Portal de CHEbro: www.chebro.es, last access: 18 September 2017.

CHE: Plan Especial de Sequía - Demarcación Hidrográfica del Ebro (Special plan for drought - Ebro basin), Confederación Hidrográfica del Ebro (CHE), 2018.

CHE: Memoria del Proyecto de Plan Hidrológico de la Demarcación Hidrográfica del Ebro - Revisión de tercer ciclo 2022-2027 (Main report for the Ebro Hydrological Plan Project - Review for the third cycle 2022-2027)., Confederación Hidrográfica del Ebro (CHE), 2022.

Chen, M., Senay, G. B., Singh, R. K., and Verdin, J. P.: Uncertainty analysis of the Operational Simplified Surface Energy Balance (SSEBop) model at multiple flux tower sites, J. Hydrol., 536, 384–399, https://doi.org/10.1016/j.jhydrol.2016.02.026, 2016.

CHJ: Plan especial de alerta y eventual sequía en la Confederación Hidrográfica del Júcar (Special plan for alert conditions and potential drought in the Júcar basin), onfederación Hidrográfica del Júcar, 2007.

Commission of the European Communities: Communication from the Commission to the European Parliament and the Council – Addressing the challenge of water scarcity and droughts in the European Union, 2007.

Crespi, A., Petitta, M., Marson, P., Viel, C., and Grigis, L.: Verification and Bias Adjustment of ECMWF SEAS5 Seasonal Forecasts over Europe for Climate Service Applications, Climate, 9, 181, https://doi.org/10.3390/cli9120181, 2021.

Crochemore, L., Ramos, M.-H., Pappenberger, F., Andel, S. J. van, and Wood, A. W.: An Experiment on Risk-Based Decision-Making in Water Management Using Monthly Probabilistic Forecasts, Bull. Am. Meteorol. Soc., 97, 541–551, https://doi.org/10.1175/BAMS-D-14-00270.1, 2016.

Crochemore, L., Cantone, C., Pechlivanidis, I. G., and Photiadou, C. S.: How Does Seasonal Forecast Performance Influence Decision-Making? Insights from a Serious Game, Bull. Am. Meteorol. Soc., 102, E1682–E1699, https://doi.org/10.1175/BAMS-D-20-0169.1, 2021.

Enenkel, M., Brown, M. E., Vogt, J. V., McCarty, J. L., Reid Bell, A., Guha-Sapir, D., Dorigo, W., Vasilaky, K., Svoboda, M., Bonifacio, R., Anderson, M., Funk, C., Osgood, D., Hain, C., and Vinck, P.: Why predict climate hazards if we need to understand impacts? Putting humans back into the drought equation, Clim. Change, 162, 1161–1176, https://doi.org/10.1007/s10584-020-02878-0, 2020.

Espluga Trenc, J.: ¿Qué está pasando con el cultivo de maíz transgénico? (What is happening with transgenic maize?), Soberanía Aliment., 26, 34–38, 2016.

Famiglietti, J., Cazenave, A., Eicker, A., Reager, J., Rodell, M., Velicogna, I., Fekete, B. M., Robarts, R. D., Kumagai, M., Nachnebel, H.-P., Odada, E., and Zhulidov, A. V.: Watching water: from sky or stream?, Science, 349, 684, https://doi.org/10.1126/science.349.6249.684-a, 2015.

FAO: CROPWAT 8.0, 2000.

Fernández-Prieto, D., Van Oevelen, P., Su, Z., and Wagner, W.: Editorial "Advances in Earth observation for water cycle science," Hydrol. Earth Syst. Sci., 16, 543–549, https://doi.org/10.5194/hess-16-543-2012, 2012.

Findlater, K., Webber, S., Kandlikar, M., and Donner, S.: Climate services promise better decisions but mainly focus on better data, Nat. Clim. Change, 11, 731–737, https://doi.org/10.1038/s41558-021-01125-3, 2021.

Foster, T., Brozović, N., Butler, A. P., Neale, C. M. U., Raes, D., Steduto, P., Fereres, E., and Hsiao, T. C.: AquaCrop-OS: An open source version of FAO's crop water productivity model, Agric. Water Manag., 181, 18–22, https://doi.org/10.1016/j.agwat.2016.11.015, 2017.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J.: The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes, Sci. Data, 2, 150066, https://doi.org/10.1038/sdata.2015.66, 2015.

García-Herrera, R., Hernández, E., Barriopedro, D., Paredes, D., Trigo, R. M., Trigo, I. F., and Mendes, M. A.: The Outstanding 2004/05 Drought in the Iberian Peninsula: Associated Atmospheric Circulation, J. Hydrometeorol., 8, 483–498, https://doi.org/10.1175/JHM578.1, 2007.

Gascoin, S., Hagolle, O., Huc, M., Jarlan, L., Dejoux, J.-F., Szczypta, C., Marti, R., and Sánchez, R.: A snow cover climatology for the Pyrenees from MODIS snow products, Hydrol. Earth Syst. Sci., 19, 2337–2351, https://doi.org/10.5194/hess-19-2337-2015, 2015.

Gil, M., Garrido, A., and Hernández-Mora, N.: Direct and indirect economic impacts of drought in the agri-food sector in the Ebro River basin (Spain), Nat. Hazards Earth Syst. Sci., 13, 2679–2694, https://doi.org/10.5194/nhess-13-2679-2013, 2013.

Gil Martínez, M.: Cebada y maíz rastrojero. Productividad económico-ambiental de la fertilización con purín (Barley and maize. Economic and environmental productivity of fertilisation with liquid manure), Gobierno de Aragón. Departamento de Agricultura, Ganadería y Medio Ambiente. Dirección General de Alimentación y Fomento Agroalimentario. Servicio de Recursos Agrícolas, Zaragoza, Spain, 2013.

Giuliani, M., Crochemore, L., Pechlivanidis, I., and Castelletti, A.: From skill to value: isolating the influence of end user behavior on seasonal forecast assessment, Hydrol. Earth Syst. Sci., 24, 5891–5902, https://doi.org/10.5194/hess-24-5891-2020, 2020.

Golembesky, K., Sankarasubramanian, A., and Devineni, N.: Improved Drought Management of Falls Lake Reservoir: Role of Multimodel Streamflow Forecasts in Setting up Restrictions, J. Water Resour. Plan. Manag., 135, 188–197, https://doi.org/10.1061/(ASCE)0733-9496(2009)135:3(188), 2009.

Graham, R. M., Browell, J., Bertram, D., and White, C. J.: The application of sub-seasonal to seasonal (S2S) predictions for hydropower forecasting, Meteorol. Appl., 29, e2047, https://doi.org/10.1002/met.2047, 2022.

Greene, C. and Ferguson, D. B.: Equity, Justice, and Drought: Lessons for Climate Services from the US Southwest, Bull. Am. Meteorol. Soc., 1, https://doi.org/10.1175/BAMS-D-22-0185.1, 2023.

Guerschman, J. P., van Dijk, A. I., Mattersdorf, G., Beringer, J., Hutley, L. B., Leuning, R., Pipunic, R. C., and Sherman, B. S.: Scaling of potential evapotranspiration with MODIS data reproduces flux observations and catchment water balance observations across Australia, J. Hydrol., 369, 107–119, 2009.

Gutiérrez López, M.: Orientaciones varietales para las siembras de cereales en Aragón. Resultado de los ensayos. Cosecha 2011 (Guidance on crop varieties for cereal cultivation in Aragón. Trial results. Season 2011), Diputación General de Aragón. Departamento de Agricultura y Alimentación. Dirección General de Desarrollo Rural, Servicio de Programas Rurales, Zaragoza, Spain, 2011.

Gutiérrez López, M.: Transferencia de resultados de la red de ensayos de maíz y girasol en Aragón. Campaña 2015, Tierras Agric., 48–65, 2016.

Haigh, T., Takle, E., Andresen, J., Widhalm, M., Carlton, J. S., and Angel, J.: Mapping the decision points and climate information use of agricultural producers across the U.S. Corn Belt, Clim. Risk Manag., 7, 20–30, https://doi.org/10.1016/j.crm.2015.01.004, 2015.

Hain, C. R., Mecikalski, J. R., and Anderson, M. C.: Retrieval of an Available Water-Based Soil Moisture Proxy from Thermal Infrared Remote Sensing. Part I: Methodology and Validation, J. Hydrometeorol., 10, 665–683, https://doi.org/10.1175/2008JHM1024.1, 2009.

Hall, D., Salomonson, V. V., and George, K.: MODIS/Terra Snow Cover 8-Day L3 Global 500m Grid, Version 5, https://doi.org/10.5067/C574UGKQQU1T, 2006.

Hall, J. W., Watts, G., Keil, M., de Vial, L., Street, R., Conlan, K., O'Connell, P. E., Beven, K. J., and Kilsby, C. G.: Towards risk-based water resources planning in England and Wales under a changing climate: Risk-based water resources planning, Water Environ. J., 26, 118–129, https://doi.org/10.1111/j.1747-6593.2011.00271.x, 2012.

Hansen, J. W.: Realizing the potential benefits of climate prediction to agriculture: issues, approaches, challenges, Agric. Syst., 74, 309–330, https://doi.org/10.1016/S0308-521X(02)00043-4, 2002.

Hansson, S. O.: Decision theory. A brief introduction, Department of Philosophy and the History of Technology Royal Institute of Technology (KTH), Stockholm, 2005.

Hansson, S. O.: Can Uncertainty Be Quantified?, Perspect. Sci., 30, 210–236, 2022.

Harrell, M. C. and Bradley, M. A.: Data collection methods. Semi-structured interviews and focus groups, RAND - National Defense Research Institute, Santa Monica, CA (US), 140 pp., 2009.

Heim, R. R.: A Review of Twentieth- Century Drought Indices Used in the United States, BAMS, August 2002, 1149-1165, 2002.

Helbing, D.: Agent-Based Modeling, in: Social Self-Organization: Agent-Based Simulations and Experiments to Study Emergent Social Behavior, edited by: Helbing, D., Springer, Berlin, Heidelberg, 25–70, https://doi.org/10.1007/978-3-642-24004-1_2, 2012.

Hernández Varela, L., Lozano Valencia, M. Á., and Soleto García, C.: Estudio de los acontecimientos meteorológicos extraordinarios en la Comunidad Autónoma del País Vasco (1870-1954) a través de la prensa, Investig. Geográficas, 165, https://doi.org/10.14198/INGEO2003.30.03, 2003.

Hernández-Mora, N., Gil, M., Garrido, A., and Rodriguez-Casado, R.: La sequía 2005–2008 en la cuenca del Ebro. Vulnerabilidad, Impactos y Medidas de Gestión. (2005–2008 drought in the Ebro basin: vulnerability, impacts and management measures), Universidad Politécnica de Madrid – CEIGRAM, 2013.

Hersbach, H.: Decomposition of the Continuous Ranked Probability Score for Ensemble Prediction Systems, Weather Forecast., 15, 559–570, https://doi.org/10.1175/1520-0434(2000)015<0559:DOTCRP>2.0.CO;2, 2000.

Hisdal, H., Tallaksen, L. M., Clausen, B., and Peters, E.: Hydrological Drought Characteristics, in: Hydrological drought, Elsevier, 157–231, 2024.

Huber, R., Bakker, M., Balmann, A., Berger, T., Bithell, M., Brown, C., Grêt-Regamey, A., Xiong, H., Le, Q. B., Mack, G., Meyfroidt, P., Millington, J., Müller, B., Polhill, J. G., Sun, Z., Seidl, R., Troost, C., and Finger, R.: Representation of decision-making in European agricultural agent-based models, Agric. Syst., 167, 143–160, https://doi.org/10.1016/j.agsy.2018.09.007, 2018.

Iglesias, A., Garrote, L., and Martín-Carrasco, F.: Drought risk management in mediterranean river basins, Integr. Environ. Assess. Manag., 5, 11–16, https://doi.org/10.1897/IEAM_2008-044.1, 2009.

Iglesias, A., Sánchez, B., Garrote, L., and López, I.: Towards Adaptation to Climate Change: Water for Rice in the Coastal Wetlands of Doñana, Southern Spain, Water Resour. Manag., 31, 629–653, https://doi.org/10.1007/s11269-015-0995-x, 2017.

Jebeile, J. and Roussos, J.: Usability of climate information: Toward a new scientific framework, WIREs Clim. Change, 14, e833, https://doi.org/10.1002/wcc.833, 2023.

Johnson, S. J., Stockdale, T. N., Ferranti, L., Balmaseda, M. A., Molteni, F., Magnusson, L., Tietsche, S., Decremer, D., Weisheimer, A., Balsamo, G., Keeley, S. P. E., Mogensen, K., Zuo, H., and Monge-Sanz, B. M.: SEAS5: the new ECMWF seasonal forecast system, Geosci. Model Dev., 12, 1087–1117, https://doi.org/10.5194/gmd-12-1087-2019, 2019.

Kallis, G.: Droughts, Annual Review of Environment and Resources, 33, https://papers.ssrn.com/abstract=1319908, 23 December 2008.

Kaune, A., Chowdhury, F., Werner, M., and Bennett, J.: The benefit of using an ensemble of seasonal streamflow forecasts in water allocation decisions, Hydrol. Earth Syst. Sci., 24, 3851–3870, https://doi.org/10.5194/hess-24-3851-2020, 2020.

Keeney, R. L.: Decision Analysis: An Overview, Oper. Res., 30, 803–838, https://doi.org/10.1287/opre.30.5.803, 1982.

Keyantash, J. and Dracup, J. A.: The Quantification of Drought: An Evaluation of Drought Indices, 2002.

Kiem, A. S., Johnson, F., Westra, S., van Dijk, A., Evans, J. P., O'Donnell, A., Rouillard, A., Barr, C., Tyler, J., Thyer, M., Jakob, D., Woldemeskel, F., Sivakumar, B., and Mehrotra, R.: Natural hazards in Australia: droughts, Clim. Change, 139, 37–54, https://doi.org/10.1007/s10584-016-1798-7, 2016.

Kirchhoff, C. J., Lemos, M. C., and Engle, N. L.: What influences climate information use in water management? The role of boundary organizations and governance regimes in Brazil and the U.S., Environ. Sci. Policy, 26, 6–18, https://doi.org/10.1016/j.envsci.2012.07.001, 2013.

Kogan, F. N.: Operational Space Technology for Global Vegetation Assessment, Bull. Am. Meteorol. Soc., 82, 1949–1964, https://doi.org/10.1175/1520-0477(2001)082<1949:OSTFGV>2.3.CO;2, 2001.

Lackstrom, K., Brennan, A., Ferguson, D., Crimmins, M., Darby, L., Dow, K., Ingram, K., Meadow, A., Reges, H., Shafer, M., and Smith, K. H.: The Missing Piece: Drought Impacts Monitoring Report from a Workshop in Tucson, AZ MARCH 5-6, 2013, Drought Mitig. Cent. Fac. Publ., 112, 22, 2013.

Ladson, A., Brown, R., Neal, B., and Nathan, R.: A standard approach to baseflow separation using the Lyne and Hollick filter, Aust. J. Water Resour., 17, https://doi.org/10.7158/W12-028.2013.17.1, 2013.

Lemos, M. C.: Usable climate knowledge for adaptive and co-managed water governance, Curr. Opin. Environ. Sustain., 12, 48–52, https://doi.org/10.1016/j.cosust.2014.09.005, 2015.

Lemos, M. C., Bell, A. R., Engle, N. L., Formiga-Johnsson, R. M., and Nelson, D. R.: Technical knowledge and water resources management: A comparative study of river basin councils, Brazil, Water Resour. Res., 46, https://doi.org/10.1029/2009WR007949, 2010.

Lemos, M. C., Kirchhoff, C. J., and Ramprasad, V.: Narrowing the climate information usability gap, Nat. Clim. Change, 2, 789–794, https://doi.org/10.1038/nclimate1614, 2012.

Li, Y., Giuliani, M., and Castelletti, A.: A coupled human–natural system to assess the operational value of weather and climate services for agriculture, Hydrol. Earth Syst. Sci., 21, 4693–4709, https://doi.org/10.5194/hess-21-4693-2017, 2017.

Linés, C., Werner, M., and Bastiaanssen, W.: The predictability of reported drought events and impacts in the Ebro Basin using six different remote sensing data sets, Hydrol. Earth Syst. Sci., 21, 4747–4765, https://doi.org/10.5194/hess-21-4747-2017, 2017.

Linés, C., Iglesias, A., Garrote, L., Sotés, V., and Werner, M.: Do users benefit from additional information in support of operational drought management decisions in the Ebro basin?, Hydrol. Earth Syst. Sci., 22, 5901–5917, https://doi.org/10.5194/hess-22-5901-2018, 2018.

Liu, Y. Y., Parinussa, R. M., Dorigo, W. A., De Jeu, R. A. M., Wagner, W., Van Dijk, A. I. J. M., McCabe, M. F., and Evans, J. P.: Developing an improved soil moisture dataset by blending passive and active microwave satellite-based retrievals, Hydrol. Earth Syst. Sci., 15, 425–436, https://doi.org/10.5194/hess-15-425-2011, 2011.

Liu, Y. Y., Dorigo, W. A., Parinussa, R. M., De Jeu, R. A. M., Wagner, W., McCabe, M. F., Evans, J. P., and Van Dijk, A. I. J. M.: Trend-preserving blending of passive and active microwave soil moisture retrievals, Remote Sens. Environ., 123, 280–297, https://doi.org/10.1016/j.rse.2012.03.014, 2012.

Llasat, M. C., Llasat-Botija, M., Barnolas, M., López, L., and Altava-Ortiz, V.: An analysis of the evolution of hydrometeorological extremes in newspapers: the case of Catalonia, 1982–2006, Nat. Hazards Earth Syst. Sci., 9, 1201–1212, https://doi.org/10.5194/nhess-9-1201-2009, 2009.

Lloveras Vilamanyà, J., Martínez de la Cuesta, E., and Santiveri Morata, P.: Influencia de la fecha de siembra del maíz en los regadios del valle del Ebro (Influence planting date on maize crops in the irrigated areas of the Ebro Valley), Vida Rural, 374, 36–40, 2014.

Lopez, A. and Haines, S.: Exploring the Usability of Probabilistic Weather Forecasts for Water Resources Decision-Making in the United Kingdom, Weather Clim. Soc., 9, 701–715, https://doi.org/10.1175/WCAS-D-16-0072.1, 2017.

López-Moreno, J. I. and García-Ruiz, J. M.: Influence of snow accumulation and snowmelt on streamflow in the central Spanish Pyrenees / Influence de l'accumulation et de la fonte de la neige sur les écoulements dans les Pyrénées centrales espagnoles, Hydrol. Sci. J., 49, 3, https://doi.org/10.1623/hysj.49.5.787.55135, 2004.

López-Moreno, J. I., Vicente-Serrano, S. M., Zabalza, J., Beguería, S., Lorenzo-Lacruz, J., Azorin-Molina, C., and Morán-Tejeda, E.: Hydrological response to climate variability at different time scales: A study in the Ebro basin, J. Hydrol., 477, 175–188, https://doi.org/10.1016/j.jhydrol.2012.11.028, 2013.

Macauley, M. K.: The value of information: Measuring the contribution of space-derived earth science data to resource management, Space Policy, 22, 274–282, https://doi.org/10.1016/j.spacepol.2006.08.003, 2006.

MAGRAMA: Resultados técnico-económicos de Cultivos Herbáceos 2014 (ecnichal-economical results of herbaceous crops 2014), Subdirección General de Análisis, Prospectiva y Coordinación, Subsecretaría. Ministerio de Agricultura, Alimentación y Medio Ambiente, Spain, 2015.

MAPA: Resultados técnico-económicos: Cultivos herbáceos - Andalucía, Aragón, Castilla y León, Castilla-La Mancha, Cataluña, Extremadura y La Rioja 2016 [Techno-economic results: herbaceous crops - Andalucia, Aragon, Castilla y Leon, Castilla-La Mancha, Cataluña, Extremadura and La Rioja 2016], Ministerio de Agricultura, Pesca y Alimentación, 2020.

Matte, S., Boucher, M.-A., Boucher, V., and Fortier Filion, T.-C.: Moving beyond the cost–loss ratio: economic assessment of streamflow forecasts for a risk-averse decision maker, Hydrol. Earth Syst. Sci., 21, 2967–2986, https://doi.org/10.5194/hess-21-2967-2017, 2017.

McKee, T. B., Doesken, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scales, Eighth Conference of Applied Meteorology, Anaheim, California, January 1993.

McMillan, H., Montanari, A., Cudennec, C., Savenije, H., Kreibich, H., Krueger, T., Liu, J., Mejia, A., Van Loon, A., Aksoy, H., Di Baldassarre, G., Huang, Y., Mazvimavi, D., Rogger, M., Sivakumar, B., Bibikova, T., Castellarin, A., Chen, Y., Finger, D., Gelfan, A., Hannah, D. M., Hoekstra, A. Y., Li, H., Maskey, S., Mathevet, T., Mijic, A., Pedrozo Acuña, A., Polo, M. J., Rosales, V., Smith, P., Viglione, A., Srinivasan, V., Toth, E., van Nooyen, R., and Xia, J.: Panta Rhei 2013–2015: global perspectives on hydrology, society and change, Hydrol. Sci. J., 61, 1174–1191, https://doi.org/10.1080/02626667.2016.1159308, 2016.

McMillan, H., Seibert, J., Petersen-Overleir, A., Lang, M., White, P., Snelder, T., Rutherford, K., Krueger, T., Mason, R., and Kiang, J.: How uncertainty analysis of streamflow data can reduce costs and promote robust decisions in water management applications, Water Resour. Res., 53, 5220–5228, https://doi.org/10.1002/2016WR020328, 2017.

Miralles, D. G., Holmes, T. R. H., De Jeu, R. A. M., Gash, J. H., Meesters, A. G. C. A., and Dolman, A. J.: Global land-surface evaporation estimated from satellite-based observations, Hydrol. Earth Syst. Sci., 15, 453–469, https://doi.org/10.5194/hess-15-453-2011, 2011.

Mishra, A. K. and Singh, V. P.: A review of drought concepts, J. Hydrol., 391, 202–216, https://doi.org/10.1016/j.jhydrol.2010.07.012, 2010.

Mishra, A. K., Desai, V. R., and Singh, V. P.: Drought Forecasting Using a Hybrid Stochastic and Neural Network Model, J. Hydrol. Eng., 12, 626–638, https://doi.org/10.1061/(ASCE)1084-0699(2007)12:6(626), 2007.

MMA: Informe balance del año hidrológico (Assessment of the hydrological year 2004–2005), Ministerio de Medio Ambiente, Madrid, Spain, 2005.

MMA: Informe balance del año hidrológico (Assessment of the hydrological year 2006–2007), Ministerio de Medio Ambiente, Madrid, Spain, 2007.

Morid, S., Smakhtin, V., and Moghaddasi, M.: Comparison of seven meteorological indices for drought monitoring in Iran, Int. J. Climatol., 26, 971–985, https://doi.org/10.1002/joc.1264, 2006.

Mu, Q., Heinsch, F. A., Zhao, M., and Running, S. W.: Development of a global evapotranspiration algorithm based on MODIS and global meteorology data, Remote Sens. Environ., 111, 519–536, https://doi.org/10.1016/j.rse.2007.04.015, 2007.

Mu, Q., Zhao, M., and Running, S. W.: Improvements to a MODIS global terrestrial evapotranspiration algorithm, Remote Sens. Environ., 115, 1781–1800, https://doi.org/10.1016/j.rse.2011.02.019, 2011.

Mylne, K. R.: Decision-making from probability forecasts based on forecast value, Meteorol. Appl., 9, 307–315, https://doi.org/10.1017/S1350482702003043, 2002.

Niemeyer, S.: New drought indices, Options Méditerranéennes Sér. Sémin. Méditerranéens, 80, 267–274, 2008.

O'Keeffe, J., Buytaert, W., Mijic, A., Brozović, N., and Sinha, R.: The use of semi-structured interviews for the characterisation of farmer irrigation practices, Hydrol. Earth Syst. Sci., 20, 1911–1924, https://doi.org/10.5194/hess-20-1911-2016, 2016.

Onoda, M. and Young, O. R. (Eds.): Satellite Earth Observations and Their Impact on Society and Policy, Springer Singapore, Singapore, 221 pp., https://doi.org/10.1007/978-981-10-3713-9, 2017.

Pechlivanidis, I. G., Crochemore, L., Rosberg, J., and Bosshard, T.: What Are the Key Drivers Controlling the Quality of Seasonal Streamflow Forecasts?, Water Resour. Res., 56, https://doi.org/10.1029/2019WR026987, 2020.

Peñuela, A., Hutton, C., and Pianosi, F.: Assessing the value of seasonal hydrological forecasts for improving water resource management: insights from a pilot application in the UK, Hydrol. Earth Syst. Sci., 24, 6059–6073, https://doi.org/10.5194/hess-24-6059-2020, 2020.

Pérez Pérez, L. and Barreiro Hurlé, J.: Assessing the socio-economic impacts of drought in the Ebro river basin, Span. J. Agric. Res., 269–280, 2009.

Piani, C., Haerter, J. O., and Coppola, E.: Statistical bias correction for daily precipitation in regional climate models over Europe, Theor. Appl. Climatol., 99, 187–192, https://doi.org/10.1007/s00704-009-0134-9, 2010.

Pinilla, V.: The development of irrigated agriculture in twentieth-century Spain: a case study of the Ebro basin, Agric. Hist. Rev., 54, 122–141, 2006.

Porter, J. J. and Dessai, S.: Mini-me: Why do climate scientists' misunderstand users and their needs?, Environ. Sci. Policy, 77, 9–14, https://doi.org/10.1016/j.envsci.2017.07.004, 2017.

Potop, V.: Evolution of drought severity and its impact on corn in the Republic of Moldova, Theor. Appl. Climatol., 105, 469–483, https://doi.org/10.1007/s00704-011-0403-2, 2011.

Purdy, A. J., Kawata, J., Fisher, J. B., Reynolds, M., Om, G., Ali, Z., Babikian, J., Roman, C., and Mann, L.: Designing Drought Indicators, Bull. Am. Meteorol. Soc., 100, 2327–2341, https://doi.org/10.1175/BAMS-D-18-0146.1, 2019.

Quintana Seguí, P.: SAFRAN analysis over Spain [Data set]. ESPRI/IPSL., 2015.

Quintana Seguí, P., Peral, C., Turco, M., Llasat, M. del C., and Martin, E.: Meteorological analysis systems in North-East Spain: validation of SAFRAN and SPAN, 2016.

Quintana-Seguí, P., Turco, M., Herrera, S., and Miguez-Macho, G.: Validation of a new SAFRAN-based gridded precipitation product for Spain and comparisons to Spain02 and ERA-Interim, Hydrol. Earth Syst. Sci., 21, 2187–2201, https://doi.org/10.5194/hess-21-2187-2017, 2017.

Quintilla, R., Portero Callejero, C., and Casterad Seral, M. A.: Apoyo a la gestión del agua en alta en la zona regable del Canal de Aragón y Cataluña con teledetección, 2014.

Quiroga, S., Garrote, L., Iglesias, A., Fernández-Haddad, Z., Schlickenrieder, J., de Lama, B., Mosso, C., and Sánchez-Arcilla, A.: The economic value of drought information for water management under climate change: a case study in the Ebro basin, Nat. Hazards Earth Syst. Sci., 11, 643–657, https://doi.org/10.5194/nhess-11-643-2011, 2011.

R Core Team: R: A language and environment for statistical computing., R Foundation for Statistical Computing, Vienna, Austria, 2016.

Raaphorst, K., Koers, G., Ellen, G. J., Oen, A., Kalsnes, B., van Well, L., Koerth, J., and van der Brugge, R.: Mind the Gap: Towards a Typology of Climate Service Usability Gaps, Sustainability, 12, 1512, https://doi.org/10.3390/su12041512, 2020.

Redmond, K. T.: The depiction of drought: A Commentary, Bull. Am. Meteorol. Soc., 83, 1143–1147, 2002.

Repo, A. J.: The dual approach to the value of information: An appraisal of use and exchange values, Inf. Process. Manag., 22, 373–383, https://doi.org/10.1016/0306-4573(86)90072-5, 1986.

Ritchie, J. W., Zammit, C., and Beal, D.: Can seasonal climate forecasting assist in catchment water management decision-making?: A case study of the Border Rivers catchment in Australia, Agric. Ecosyst. Environ., 104, 553–565, https://doi.org/10.1016/j.agee.2004.01.029, 2004.

Roulin, E.: Skill and relative economic value of medium-range hydrological ensemble predictions, Hydrol. Earth Syst. Sci., 11, 725–737, https://doi.org/10.5194/hess-11-725-2007, 2007.

Rouse, J. W., Hass, R. H., Schell, J. A., Deering, D. W., and Harlan, J. C.: Monitoring the vernal advancement and retrogradation (Greenwave effect) of natural vegetation, Texas A&M University Remote Sensing Center, 1974.

Running, S. W. and Zhao, M.: Daily GPP and Annual NPP (MOD17A2/A3) Products NASA Earth Observing System MODIS Land Algorithm, 2015.

Schepen, A., Zhao, T., Wang, Q. J., and Robertson, D. E.: A Bayesian modelling method for post-processing daily sub-seasonal to seasonal rainfall forecasts from global climate models and evaluation for 12 Australian catchments, Hydrol. Earth Syst. Sci., 22, 1615–1628, https://doi.org/10.5194/hess-22-1615-2018, 2018.

Schrieks, T., Botzen, W. J. W., Wens, M., Haer, T., and Aerts, J. C. J. H.: Integrating Behavioral Theories in Agent-Based Models for Agricultural Drought Risk Assessments, Front. Water, 3, 2021.

Scott, C. A., Bastiaanssen, W. G. M., and Ahmad, M.-D.: Mapping Root Zone Soil Moisture Using Remotely Sensed Optical Imagery, J. Irrig. Drain. Eng., 129, 326–335, https://doi.org/10.1061/(ASCE)0733-9437(2003)129:5(326), 2003.

Senay, G. B., Bohms, S., Singh, R. K., Gowda, P. H., Velpuri, N. M., Alemu, H., and Verdin, J. P.: Operational Evapotranspiration Mapping Using Remote Sensing and Weather Datasets: A New Parameterization for the SSEB Approach, JAWRA J. Am. Water Resour. Assoc., 49, 577–591, https://doi.org/10.1111/jawr.12057, 2013.

Sepulcre-Canto, G., Horion, S., Singleton, A., Carrao, H., and Vogt, J.: Development of a Combined Drought Indicator to detect agricultural drought in Europe, Nat. Hazards Earth Syst. Sci., 12, 3519–3531, https://doi.org/10.5194/nhess-12-3519-2012, 2012.

Sheffield, J., Wood, E. F., Chaney, N., Guan, K., Sadri, S., Yuan, X., Olang, L., Amani, A., Ali, A., Demuth, S., and Ogallo, L.: A Drought Monitoring and Forecasting System for Sub-Sahara African Water Resources and Food Security, Bull. Am. Meteorol. Soc., 95, 861–882, https://doi.org/10.1175/BAMS-D-12-00124.1, 2014.

Shukla, S., Arsenault, K. R., Hazra, A., Peters-Lidard, C., Koster, R. D., Davenport, F., Magadzire, T., Funk, C., Kumar, S., McNally, A., Getirana, A., Husak, G., Zaitchik, B., Verdin, J., Nsadisa, F. D., and Becker-Reshef, I.: Improving early warning of drought-driven food insecurity in southern Africa using operational hydrological monitoring and forecasting products, Nat. Hazards Earth Syst. Sci., 20, 1187–1201, https://doi.org/10.5194/nhess-20-1187-2020, 2020.

Sivapalan, M., Savenije, H. H. G., and Blöschl, G.: Socio-hydrology: A new science of people and water, Hydrol. Process., 26, 1270–1276, https://doi.org/10.1002/hyp.8426, 2012.

Smakhtin, V. U. and Schipper, E. L. F.: Droughts: The impact of semantics and perceptions, Water Policy, 10, 131–143, https://doi.org/10.2166/wp.2008.036, 2008.

Sonnett, J., Morehouse, B. J., Finger, T. D., Garfin, G., and Rattray, N.: Drought and declining reservoirs: Comparing media discourse in Arizona and New Mexico, 2002–2004, Glob. Environ. Change, 16, 95–113, https://doi.org/10.1016/j.gloenvcha.2005.11.004, 2006.

Spinoni, J., Naumann, G., Vogt, J. V., and Barbosa, P.: The biggest drought events in Europe from 1950 to 2012, J. Hydrol. Reg. Stud., 3, 509–524, https://doi.org/10.1016/j.ejrh.2015.01.001, 2015.

Stagge, J. H., Tallaksen, L. M., Gudmundsson, L., Van Loon, A. F., and Stahl, K.: Candidate Distributions for Climatological Drought Indices (SPI and SPEI), Int. J. Climatol., 35, 4027–4040, https://doi.org/10.1002/joc.4267, 2015.

Stahl, K., Kohn, I., Blauhut, V., Urquijo, J., De Stefano, L., Acácio, V., Dias, S., Stagge, J. H., Tallaksen, L. M., Kampragou, E., Van Loon, A. F., Barker, L. J., Melsen, L. A., Bifulco, C., Musolino, D., de Carli, A., Massarutto, A., Assimacopoulos, D., and Van Lanen, H. A. J.: Impacts of European drought events: insights from an international database of text-based reports, Nat. Hazards Earth Syst. Sci., 16, 801–819, https://doi.org/10.5194/nhess-16-801-2016, 2016.

Stanski, H. R., Wilson, L. J., and Burrows, W. R.: Survey of common verification methods in meteorology, Atmospheric Environment Service, Downsview, Ontario, Canada, 1989.

Steinemann, A., Iacobellis, S. F., and Cayan, D. R.: Developing and Evaluating Drought Indicators for Decision-Making, J. Hydrometeorol., 16, 1793–1803, https://doi.org/10.1175/JHM-D-14-0234.1, 2015.

Steinemann, A. C.: Using Climate Forecasts for Drought Management, J. Appl. Meteorol. Climatol., 45, 1353–1361, https://doi.org/10.1175/JAM2401.1, 2006.

Steinemann, A. C. and Cavalcanti, L. F. N.: Developing Multiple Indicators and Triggers for Drought Plans, J. Water Resour. Plan. Manag., 132, 164–174, https://doi.org/10.1061/(ASCE)0733-9496(2006)132:3(164), 2006.

Su, Z.: The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes, Hydrol. Earth Syst. Sci., 6, 85–100, https://doi.org/10.5194/hess-6-85-2002, 2002.

Svoboda, M. and Fuchs, B.: Handbook of Drought Indicators and Indices, World Meteorological Organization (WMO) and Global Water Partnership (GWP), Geneva, 2016.

Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., Miskus, D., and Stephens, S.: The drought monitor, Bull. Am. Meteorol. Soc., 83, 1181–1190, https://doi.org/10.1175/1520-0477-83.8.1181, 2002.

Tsakiris, G., Pangalou, D., and Vangelis, H.: Regional Drought Assessment Based on the Reconnaissance Drought Index (RDI), Water Resour. Manag., 21, 821–833, https://doi.org/10.1007/s11269-006-9105-4, 2007.

Turner, S. W. D., Bennett, J. C., Robertson, D. E., and Galelli, S.: Complex relationship between seasonal streamflow forecast skill and value in reservoir operations, Hydrol. Earth Syst. Sci., 21, 4841–4859, https://doi.org/10.5194/hess-21-4841-2017, 2017.

UNESCO (Ed.): The United Nations world water development report, UNESCO publ, Paris, 2012.

UNISDR: Drought risk reduction framework and practices: contributing to the implementation of the hyogo framework for ac- tion, United Nations secretariat of the International Strategy for Disaster Reduction (UNISDR), Geneva, Switzerland, 2009.

Urquijo-Reguera, J., Gómez-Villarino, M. T., Pereira, D., and De Stefano, L.: An Assessment Framework to Analyze Drought Management Plans: The Case of Spain, Agronomy, 12, 970, https://doi.org/10.3390/agronomy12040970, 2022.

Valipour, M., Banihabib, M. E., and Behbahani, S. M. R.: Comparison of the ARMA, ARIMA, and the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir, J. Hydrol., 476, 433–441, https://doi.org/10.1016/j.jhydrol.2012.11.017, 2013.

Van Dijk, A. I. J. M. and Renzullo, L. J.: Water resource monitoring systems and the role of satellite observations, Hydrol. Earth Syst. Sci., 15, 39–55, https://doi.org/10.5194/hess-15-39-2011, 2011.

Van Loon, A. F., Gleeson, T., Clark, J., Van Dijk, A. I. J. M., Stahl, K., Hannaford, J., Di Baldassarre, G., Teuling, A. J., Tallaksen, L. M., Uijlenhoet, R., Hannah, D. M., Sheffield, J., Svoboda, M., Verbeiren, B., Wagener, T., Rangecroft, S., Wanders, N., and Van Lanen, H. A. J.: Drought in the Anthropocene, Nat. Geosci., 9, 89–91, https://doi.org/10.1038/ngeo2646, 2016.

Vasiliades, L., Loukas, A., and Liberis, N.: A Water Balance Derived Drought Index for Pinios River Basin, Greece, Water Resour. Manag., 25, 1087–1101, https://doi.org/10.1007/s11269-010-9665-1, 2011.

Verkade, J. S. and Werner, M. G. F.: Estimating the benefits of single value and probability forecasting for flood warning, Hydrol. Earth Syst. Sci., 15, 3751–3765, https://doi.org/10.5194/hess-15-3751-2011, 2011.

Verma, M., Friedl, M. A., Richardson, A. D., Kiely, G., Cescatti, A., Law, B. E., Wohlfahrt, G., Gielen, B., Roupsard, O., Moors, E. J., Toscano, P., Vaccari, F. P., Gianelle, D., Bohrer, G., Varlagin, A., Buchmann, N., Van Gorsel, E., Montagnani, L., and Propastin, P.: Remote sensing of annual terrestrial gross primary productivity from MODIS: an assessment using the FLUXNET La Thuile data set, Biogeosciences, 11, 2185–2200, https://doi.org/10.5194/bg-11-2185-2014, 2014.

Vicente-Serrano, S. M., Cuadrat-Prats, J. M., and Romo, A.: Early prediction of crop production using drought indices at different time-scales and remote sensing data: application in the Ebro Valley (north-east Spain), Int. J. Remote Sens., https://doi.org/10.1080/01431160500296032, 2006.

Vicente-Serrano, S. M., Beguería, S., Lorenzo-Lacruz, J., Camarero, J. J., López-Moreno, J. I., Azorin-Molina, C., Revuelto, J., Morán-Tejeda, E., and Sanchez-Lorenzo, A.: Performance of Drought Indices for Ecological, Agricultural, and Hydrological Applications, Earth Interact., 16, 1–27, https://doi.org/10.1175/2012EI000434.1, 2012.

Wagner, W., Dorigo, W., De Jeu, R., Fernandez, D., Benveniste, J., Haas, E., and Ertl, M.: Fusion of active and passive microwave observations to create an essential climate variable data record on soil moisture, ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci., I–7, 315–321, https://doi.org/10.5194/isprsannals-I-7-315-2012, 2012.

Wens, M., Johnson, J. M., Zagaria, C., and Veldkamp, T. I. E.: Integrating human behavior dynamics into drought risk assessment—A sociohydrologic, agent-based approach, WIREs Water, 6, e1345, https://doi.org/10.1002/wat2.1345, 2019.

Wens, M. L. K.: Farmers facing droughts: Capturing adaptation dynamics in disaster risk models, Vrije Universiteit Amsterdam, 2022.

White, C. J., Domeisen, D. I. V., Acharya, N., Adefisan, E. A., Anderson, M. L., Aura, S., Balogun, A. A., Bertram, D., Bluhm, S., Brayshaw, D. J., Browell, J., Büeler, D., Charlton-Perez, A., Chourio, X., Christel, I., Coelho, C. A. S., DeFlorio, M. J., Delle Monache, L., Di Giuseppe, F., García-Solórzano, A. M., Gibson, P. B., Goddard, L., González Romero, C., Graham, R. J., Graham, R. M., Grams, C. M., Halford, A., Huang, W. T. K., Jensen, K., Kilavi, M., Lawal, K. A., Lee, R. W., MacLeod, D., Manrique-Suñén, A., Martins, E. S. P. R., Maxwell, C. J., Merryfield, W. J., Muñoz, Á. G., Olaniyan, E., Otieno, G., Oyedepo, J. A., Palma, L., Pechlivanidis, I. G., Pons, D., Ralph, F. M., Reis, D. S., Remenyi, T. A., Risbey, J. S., Robertson, D. J. C., Robertson, A. W., Smith, S., Soret, A., Sun, T., Todd, M. C., Tozer, C. R., Vasconcelos, F. C., Vigo, I., Waliser, D. E., Wetterhall, F., and Wilson, R. G.: Advances in the Application and Utility of Subseasonal-to-Seasonal Predictions, Bull. Am. Meteorol. Soc., 103, E1448–E1472, https://doi.org/10.1175/BAMS-D-20-0224.1, 2022.

Wilhite, D. A.: Chapter 1 Drought as a Natural Hazard: Concepts and Definitions, Drought Mitig. Cent. Fac. Publ., 69, 2000.

Wilhite, D. A.: National Drought Policies: Addressing Impacts and Societal Vulnerability, Drought Mitig. Cent. Fac. Publ., 80, 22, 2011.

Wilhite, D. A. and Glantz, M. H.: Understanding the Drought Phenomenon: The Role of Definitions, WATER Int., 1985.

Wilhite, D. A. and Vanyarkho, O. V.: Drought: Pervasive Impacts of a Creeping Phenomenon, 2000.

Wilhite, D. A., Svoboda, M. D., and Hayes, M. J.: Understanding the complex impacts of drought: A key to enhancing drought mitigation and preparedness, Water Resour. Manag., 21, 763–774, https://doi.org/10.1007/s11269-006-9076-5, 2007.

Wilks, D. S.: Forecast value: prescriptive decision studies., in: Economic Value of Weather and Climate Forecasts, Cambridge University Press, 109–145, 1997.

Wilks, D. S.: Statistical Methods in the Atmospheric Sciences, 4, 2011.

Wilks, D. S. and Murphy, A. H.: A decision-analytic study of the joint value of seasonal precipitation and temperature forecasts in a choice-of-crop problem, Atmosphere-Ocean, 24, 353–368, https://doi.org/10.1080/07055900.1986.9649257, 1986.

Williamson, R. A., Hertzfeld, H. R., Cordes, J., and Logsdon, J. M.: The socioeconomic benefits of Earth science and applications research: reducing the risks and costs of natural disasters in the USA, Space Policy, 18, 57–65, https://doi.org/10.1016/S0265-9646(01)00057-1, 2002.

Winsemius, H. C., Dutra, E., Engelbrecht, F. A., Archer Van Garderen, E., Wetterhall, F., Pappenberger, F., and Werner, M. G. F.: The potential value of seasonal forecasts in a changing climate in southern Africa, Hydrol. Earth Syst. Sci., 18, 1525–1538, https://doi.org/10.5194/hess-18-1525-2014, 2014.

WMO: Standardized Precipitation Index User Guide, edited by: Svoboda, M., Hayes, M., and Wood, D., Geneva, Switzerland, 2012.

Yihdego, Y., Vaheddoost, B., and Al-Weshah, R. A.: Drought indices and indicators revisited, Arab. J. Geosci., 12, 69, https://doi.org/10.1007/s12517-019-4237-z, 2019.

Yuan, S., Li, X., and Du, E.: Effects of farmers' behavioral characteristics on crop choices and responses to water management policies, Agric. Water Manag., 247, 106693, https://doi.org/10.1016/j.agwat.2020.106693, 2021.

Yuan, X., Wood, E. F., and Ma, Z.: A review on climate-model-based seasonal hydrologic forecasting: physical understanding and system development, WIREs Water, 2, 523–536, https://doi.org/10.1002/wat2.1088, 2015.

Zargar, A., Sadiq, R., Naser, B., and Khan, F. I.: A review of drought indices, Environ. Rev., 19, 333–349, https://doi.org/10.1139/a11-013, 2011.

Zhang, F., Chen, J. M., Chen, J., Gough, C. M., Martin, T. A., and Dragoni, D.: Evaluating spatial and temporal patterns of MODIS GPP over the conterminous U.S. against flux measurements and a process model, Remote Sens. Environ., 124, 717–729, https://doi.org/10.1016/j.rse.2012.06.023, 2012.

Zhao, T., Bennett, J. C., Wang, Q. J., Schepen, A., Wood, A. W., Robertson, D. E., and Ramos, M.-H.: How Suitable is Quantile Mapping For Postprocessing GCM Precipitation Forecasts?, J. Clim., 30, 3185–3196, https://doi.org/10.1175/JCLI-D-16-0652.1, 2017.

Zhu, Y., Toth, Z., Wobus, R., Richardson, D., and Mylne, K.: The economic value of ensemble-based weather forecasts, Bull. Am. Meteorol. Soc., 83, 73–84, https://doi.org/10.1175/1520-0477(2002)083<0073:TEVOEB>2.3.CO;2, 2002.

CODE AND DATA AVAILABILITY

CHAPTER 2

The remote sensing data used for Chapter 2 is openly available. The sources are mentioned in Section 2.2.2. In situ data from the basin measurement network can be downloaded from the Ebro Basin authority site (www.chebro.es). Crop yield data can be downloaded from the site of the Aragón government (www.aragon.es). The dataset derived from the review of newspaper records is available in GitHub (https://github.com/lnscl/SM/tree/main). The corresponding news articles can be accessed online at www.elperiodicodearagon.com.

CHAPTER 3

All in situ and remote sensing data used for this Chapter are openly available. The sources are mentioned in Section 3.5.1. The crop models, Aquacrop-OS and Cropwat, are open-source and available from https://github.com/aquacropos/aquacrop-matlab and http://www.fao.org/land-water/databases-and-software/cropwat/ respectively. The code for the decision model is available in GitHub (https://github.com/lnscl/SM/tree/main).

CHAPTER 4

Seasonal forecast data from ECMWF SEAS5 is available from the ECMWF MARS archive (https://www.ecmwf.int/). Seasonal forecast data (raw and bias corrected) sampled to the catchment is available in GitHub (https://github.com/lnscl/SM/tree/main, see input_files/seasonal_forecast).

SAFRAN data is published under DOI 10.14768/MISTRALS-HYMEX.1388. See https://www.obsebre.es/en/en-safran for additional information.

Streamflow data from the Spanish national gauging station network (Red Integrada de Estaciones de Aforo, ROEA) is openly available at https://sig.mapama.gob.es/geoportal/. See https://www.miteco.gob.es/en/cartografia-y-sig/ide/descargas/agua/anuario-de-aforos.html for additional information.

The code for the decision model is available in GitHub (https://github.com/lnscl/SM/tree/main). AquacropOS input files (used for barley and maize simulation) containing the crop model parameters available in the same GitHub folder (see input_files/crop_model_files subfolder). For Cropwat the default parameter files for alfalfa and peach were used.

APPENDICES

APPENDIX A: THE EBRO BASIN

The Ebro basin is located in the northeast of Spain and limited by the Pyrenees to the north and the Iberian System to the south. The enclosed valley is crossed from the northwest to the southeast by the Ebro River (970 km), which flows from the Cantabrian mountains to the Mediterranean Sea, where it forms a large delta.

The Ebro basin is the largest catchment in the country, covering about a sixth of the country's surface (85,600 km^2). It is shared by 18 provinces from 9 Autonomous Regions, with a small part of the catchment falling in Andorra and France.

The area is scarcely populated, with almost half of its 3,675,000 inhabitants located in the cities of Zaragoza, Vitoria, Logroño, Pamplona, Huesca and Lleida.

Climate

The Ebro basin has a Mediterranean climate with varied geographical influences that result in different subtypes (Atlantic in the northeast, continental in the interior, mountain in the Pyrenees and Iberian System and coastal close to the Mediterranean Sea) and high differences of precipitation and temperature ranges within the basin (Table A-1). The average total annual precipitation for the basin is around 600 mm for the period 1980-2018, but it has a high inter-annual variability, ranging from 430 to 830 mm in that period (CHE, 2022). Spring and autumn receive the highest amount of precipitation; the summer tends to be dry with occasional storms, and the winter sees extended periods of anticyclonic conditions too (López-Moreno et al., 2013). In the upper part of the northern catchments, which fall in the Pyrenees, precipitation falls mostly as snow from November to the end of April and remains as snow cover at high elevations (> 1600 m) (López-Moreno and García-Ruiz, 2004).

Table A-1. Mediterranean climate subtypes in the Ebro basin (CHE, 2022).

Subtype	P (mm/year)	Seasonal P variation
Mountain	800-1800	Tendency to min. in summer
Transition	700-900	Max. in spring, min. in winter
Continental sub-humid	500-700	Min. in winter

Continental dry	350-500	Max. in spring and autumn
Pre-costal	600-800	Max. in spring and autumn
Costal	500-600	Max. in autumn

Hydrology

The Ebro has more than 200 tributaries and an annual mean discharge in natural conditions of roughly 500 m^3/s (CHE, 2022). The highest contribution arrives from the northern bank tributaries, where the main tributaries are Aragón, Gállego, Cinca and Segre rivers. Southern bank tributaries contribute around a 5 % to the total runoff (Batalla et al., 2004).

It is a highly regulated basin with 125 reservoirs (>1 hm^3) and a total storage capacity of more than 7800 Mm^3 (CHE, 2018), with water in most reservoir completely used within the season (Batalla et al., 2004).

Groundwater use contributes around the 7 % of the water resources used in the basin, with aquifers located mainly in the southern bank catchments such as Cidacos, Jalón an Huerva rivers. In other catchments such as Ésera-Noguera Ribagozana, Garona, Matarranya or Najerilla less than 1 % of the water used for supply comes from groundwater (CHE, 2022).

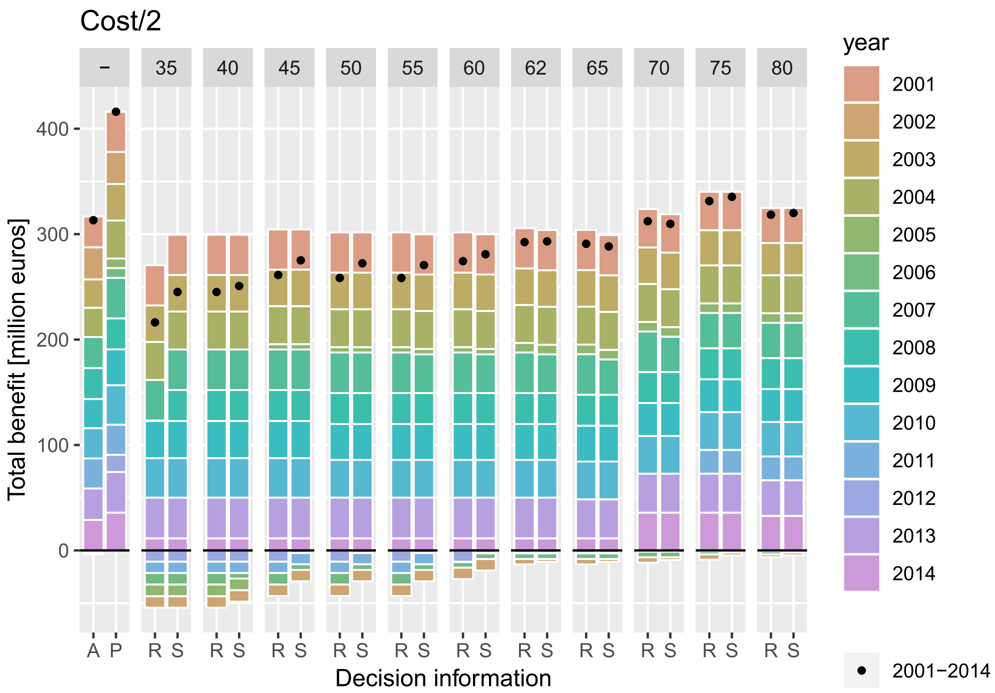
The response to previous climatic conditions is varied across the basin due to differences in altitude, groundwater storage, reservoir operations and snow accumulation. Unregulated Pyrenees basins showed responses at shorter time scales (2-4 months) than other areas in the basin, with longer response times in the winter and spring when the snow is present (López-Moreno and García-Ruiz, 2004). The snow accumulation in the Pyrenees part of the catchment is a key factor for reservoir management and irrigation supply (López-Moreno and García-Ruiz, 2004).

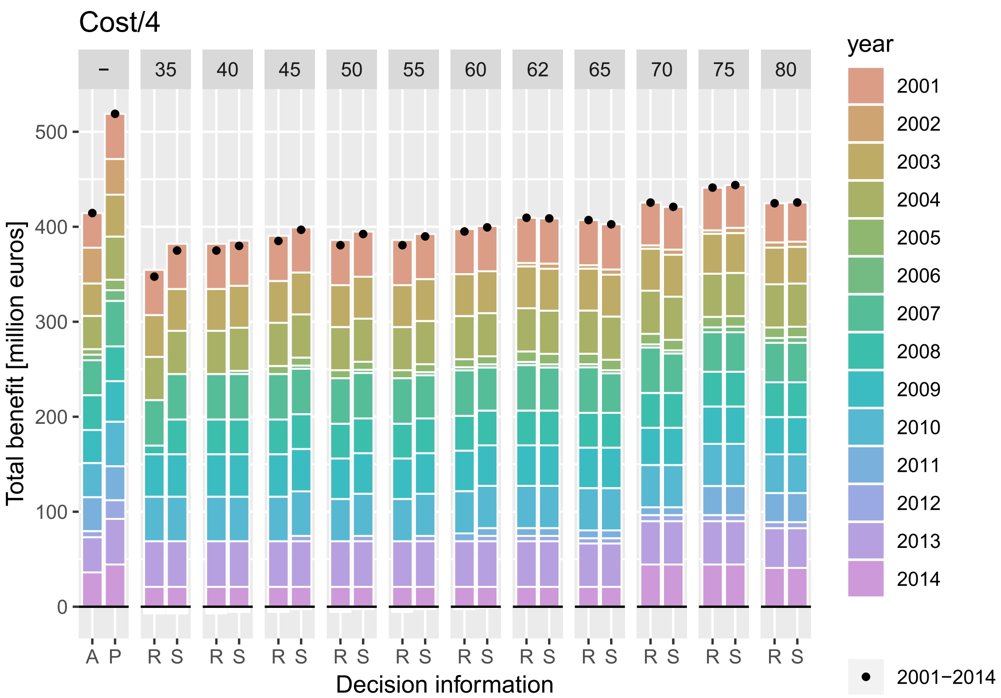
Water uses

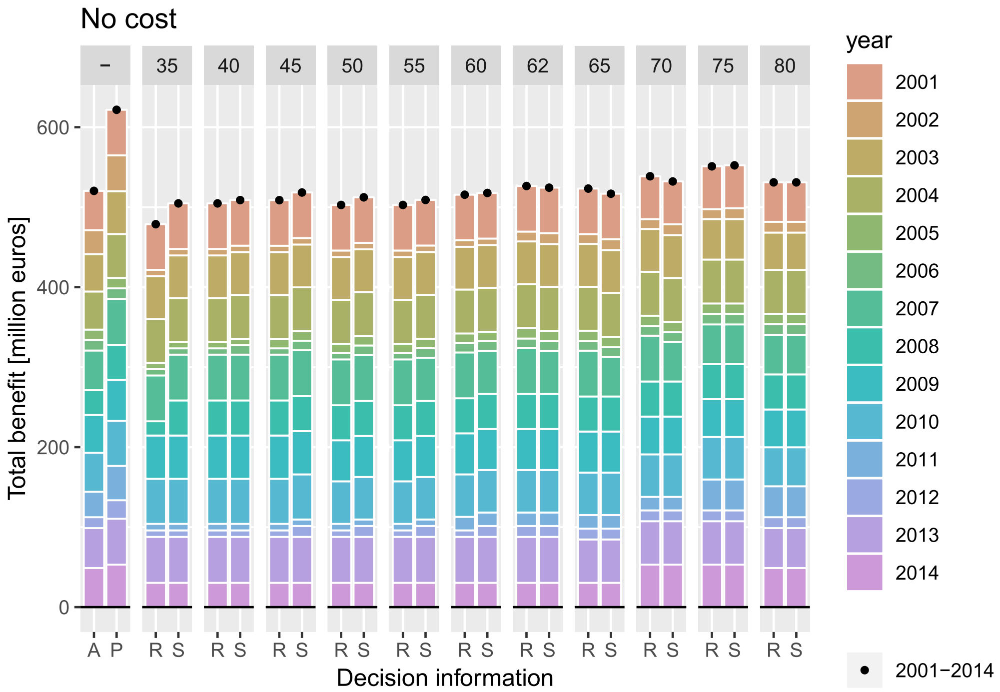
Over 90 % of the water supplied in the basin in 2016 was used for irrigated agriculture (CHE, 2022). The basin has over 900,000 ha dedicated to irrigated agriculture, from which over 780,000 ha were irrigated in 2019 according to survey data (CHE, 2022). Other uses include supply to population (> 5 % of the water supplied), industrial uses (> 2 %), animal husbandry, fish farming, hydroelectricity (> 350 plants in use), refrigeration and recreational uses.

APPENDIX B: SUPPLEMENTARY MATERIALS CHAPTER 3

B1 Total benefit for different costs

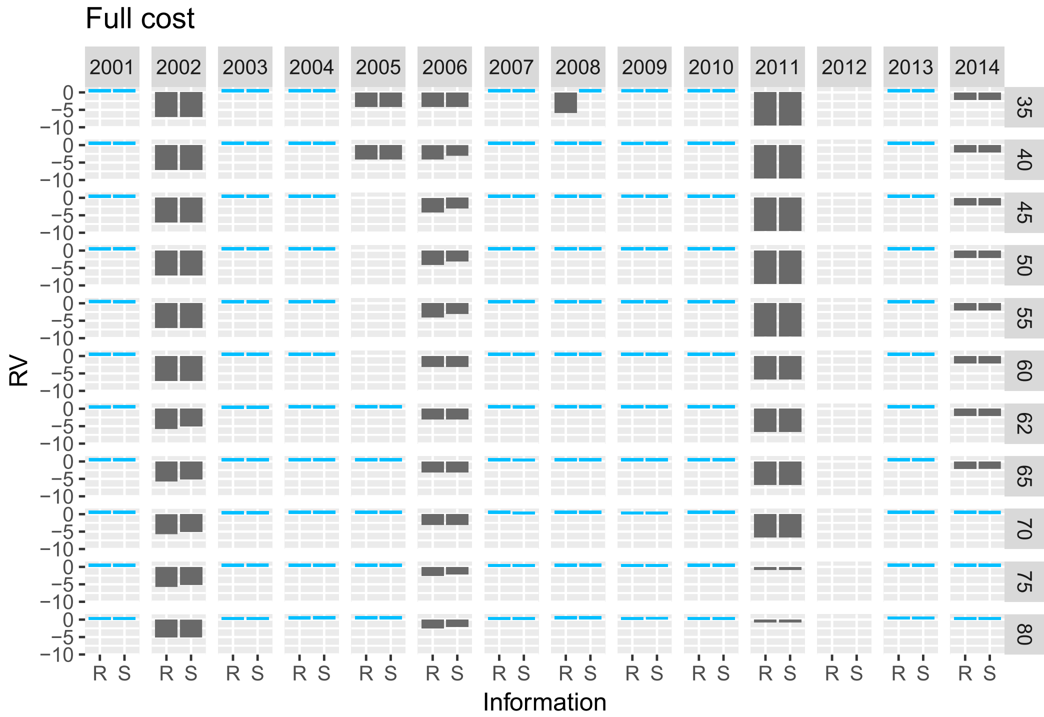


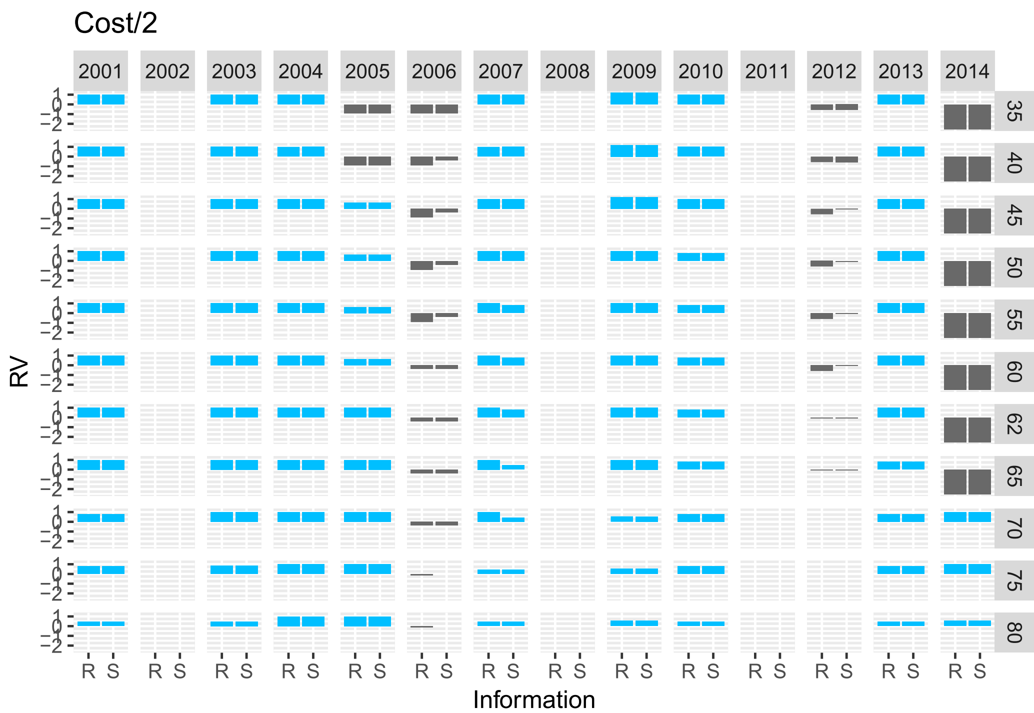


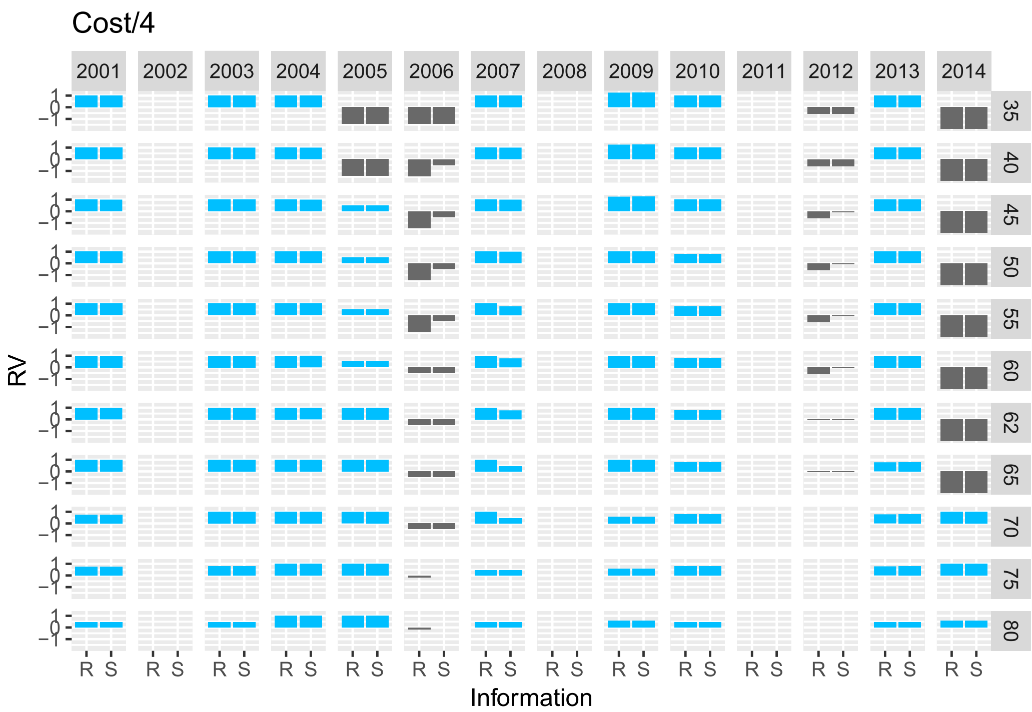


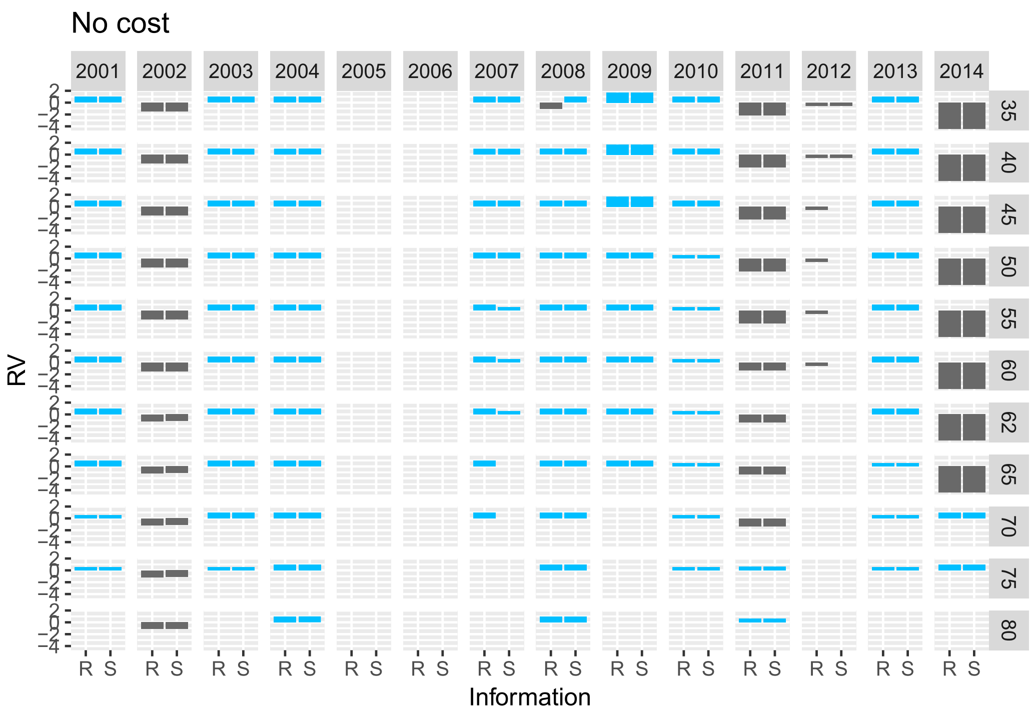
B2 Yearly relative value

Yearly Relative Value for decisions informed by reservoir level alone (R) and with the addition of snow information (S) for the 10 sets of thresholds and the optimized thresholds (labelled as 62). When the uninformed decision results in the same benefit as the perfect information the Relative Value is -Infinite and is left blank in the plot.


Full cost
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
35
40
45
50
55
60
62
65
70
75
80
0
−5
−10
RV
R S
Information


Cost/2
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
35
40
45
50
55
60
62
65
70
75
80
1
0
−1
−2
RV
R S
Information





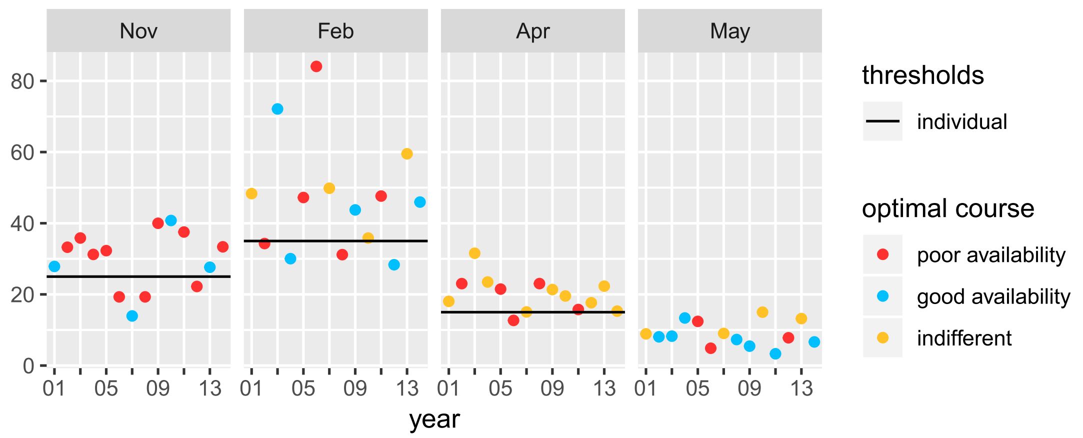
B3 Total benefit for different costs

Ten additional runs were performed with random snow values. The objective is to test if the improvements in the decisions observed when the model is run with additional information are indeed the result of better information and not a casual effect.

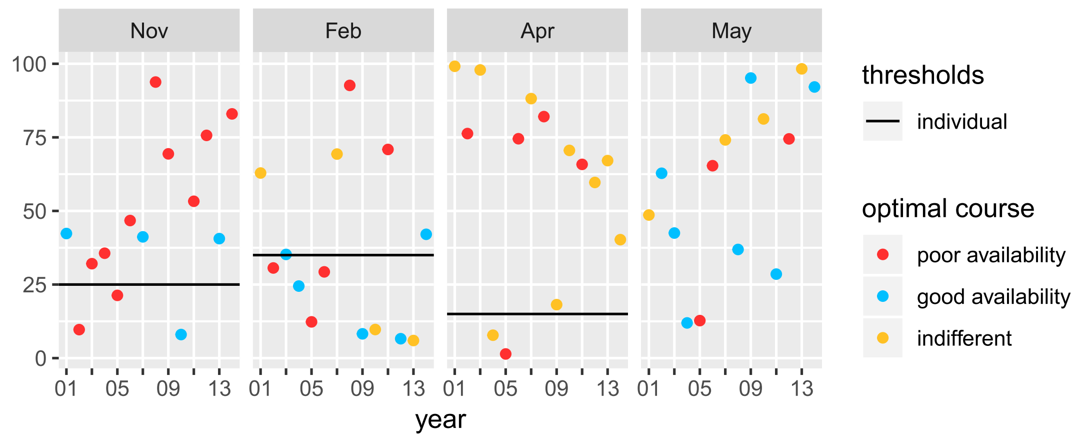
The first run (run 00) corresponds to MODIS snow data and the following runs (run 02-10) to the generated random data. One of the runs with random data is included here as an example, the full set can be accessed in the paper supplementary materials (https://hess.copernicus.org/articles/22/5901/2018/hess-22-5901-2018-supplement.pdf).

(a) Snow data

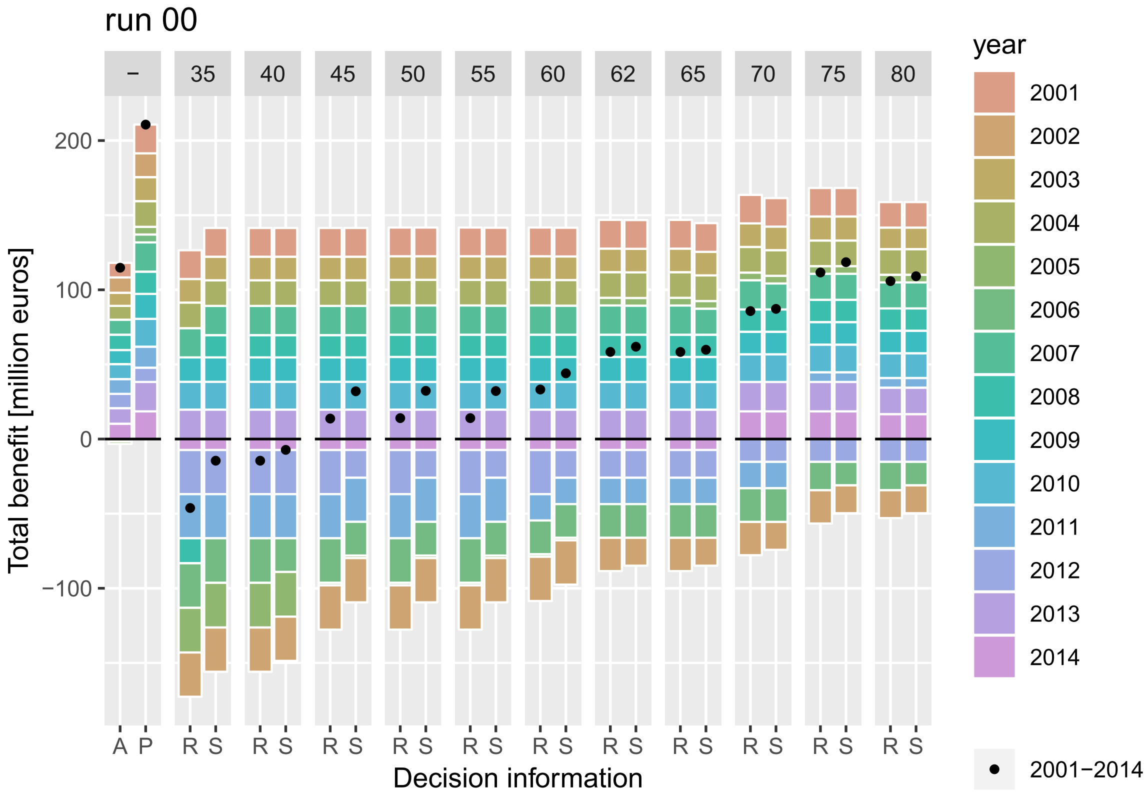
Run 00



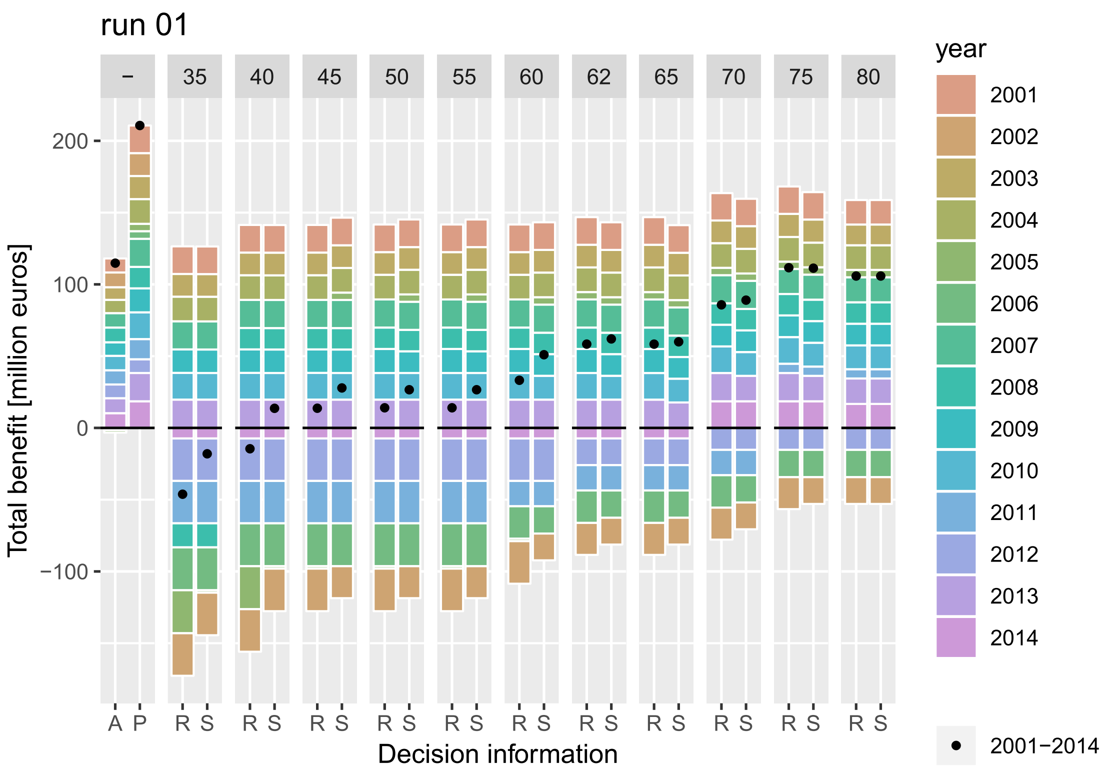
Run 01



(b) Total benefit (stacked values)



run 00
year
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2001−2014
Total benefit [million euros]
200
100
0
−100
–
35
40
45
50
55
60
62
65
70
75
80
A P
R S
Decision information



run 01
year
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2001−2014
Total benefit [million euros]
200
100
0
−100
–
35
40
45
50
55
60
62
65
70
75
80
A P
R S
Decision information

APPENDIX C: SUPPLEMENTARY MATERIALS CHAPTER 4

C1 Seasonal Forecast Data, bias correction and skill assessment

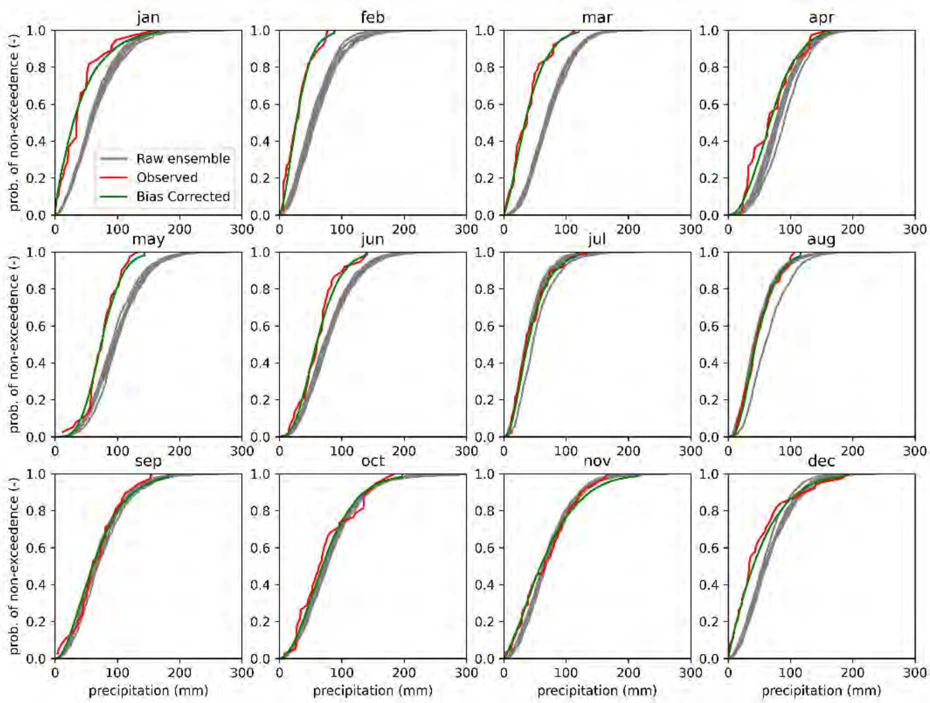


Figure C1-1. Cumulative empirical distributions of catchment averaged observed precipitation (SAFRAN, red lines) and seasonal forecasts (ECMWF SEAS5, grey lines) and bias corrected seasonal forecasts (green line) for each month. Precipitation data is averaged over the catchment area of the Barasona catchment (see main text, Figure 1). Grey lines show distributions for each 7 month lead time, but these are pooled prior to bias correcting. ECMWF-SEAS5 forecasts was found to include spurious extreme precipitation events (SPI1>2), which we censored to a maximum of SPI1=2.

Table C1-1. Parameters of the 2 parameter Gamma distribution (location=0) for each month for observed and forecast data used for bias correction. p-values established with Cramér-von-Mises test show Gamma distribution is acceptable at the 5% significant level. Given the large sample size, p-values for the forecast distributions were established as the median p-value of 100 randomly drawn samples with the same length as the number of observed years. Note that these parameters are for the full dataset. Parameters for the leave-one-year-out cross validation, where for data for the year for which a forecast is made is left out in fitting distributions and models.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
						Observed						
Alpha	0.89	1.95	1.70	3.43	6.95	3.92	2.49	3.36	2.36	2.59	1.62	1.12
Scale	46.03	15.76	23.32	20.64	10.90	16.09	17.94	14.68	28.90	29.43	42.97	46.29
p-value	0.28	0.86	0.89	0.60	0.69	0.80	0.96	0.99	0.60	0.83	0.66	0.99
						Forecast						
Alpha	2.44	2.58	3.85	5.07	5.73	3.70	2.61	2.75	2.94	2.86	2.77	2.54
Scale	25.84	23.00	18.68	16.25	17.17	21.37	16.44	18.43	24.01	28.30	25.44	25.46
p-value	0.49	0.50	0.49	0.52	0.37	0.52	0.47	0.47	0.48	0.50	0.46	0.41

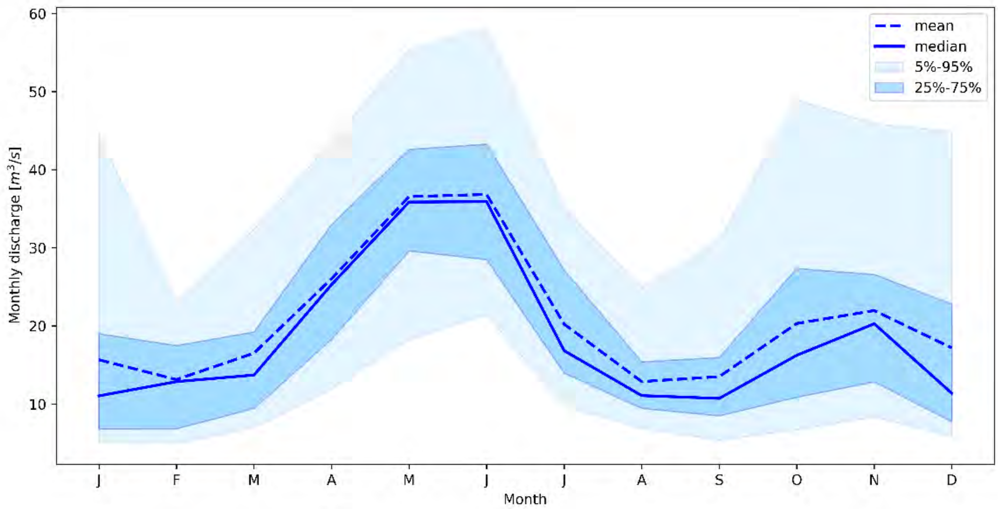


Figure C1-2. Climatological mean monthly inflow discharge to the Barasona reservoir (combined inflow of the Isábena and Ésera rivers).

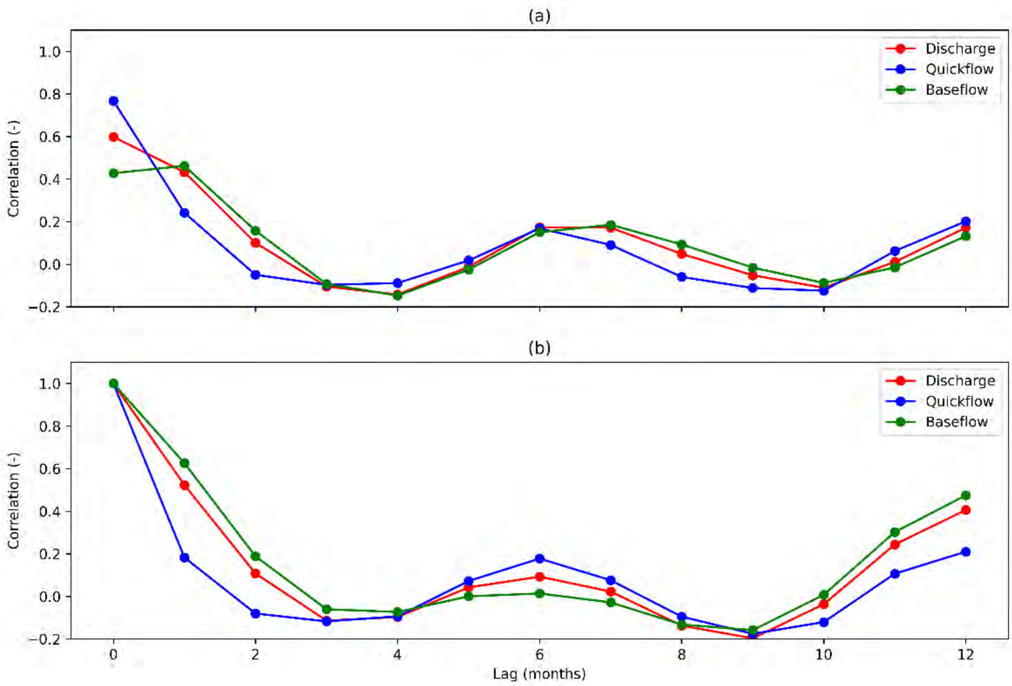


Figure C1-3. (a) lag-correlation between catchment average precipitation and discharge. (b) Auto-correlation of the (total) discharge, baseflow and quickflow.

Table C1-2. Upper table shows the parameters of the 2 parameter Gamma distribution (location=0) for each month fitted to the baseflow derived through baseflow separation from the total observed flow. p-values established with Cramér-von-Mises test show Gamma distribution is acceptable at the 5% significant level for all months. Lower table shows the parameters of the linear regression model fitted using ordinary least squares to each month to predict quickflow from the monthly precipitation. Adjusted-R2 shows lower predictive for snowmelt season as well as for low-flow summer months. Note that these parameters are for the full dataset. Parameters for the leave-one-year-out cross validation, where for data for the year for which a forecast is made is left out in fitting distributions and models.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Gamma distribution parameters to transform baseflow to SRI1 used in the ARIMAX model												
Alpha	3.92	3.06	5.00	10.39	14.85	11.93	12.63	7.56	8.42	7.00	9.36	9.14
Scale	13.86	13.48	7.44	4.53	4.18	5.85	4.84	6.93	6.48	9.18	7.64	7.22
p-value	0.98	0.91	0.85	0.52	0.89	0.67	0.48	0.92	0.90	0.87	0.92	0.51
Linear regression model used to predict quickflow from monthly precipitation												
Slope	0.12	0.07	0.11	0.09	0.07	0.07	0.04	0.04	0.08	0.13	0.11	0.10
Constant	-0.91	0.48	0.04	1.52	3.57	2.96	1.95	1.13	-1.11	-2.25	-0.19	0.08
Adj- R2	0.77	0.53	0.52	0.59	0.28	0.17	0.25	0.29	0.61	0.76	0.68	0.66

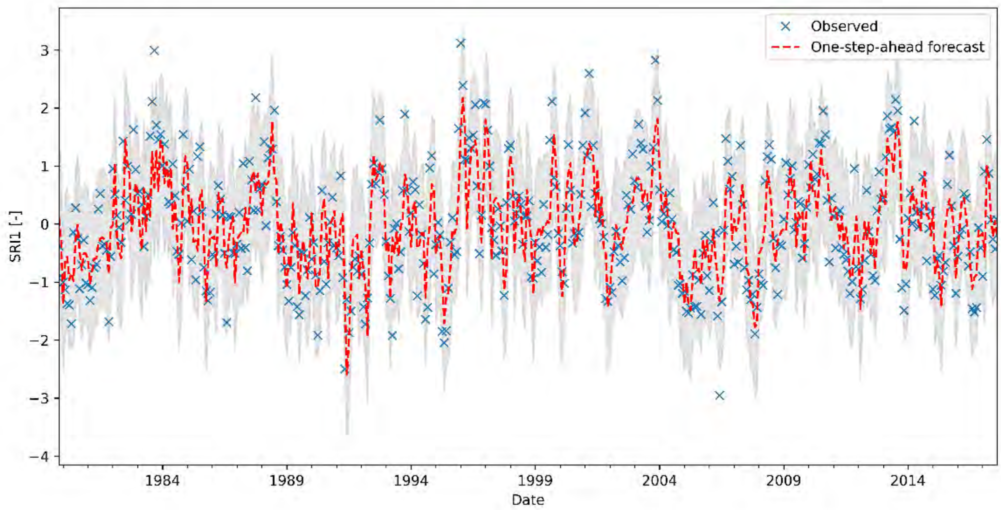


Figure C1-4. One-step ahead predictions using the ARIMAX model for predicting baseflow. Selected best performing model has ARIMA model structure [1,0,1], with parameters AR=0.78 and MA=-0.37. Monthly precipitation for the predicted month is exogenous variable X=0.57 and is derived from here from observed precipitation and in forecast mode from bias corrected ECMWF-SEAS5 precipitation. Predicted SRI1 values are back-transformed to discharge using Gamma distribution parameters in Table C1-2. R^2 of the 1-step ahead prediction is 0.63, with a bias of -0.003.

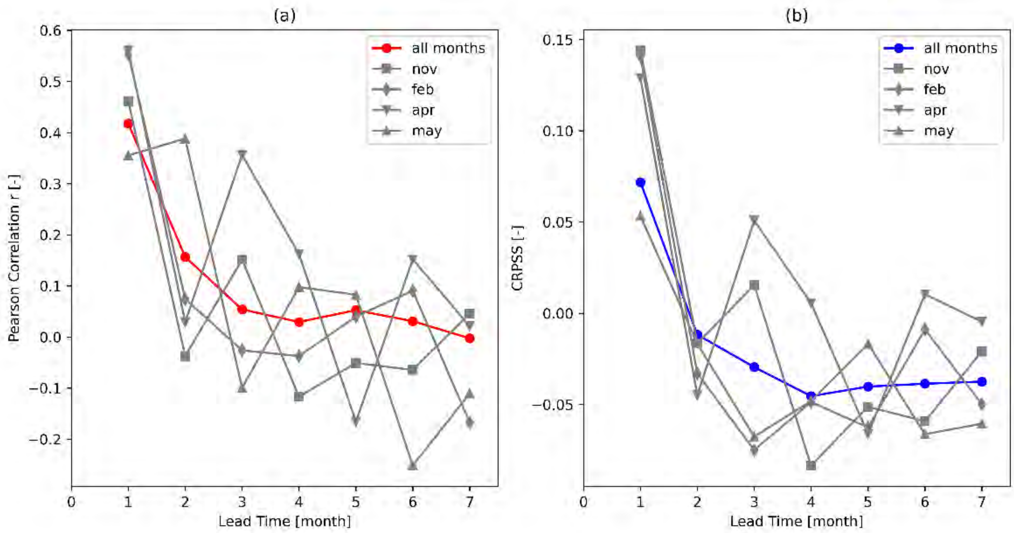


Figure C1-5. Skill assessment of the bias-corrected ECMWF-SEAS5 precipitation forecast for the Barasona catchment. (a) shows the Pearson correlation coefficient of the ensemble mean of the monthly precipitation for all forecast months, with grey lines showing the skill for months in which decisions are made (see decision model, main text. (b) shows the same for the CRPSS with forecast skill calculated using climatology as a reference forecast. Skill is assessed using a leave-one-year-out cross validation strategy, where observed data for *the year of the initiation date of the forecast is not considered in deriving parameters for distributions and forecast models.*

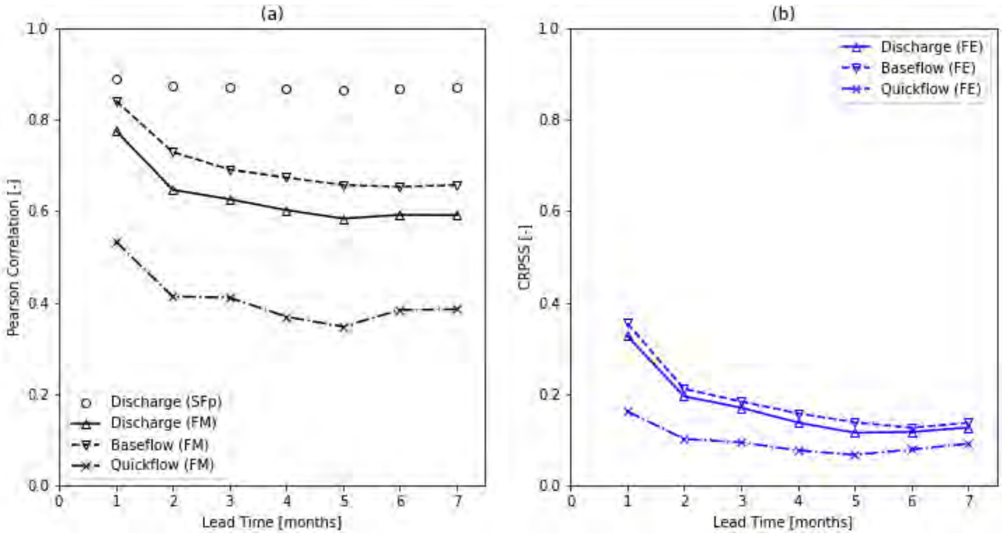


Figure C1-6. Skill assessment of the inflow to the Barasona reservoir using bias corrected precipitation. (a) Correlation of the ensemble mean (solid lines) for lead times 1 through 7 months, with the correlation for the baseflow and quickflow components (using respective models) also shown. Circles show the correlation of the streamflow prediction using perfect (observed) precipitation to force the streamflow forecast model. (b) Continuous Ranked Probability Skill Score, using climatology as a reference, for the ensemble streamflow forecast (solid line) as well as for the baseflow (dashed) and the quickflow (dash-dot). Skill is assessed using a leave-one-year-out cross validation strategy.

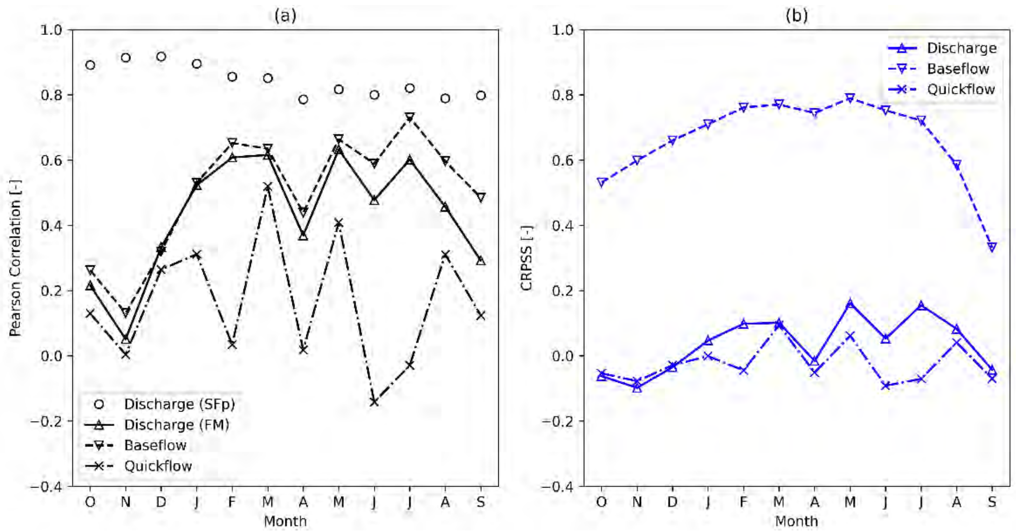


Figure C1-7. Skill assessment for the accumulated inflow to the Barasona reservoir, evaluated using the accumulated inflow from the start of forecast through to the end of the irrigation season at the end of September. (a) Correlation of the ensemble mean (solid line) for each accumulation, with the correlation for the baseflow and quickflow components (using respective models) also shown. Circles show the correlation of the accumulated streamflow prediction using perfect (observed) precipitation to force the streamflow forecast *model. (b) Continuous Ranked Probability Skill Score, using climatology as a reference, for the ensemble streamflow forecast (solid line) as well as for the baseflow (dashed) and the quickflow (dash-dot). Skill is assessed using a leave-one-year-out cross validation strategy.*

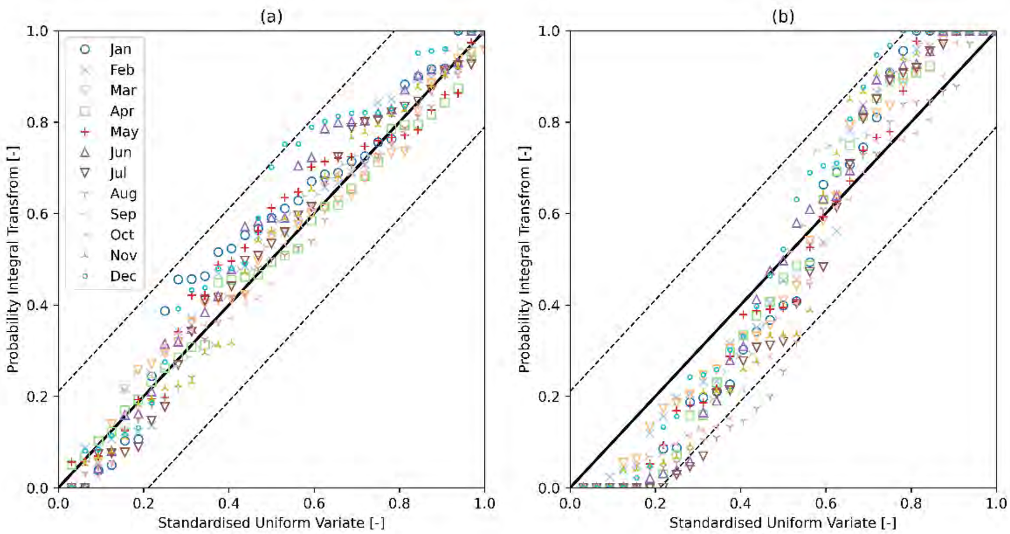


Figure C1-8. Probability Integral Transform plots of (a) accumulated (bias corrected) precipitation and (b) accumulated streamflow forecasts from the month start of prediction to the end of season at the end of September. A perfectly reliable forecast follows the main diagonal, with dotted lines showing the 95% confidence intervals for the Kolmogorov-Smirnoff test. Skill is assessed using a leave-one-year-out cross validation strategy.

C2 Crop yields

Table C2-1. Yields (in tonnes per hectare) for long-cycle maize (LCM), long-cycle barley (LCB), short-cycle maize (SCM) and short-cycle barley (SCB) obtained in AquacropOS.

	LCM	LCB	SCM	SCB
1984	17.61	10.07	15.09	4.03
1985	17.73	9.79	14.82	3.89
1986	17.98	10.06	15.03	4.01
1987	17.82	10.21	14.63	4.06
1988	18.6	10.12	15.52	4.02
1989	17.74	10.35	14.95	4.17
1990	17.69	9.95	14.72	4.02
1991	17.58	9.88	14.57	3.96
1992	18.64	10.11	14.89	4.04
1993	18.49	10.45	15.55	4.19
1994	17.76	10.54	14.78	4.21
1995	18.16	10.53	15.1	4.22
1996	18.58	10.61	15.97	4.3
1997	18.26	10.66	15.63	4.26
1998	17.97	10.48	15.1	4.21
1999	17.29	10.62	14.43	4.28
2000	17.75	10.72	14.96	4.32
2001	18.00	10.91	15.22	4.37
2002	18.56	10.6	15.71	4.23
2003	16.77	10.63	14.21	4.26
2004	17.42	10.51	14.56	4.2
2005	17.8	10.7	15.13	4.24
2006	17.37	10.95	14.58	4.38
2007	18.14	11.08	15.27	4.44
2008	18.24	10.99	15.11	4.44
2009	16.95	11.02	14.21	4.39
2010	18.05	11.08	14.81	4.42
2011	17.72	10.97	14.68	4.4
2012	17.27	11.33	14.46	4.48
2013	18.2	11.41	15.2	4.56
2014	17.65	11.12	14.7	4.41
2015	17.48	11.59	14.62	4.67
2016	17.58	11.48	14.56	4.66

LIST OF ACRONYMS

AEMET	Agencia Estatal de Meteorología (Spanish Meteorological Agency)
ALEXI	Atmosphere–Land Exchange Inverse Model
CAyC	Canal de Aragón y Cataluña (Aragón and Cataluña Chanel)
CCF	Cross-correlation function
CCI	Climate Change Initiative
CHE	Confederación Hidrográfica del Ebro
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CLC	Corine Land Cover
CRPSS	Continuous Ranked Probability Skill Score
DIR	Drought Impact Reporter
ECWMF	European Centre for Medium-Range Weather Forecasts
ECV	Essential Climate Variables
EDII	European Drought Impact Report Inventory
EO	Earth Observation
ET	Evapotranspiration
GLEAM	Global Land Evaporation Amsterdam Model
GPP	Gross Primary Production
LST	Land Surface temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalised Difference Vegetation Index

NTSG	Numerical Terradynamic Simulation Group
P	Precipitation
ROEA	Red Integrada de Estaciones de Aforo (Integrated Gauging Stations Network)
RV	Relative Value
SAIH	Sistema Automático de Información Hidrológica (Automatic Hydrologic Information System)
SEBS	Surface Energy Balance System
SM	Soil Moisture
SPEI	Standardised Precipitation Evapotranspiration Index
SPI	Standardised Precipitation Index
TRMM	Tropical Rainfall Measuring Mission
VOI	Value of Information
VOPI	Value of Perfect Information

List of Tables

Table 2-1. Selected remote sensing products. 18

Table 3-1. Possible paths for farmers 53

Table 3-2. Most profitable choice for the farmers for each of the years of the period 2001–2014 in function of the available water determined by the allocation factor 56

Table 4-1. Model parameters 77

Table 4-2. Definition and formula for the selected scores. 79

Table A-1. Mediterranean climate subtypes in the Ebro basin (CHE, 2022). 125

Table C1-1. Parameters of the 2 parameter Gamma distribution (location=0) for each month for observed and forecast data used for bias correction.. 134

Table C1-2. Parameters of the 2 parameter Gamma distribution (location=0) for each month fitted to the baseflow.. 135

Table C2-1. Yields (in tonnes per hectare) for long-cycle maize (LCM), long-cycle barley (LCB), short-cycle maize (SCM) and short-cycle barley (SCB) obtained in AquacropOS…………………………………………………………………135

LIST OF FIGURES

Figure 2-1. The north-eastern part of the Ebro Basin with selected agricultural land cover information. 15

Figure 2-2. Timeline of drought events (upper part) and impacts (lower part) for the north-eastern Ebro Basin during the period 2001 to 2012 20

Figure 2-3. Cross correlation of drought indicators and drought events at multiple time lags........ 24

Figure 2-4. Cross correlation of remote sensing data sets against the timeline of reported drought impacts. 25

Figure 2-5. Correlation between remote sensing drought indicators and crop yield data 28

Figure 2-6. Correlation between drought indices (SPI and state index) and crop yield..29

Figure 2-7. Correlation of the remote sensing drought indicators for the month of March to annual rain-fed two-row barley yield in Monegros-Bajo Cinca districts (MB) 31

Figure 3-1. Canal de Aragón y Cataluña: irrigated area and catchment........ 42

Figure 3-2. Research phases and spatial scales 43

Figure 3-3. Crop options considered in the model for farmers 48

Figure 3-4. Model decisions, parameters that inform them and decision outputs........ 49

Figure 3-5. The position of the points represents reservoir levels (a) and snow cover (b) for the period 2001–2014, with points coloured according to the decisions made with perfect information at those decision points........ 58

Figure 3-6. Total benefit for decisions informed by reservoir level alone and with the addition of snow information for the 10 sets of thresholds and the optimized thresholds........ 60

Figure 3-7. Total Relative Value for the period 2001–2014 for decisions informed by reservoir level alone and with the addition of snow information for the 10 sets of thresholds and the optimized thresholds........ 61

Figure 3-8. Relative value with different levels of cost for planting for decisions informed by reservoir level alone and with the addition of snow information for the 10 sets of thresholds and the optimized thresholds........ 62

Figure 4-1. Study area: Canal de Aragón y Cataluña (CAyC) irrigation district in the Ebro basin........ 73

Figure 4-2. Crop options for the different types of farmers: single-crop farmers (T1) and double-crop farmers.......... 76

Figure 4-3. Accumulated inflow to the end of season estimated at each of the decision points in November, February, April, May and observed at the end of the season on 30th September. 81

Figure 4-4. Decisions taken at each decision point based on the expected water balance to end of season 83

Figure 4-5. Benefit obtained each year from the variable crops depending on the information used to decide what to plant. 84

Figure 4-6. Scores for the outcomes of the decision model as a function of information scenario used, separated per farmer type. 85

Figure 4-7. Benefit per hectare over the whole period by farmer types 86

Figure 4-8. Relative value of information over the period of study and sensitivity to crop value variation for each farmer type: Relative value with either the value of maize or barley doubled 87

Figure C1-1. Cumulative empirical distributions of catchment averaged observed precipitation (SAFRAN) and seasonal forecasts (ECMWF SEAS5) and bias corrected seasonal forecasts for each month..........129

Figure C1-2. Climatological mean monthly inflow discharge to the Barasona reservoir (combined inflow of the Isábena and Ésera rivers)..........130

Figure C1-3. (a) lag-correlation between catchment average precipitation and discharge. (b) Auto-correlation of the (total) discharge, baseflow and quickflow..........131

Figure C1-4. One-step ahead predictions using the ARIMAX model for predicting baseflow..........132

Figure C1-5. Skill assessment of the bias-corrected ECMWF-SEAS5 precipitation forecast for the Barasona catchment..........132

Figure C1-6. Skill assessment of the inflow to the Barasona reservoir using bias corrected precipitation..........133

Figure C1-7. Skill assessment for the accumulated inflow to the Barasona reservoir, evaluated using the accumulated inflow from the start of forecast through to the end of the irrigation season at the end of September..........133

Figure C1-8. Probability Integral Transform plots of (a) accumulated (bias corrected) precipitation and (b) accumulated streamflow forecasts from the month start of prediction to the end of season at the end of September..........134

ABOUT THE AUTHOR

Clara Linés Díaz received a bachelor's and master's degree in Environmental Sciences from the Autonomous University of Madrid, with a thesis on hydraulic models for flood hazard cartography in collaboration with the Spanish Geologic and Mining Institute (IGME). After that, she worked on geomorphology and permafrost cartography for a research group at the Geology and Geochemistry Department of the same university. In 2011, she started a traineeship program at the European Space Agency in Frascati (Italy), working on identifying user needs of specific UN convections (Convention on Biological Diversity and Convention to Combat Desertification) as remote sensing users and exploring how the Agency could help fulfil those needs.

In 2014, she joined IHE-Delft as a PhD researcher and started collaborating on the 4-year EU FP7 project Earth2Observe (Global Earth Observations for integrated water resources assessment). After the end of the project, she moved to Edinburgh and became part of the water resources team at Scottish Water, where she had the opportunity to work on operational drought management, among other tasks. In 2023, she joined the Digital Curation Centre at the University of Edinburgh.

Publications

Journal articles

Linés, C. and Werner, M.: How useful are seasonal forecasts for farmers facing drought? A user-based modelling approach. Climate Services (submitted for publication), 2023.

Strohmeier, S., López López, P., Haddad, M., Nangia, V., Karrou, M., Montanaro, G., Boudhar, A., Linés, C., Veldkamp, T., and Sterk, G. (2020) Surface Runoff and Drought Assessment Using Global Water Resources Datasets - from Oum Er Rbia Basin to the Moroccan Country Scale. *Water Resour Manage* 34, 2117–2133. https://doi.org/10.1007/s11269-019-02251-6, 2020.

Linés, C., Iglesias, A., Garrote, L., Sotés, V., and Werner, M.: Do users benefit from additional information in support of operational drought management decisions in the Ebro basin?, Hydrol. Earth Syst. Sci., 22, 5901–5917, https://doi.org/10.5194/hess-22-5901-2018, 2018.

Linés, C., Werner, M., and Bastiaanssen, W.: The predictability of reported drought events and impacts in the Ebro Basin using six different remote sensing data sets, Hydrol. Earth Syst. Sci., 21, 4747–4765, https://doi.org/10.5194/hess-21-4747-2017, 2017.

Project publications:

Werner, M., Linés, C., Kaune Schmidt, A., Gründemann, G., and Casson, D.: Verification/value of datasets in supporting operational decisions. Earth2Observe project Deliverable No: D.2.10. Available at http://www.earth2observe.eu, 2017.

Jindrova, M., Sperna-Weiland, F., Linés, C., Stevens, L., Kossida, M., Quintana Seguì, P., Werner, M.: Report on opportunities for complementing data requirements in support of European policies through remotely sensed data products. Earth2Observe project Deliverable No: D.2.7. Available at http://www.earth2observe.eu, 2017.

Kaune Schmidt, A. and Linés, C.: Gap analysis of input data requirements in support of decision making of water allocation in (trans-boundary) basins. Earth2Observe project Deliverable No: D.2.5. Available at http://www.earth2observe.eu, 2015.

Kaune Schmidt, A. and Linés, C.: Review of stakeholders, relevant policies in non-European case study river basins. Earth2Observe project Deliverable No: D.2.3. Available at http://www.earth2observe.eu, 2014.

Conference abstracts

Werner, M. and Linés, C.: Seasonal forecasts to support cropping decisions: To whom are these useful, and when? [oral presentation]. EGU General Assembly, Vienna, Austria, 14-19 April. 10.5194/egusphere-egu24-13436, 2024.

Linés, C., Iglesias, A., Garrote, L., Sotés, V., Werner, M.: Potential of global spatial data to operational drought management decisions in the Ebro basin [oral presentation]. 10th Hymex Workshop, Barcelona, Spain, 3-7 July. Available at: https://diposit.ub.edu/dspace/bitstream/2445/113872/1/IdRA_Documents_003.pdf, 2017.

Linés, C., Werner, M., and Bastiaanssen, W.: Anticipation of drought impacts in the Ebro basin using remote sensing data [poster]. EGU General Assembly, 23-28 April, EGU2017-15398, 2017.

Linés, C., and Werner, M.: Evaluating the connection of drought indicators and drought impact [oral presentation]. Hymex Workshop on Drought and Water Resources, Zaragoza, Spain, 5-7 April, https://www.hymex.org/public/contents/drought-wr-workshop/, 2016.

Linés, C., Quintana-Seguí, P, Werner, M.: National drought alert system in Spain: information needs and gaps [oral presentation]. 9th Hymex Workshop, Mykonos, Greece, 21-25 September, 2015.

Linés, C., Werner, M., and Mynett, A.: Drought management decisions and information requirements [poster]. EGU General Assembly, Vienna, Austria, 12-17 April, EGU2015-14788, 2015.

Netherlands Research School for the
Socio-Economic and Natural Sciences of the Environment

D I P L O M A

for specialised PhD training

The Netherlands research school for the
Socio-Economic and Natural Sciences of the Environment
(SENSE) declares that

Clara Linés Díaz

born on 24 August 1985 in Madrid, Spain

has successfully fulfilled all requirements of the
educational PhD programme of SENSE.

Delft, 7 April 2025

Chair of the SENSE board

Prof. dr. Martin Wassen

The SENSE Director

Prof. Philipp Pattberg

The SENSE Research School has been accredited by the Royal Netherlands Academy of Arts and Sciences (KNAW)

KONINKLIJKE NEDERLANDSE
AKADEMIE VAN WETENSCHAPPEN

The SENSE Research School declares that **Clara Linés Díaz** has successfully fulfilled all requirements of the educational PhD programme of SENSE with a work load of 37.6 EC, including the following activities:

SENSE PhD Courses

- Environmental research in context (2014)
- Research in context activity: 'Co-organisation of the IHE PHD Symposium 2018'

Other PhD and Advanced MSc Courses

- Where there is little data: How to estimate design variables in poorly gauged basins, IHE-Delft (2014)

External training at a foreign research institute

- Visiting researcher, CEIGRAM/UCM, Spain (2017)

Management and Didactic Skills Training

- Organising 5 stakeholder workshops for the E2O project (2015-2017)
- Assisting during the MSc course 'Hydrology, Water Supply and Water Demand Management and GIS' (2014-2015)
-

Oral Presentations

- *Evaluating the connection of drought indicators and drought impact.* Hymex workshop on drought and water resources, 05-07 April 2016, Zaragoza, Spain
- *National drought alert system in Spain: Information needs and gaps*. 9th Hymex workshop, 21-25 September 2015, Mykonos, Greece
- *Potential contribution of global spatial data to operational drought management decisions in the Ebro basin*. 10th Hymex workshop, 03-07 July 2017, Barcelona, Spain

SENSE coordinator PhD education

Dr. ir. Peter Vermeulen

IHE DELFT

Institute for Water Education
under the auspices of UNESCO

TU Delft
Delft University of Technology

This thesis examines how information can benefit drought management decisions at the basin scale through three perspectives: a data-centric perspective, assessing the ability of remotely sensed datasets to detect drought early enough to inform operational water management practices; a user-centric perspective, identifying the information use and needs of farmers and reservoir operators water allocation decisions and modelling the value of information to these decisions; and a combined approach, assessing the usefulness of seasonal forecasts of water availability to support water allocation decisions in irrigated agriculture.

These perspectives show that multiple factors influence the usefulness of information. Notably, the ability to provide the timely observations or predictions needed by decision-makers, and their capacity to change the course of action accordingly. Results indicate that these factors depend on the options available to the decision-makers, which may vary depending on their level of risk aversion and technical abilities, as well as the context of the decision. Changes in the market value of goods or weather variability may also impact the usefulness of information.

Bringing these perspectives and their respective methods together contributes to filling the gap between technical and human-centred approaches in assessing the usefulness of information for drought management decisions.

This book is printed on paper from sustainably managed forests and controlled sources

9 789073 445710