Multi-objective optimization of rainfed and irrigated agricultural areas considering production and environmental criteria: A case study of wheat production in Spain

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ABSTRACT

Meeting the growing food demand with minimum impact on the environment is a major challenge to face for ensuring a more sustainable food production. To tackle this problem, in this article we present a novel systematic method for agriculture planning that optimally allocates rainfed and irrigated cropping areas, thereby enhancing food availability and reducing the environmental impact of agriculture. The allocation problem is mathematically formulated as a multi-objective linear programming model that simultaneously accounts for the maximization of the crop production and the minimization of the environmental impact caused by water consumption. To quantify the environmental damage, life cycle assessment principles and water footprint concepts are integrated into the model. The capabilities of our tool are illustrated through its application to a real case study that considers wheat production in Spain. The results show that the current allocation of rainfed and irrigated wheat areas in Spain is sub-optimal. Our tool provides a set of alternatives to optimally reallocating these wheat areas that ultimately achieve significant reductions in environmental impact while maintaining or even increasing the production level. The analysis clearly demonstrates that the optimal allocation of rainfed and irrigated cropping areas is a potential pathway

to minimise the environmental impact of water consumption in food production. Our systematic decision-support tool aims to assist famers and policy-makers in the transition towards a more sustainable agricultural sector.

KEYWORDS

Multi-objective optimization; Agriculture; Linear programming; Water footprint; Life cycle assessment; Decision-making tool

1. INTRODUCTION

Unsustainable use of freshwater is a major issue that can potentially generate unacceptable environmental changes at the global as well as local scales (Rockström et al., 2009; Steffen et al., 2015). Freshwater resource availability is rapidly decreasing and experts expect that more than two-thirds of the world's population will be affected by water scarcity over the next decades (Rijsberman, 2006).

In practise, agriculture is by far the largest consumer of freshwater worldwide (FAO, 2014; UNEP, 2007). In particular, irrigated agriculture accounts for more than 70% of freshwater withdrawals from rivers, lakes and aquifers (Garrido et al., 2010), while rainfed agriculture is the largest consumer of water from precipitation (Liu et al., 2009; Postel et al., 1996). Overall, water consumption in global crop production is causing significant environmental impacts on natural resources, ecosystem quality and human health (Núñez et al., 2013) that cannot be ignored. In this backdrop, future agriculture will face a great challenge: meeting the growing food demand while simultaneously reducing freshwater consumption and the associated environmental impact.

Hence, managing water resources in the agricultural sector in an efficient manner becomes a critical issue to look at when moving towards a sustainable economy (Ridoutt and Pfister, 2010). To manage water resources efficiently and minimise the impact of water consumption, it is necessary to define appropriate metrics and integrate them into tailored systematic decision-support tools. Research efforts in this area have been devoted mainly to assess the environmental impact of water consumption through descriptive metrics based on two main approaches: water footprint (WF) and life cycle assessment (LCA) (Boulay et al., 2015; Jefferies et al., 2012). In contrast, the literature on decision- support tools for the sustainable management of water and crops in agriculture is still quite scarce.

The WF concept, which was originally introduced by Hoekstra (Hoekstra, 2003), is a descriptive indicator that quantifies the total volume of freshwater used per unit of mass produced during the entire crop production growing period (Hoekstra et al., 2011). On the other hand, LCA is a tool which measures the environmental impact caused by products along their entire life cycle (Finnveden et al., 2009). The impact of water consumption was traditionally neglected in LCA studies (Milà i Canals et al., 2008), but several attempts have been recently made to overcome this limitation (Berger and Finkbeiner, 2010). For instance, Milà i Canals et al. (2008) introduced the concept of freshwater ecosystem impact as an indicator of the effects of direct water consumption on ecosystem health, while Hospido et al. (2012) applied this indicator to estimate the impact of irrigated products in Spain. Other authors employed both WF and LCA approaches to assess the potential impacts of different crops, such as tea and margarine (Jefferies et al., 2012) as well as tomatoes (Chapagain and Orr, 2009). These authors argue that classical LCA could benefit from WF methods by integrating water assessment with other environmental indicators. Recently, the WF concept has been combined with the LCA approach to quantify the impact of water consumption on all of the stages in the life cycle of a product (Pacetti et al., 2015; Pfister et al., 2009). Pfister et al. (2009) developed a method based on the WaterGAP2 model (Alcamo et al., 2003) that combines WF and LCA. This approach was later applied by Pfister and Bayer (2013) to assess 160 crops worldwide. Moreover, Pacetti et al. (2015) analysed the environmental performance of biogas production from energy crops through the integration of WF and LCA.

The integration of WF and LCA enables a comprehensive assessment of the environmental impact derived from water consumption. Despite its benefits, the approaches mentioned above are still descriptive in nature. That is, they quantify the environmental impact of water consumption, but offer no guidelines on how to minimise such an impact. Obtaining "more crop and nature per drop", that is, maintaining or even increasing the productivity while minimising the environmental impact is the paradigm to be achieved in agriculture (Aldaya et al., 2009). This goal cannot be addressed using exclusively descriptive approaches. It is necessary to resort to optimization methods that can generate in a systematic manner a large number of alternatives and identify the best ones among them. Despite their high potential, however, the use of optimisation in the field of agriculture has been quite scarce. The few approaches proposed so far based on optimisation have concentrated primarily on optimising water resources (Singh, 2012a) and cropping patterns (Singh, 2012b) according to economic criteria, thereby disregarding the environmental impact of water use.

Multi-objective optimization (MOO) allows to optimise systems according to different criteria, including environmental and economic aspects (Azapagic, 1999). In particular, MOO (Chankong and Haimes, 1983; Ehrgott, 2000) can treat environmental concerns as decision-making objectives rather than as constraints imposed on the system (García et al., 2014; Grossmann and Guillén-Gosálbez, 2010; Guillen-Gosalbez et al., 2007). MOO generates a set of alternatives (called Pareto optimal solutions) which are non-dominated (none of the objectives in a Pareto optimal point can be improved in value by any other feasible solution without worsening at least another objective value). The analysis of these solutions provides insight into the trade-off between objectives (Azapagic and Perdan, 2005; Branke et al., 2008). In a seminar work, Azapagic and Clift (Azapagic and Clift, 1999; Azapagic, 1999) proposed to combine LCA and MOO into a single framework. This approach has been applied in a plethora of engineering problems in order to automate the search for more sustainable alternatives (Grossmann and Guillén-Gosálbez, 2010; Pieragostini et al., 2012; Yue et al., 2016).

In the agricultural area, MOO has been successfully employed in the management of resources in arid and semiarid areas. Along these lines, Xevi and Khan (2005) applied MOO to optimise reservoir operations and water allocation for irrigation, while Chen et al. (2013) used MOO to realise the optimum allocation of multiple reservoirs in a basin. MOO has also been employed to analyse crop planning problems, most of them focusing either on economic criteria (Dury et al., 2011; Sarker and Ray, 2009; Zeng et al., 2010) or on environmental objectives (Khoshnevisan et al., 2015). To the best of our knowledge, however, MOO and LCA have never been integrated into a single unified framework in the context of agriculture.

In this work we develop a tool to optimise the allocation of crops, an area that offers large potential for enhancing food availability and reducing the environmental impact of agriculture (Foley et al., 2011). A systematic MOO tool is presented which integrates a descriptive LCA-based methodology (that quantifies the impact of water consumption) with an MOO optimisation model that identifies optimal cropping patterns (i.e., optimal rainfed and irrigated agricultural areas in a specific region of interest) that simultaneously maximise the productivity and minimise the environmental impact of water consumption. The capabilities of the proposed tool are illustrated through its application to a real case study based on wheat production in Spain.

2. MODEL DESCRIPTION AND SOLUTION METHOD

In this section we present the mathematical model for solving the rainfed and irrigated cropping areas allocation problem, followed by the solution procedure.

2.1. MULTI-OBJECTIVE LINEAR PROGRAMMING MODEL

The problem addressed in the paper is formulated in mathematical terms using a linear programming model (LP) containing four sets of equations: objective function equations, demand satisfaction constraints, capacity limitations constraints and water demand constraints. These equations are described in detail next.

Objective functions equations

The model seeks to minimise the environmental impact while simultaneously maximising the amount of crop produced. This general goal is expressed through the following three objective functions: maximise production (Eq.(1)), minimise damage to ecosystem quality (Eq.(2)), and minimise damage to resources (Eq.(3)).

The total crop production is calculated via Eq.(1) as the summation of the amount of crop produced in the rainfed and irrigated areas in each watershed j (expressed in tons [t]).

$$Production = \sum_j \left[\left(\mathrm{Yield}_j^{\mathrm{DRY}} \cdot Surface_j^{DRY}\right) + \left(\mathrm{Yield}_j^{\mathrm{IRR}} \cdot Surface_j^{IRR}\right)\right] \qquad (1)$$

where $Surface_j^{DRY}$ and $Surface_j^{IRR}$ are continuous variables that represent, respectively, the rainfed and irrigated areas in each watershed j devoted to a given crop (expressed in hectare [ha]). In the same equation, $Yield_j^{DRY}$ and $Yield_j^{IRR}$ are production rate parameters associated with the rainfed and irrigated areas within each watershed j (i.e., the ratio between amount of crop produced per unit of land area expressed in tons per hectare $[\mathrm{t} \cdot \mathrm{ha}^{-1}]$).

The environmental impact derived from water consumption is determined mathematically via Eqs. (2) and (3), where EQ represents the damage to ecosystem quality (quantified in square metres per year as land occupation $[\mathrm{m}^2\mathrm{year}]$), and RD represents the damage to resources depletion (expressed in surplus of energy$[\mathrm{MJ}]$).

$$EQ = \sum_j \left[\mathrm{CF}_\mathrm{j}^{\mathrm{EQ}} \cdot CWR_j\right] \tag{2}$$

$$RD = \sum_j \left[\mathrm{CF}_\mathrm{j}^{\mathrm{RD}} \cdot CWR_j\right] \tag{3}$$

Here CF_j^{EQ} and CF_j^{RD} are parameters denoting, respectively, the environmental damage in ecosystems and resources caused by water consumption; and CWR_j is a variable that represents the total crop water requirements in each watershed j (expressed in cubic metre $[\mathrm{m}^3]$). CF_j^{EQ} and CF_j^{RD} are environmental damage factors taken from Pfister et al. (2009), which in our case were calculated following LCA principles, using a 0.5° grid cell resolution and aggregating the watersheds by country. CF_j^{EQ} is the ecosystem quality damage factor that represents the surface that suffers the environmental damage caused by water consumption during one year (expressed in square metre-year per cubic metre $[\mathrm{m}^2\mathrm{year} \cdot \mathrm{m}^{-3}]$) (note that this approach is similar to the concept of land use impact). CF_j^{RD} is the characterization factor for freshwater depletion and represents the surplus of energy needed to extract the same amount of water in the future (expressed in mega joules per cubic metre $[\mathrm{MJ} \cdot \mathrm{m}^{-3}]$). For further details on these metrics, the reader is referred to (Pfister et al., 2009).

Demand satisfaction constraint

As already mentioned, the model seeks to maximise the crop production rate. However, there is a minimum production that should be attained in order to ensure that a minimum demand is met. This condition is enforced using the following equation (Eq.(4)):

$$Production \geq \mathrm{Demand} \tag{4}$$

where *Demand* is a parameter (expressed in tons [t]) that represents the minimum amount of crop that needs to be produced.

Capacity limitation constraints

To ensure that the solution found by the algorithm can be implemented in practice, Eq.(5) forces the optimal surfaces in each watershed *j* to be below the available surface in the watershed *j* (parameter $Surface_j^{AVA}$).

$$Surface_j^{DRY} + Surface_j^{IRR} \leq \mathrm{Surface_j^{AVA}} \quad \forall j \tag{5}$$

The available surface for one crop in each watershed *j* should be limited to the current harvested areas dedicated to this crop (Eq.(6)). Hence, this constraint ensures that the optimal areas are suitable and available for the crop growth, that is, they meet the soil and climate conditions for the crop. Therefore, the available surface is obtained as the summation of the current cultivated rainfed and irrigated areas, denoted by parameters SR_j^{DRY} and SR_j^{IRR}, respectively. The reader should not confuse these parameters with the continuous variables $Surface_j^{DRY}$ and $Surface_j^{IRR}$.

$$\mathrm{Surface_j^{AVA}} = \mathrm{SR_j^{DRY}} + \mathrm{SR_j^{IRR}} \quad \forall j \tag{6}$$

In addition, the rainfed and irrigated surfaces in each watershed *j* (denoted by continuous variables $Surface_j^{DRY}$ and $Surface_j^{IRR}$) are constrained within lower and upper bounds, as shown in Eqs. (7) and (8).

$$\underline{\mathrm{SR_j^{DRY}}} \leq Surface_j^{DRY} \leq \overline{\mathrm{SR_j^{DRY}}} \quad \forall j \tag{7}$$

$$\underline{\mathrm{SR}_{\mathrm{j}}^{\mathrm{IRR}}} \leq Surface_j^{IRRI} \leq \overline{\mathrm{SR}_{\mathrm{j}}^{\mathrm{IRR}}} \quad \forall j \tag{8}$$

where $\underline{SR_j^{DRY}}$ and $\overline{SR_j^{DRY}}$ denote, respectively, the lower and upper bounds imposed on the rainfed areas; and $\underline{SR_j^{IRR}}$ and $\overline{SR_j^{IRRI}}$ the corresponding bounds on the irrigated areas. These bounds are calculated as a percentage change with respect to the current areas cultivated in each watershed *j*.

Agricultural water demand constraints

The crop water requirements in each watershed are determined via Eq.(9) as the summation of its individual components (i.e., green, blue and grey water):

$$CWR_j = W_J^{GREEN} + W_J^{BLUE} + W_J^{GREY} \quad \forall j \tag{9}$$

where W_J^{GREEN} represents the total volume of green water (i.e., rainfall water) consumed by the rainfed and irrigated surfaces in each watershed *j* (expressed in cubic metre [m^3]). W_J^{BLUE} represents the total volume of blue water (i.e., irrigation water) consumed by the irrigated surfaces in each watershed *j* (expressed in cubic metre [m^3]). W_J^{GREY} represents the total volume of grey water consumed (i.e., water needed to assimilate the pollutants) in each watershed *j* (expressed in cubic metre [m^3]). The total green, blue and grey water consumed are calculated via Eqs. (10), (11) and (12), respectively, as follows:

$$W_J^{GREEN} = \mathrm{CWU}_{\mathrm{j}}^{\mathrm{GREEN}} \cdot \left[Surface_j^{DRY} + Surface_j^{IRR}\right] \quad \forall j \tag{10}$$

$$W_J^{BLUE} = \mathrm{CWU}_{\mathrm{j}}^{\mathrm{BLUE}} \cdot Surface_j^{IRR} \quad \forall j \tag{11}$$

$$W_J^{GREY} = \mathrm{CWU}_{\mathrm{j}}^{\mathrm{GREY}} \cdot \left[Surface_j^{DRY} + Surface_j^{IRR}\right] \quad \forall j \tag{12}$$

where CWU_j^{GREEN}, CWU_j^{BLUE} and CWU_j^{GREY} are parameters which represent the green, blue and grey water crop requirements in a specific watershed *j* (expressed in cubic metre [$\mathrm{m}^3 \cdot \mathrm{ha}^{-1}$]). As defined by Hoekstra et al., (2011), the CWU_j^{GREEN} refers to the consumption of the green water resources that are available for the crop in the soil (rainwater insofar as it does not become run-off), CWU_j^{BLUE} refers to the consumption of blue water resources (surface and groundwater consumed/extracted for irrigation), and CWU_j^{GREY} refers to the volume of freshwater that is required to assimilate the load of pollutants (considering natural background concentrations and existing ambient water quality standards).

The crop water requirements can be either determined based on real/experimental data or estimated following the WF assessment method proposed by Hoekstra et al. (2011) and implemented in the CROPWAT 8.0 software developed by the Food and Agriculture Organization (Allen Richard et al., 1998; FAO, 2010) . Note that for rainfed crop production, CWU_j^{BLUE} is zero (no irrigated water), while for irrigated crop production, CWU_j^{GREEN} is assumed to be equal to the rainfed crop production (see details of the method in Appendix A).

2.2. SOLUTION METHOD: MULTI-OBJECTIVE OPTIMIZATION

The overall problem can be formulated as a multi-objective linear programming model that is expressed in compact form as follows:

$$\min \quad [-f_1(x), f_2(x), f_3(x)]$$

$$\text{subject to} \quad \text{Eqs.4-12}$$

$$x \in \mathbb{R}$$

Where function f_1 is the production (Eq.(1)), f_2 is the damage to ecosystem quality (Eq.(2)), and f_3 is the damage to resources depletion (Eq.(3)) (note that minimising the negative of a function is equivalent to maximising the same function). Continuous decision variables x represent the rainfed and irrigated harvested areas in each watershed. We aim to minimise simultaneously the three objective functions subject to the constraints imposed by Eqs. 4-12.

The multi-objective LP is solved using the epsilon-constraint method (Ehrgott, 2008), which is based on formulating an auxiliary model in which one objective is kept as main objective and the remaining ones are transferred to auxiliary constraints that impose epsilon bounds (ε) on their values. This method generates single objective sub-problems by systematically varying the ε-constraint bounds imposed on the auxiliary objectives (Chankong and Haimes, 1983; Haimes et al., 1971). Further details on this method can be found elsewhere (Ehrgott, 2008). Therefore, the auxiliary single-objective models are expressed in compact form as follows:

$$
\begin{aligned}
\max \quad & f_1(x) \\
\text{subject to} \quad & f_2(x) \le \varepsilon_2 \\
& f_3(x) \le \varepsilon_3 \\
& \text{Eqs. 4-12} \\
& x \in \mathbb{R}
\end{aligned}
$$

These models are solved for different epsilon values, thereby generating in each run a different Pareto solution. Therefore, the solution of the multi-objective problem is given by a set of Pareto alternatives that represent the optimal trade-off between the objectives. These solutions cannot be improved in one of the objectives without necessarily worsening at least another criterion. The set of Pareto alternatives forms the Pareto set, which contains all the non-inferior or non-dominated solutions.

Fig. 1 illustrates the concept of Pareto optimality for a simple case with two objectives (e.g. production and environmental impact). Points lying above the curve are sub-optimal solutions that can be improved in both criteria simultaneously. The region below the Pareto curve contains unfeasible solutions, since there is no single point showing better performance than the Pareto solutions simultaneously in both indicators.

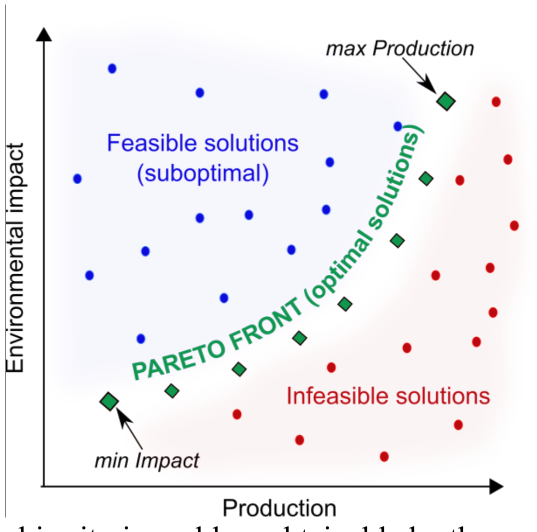

Fig. 1 Pareto Front of a bi-criteria problem obtainable by the multi-objective optimization method.

Each solution of the Pareto curve is optimal and represents a unique combination of both objectives entailing a particular rainfed and irrigated area in each watershed. Decision and policy-makers will select a solution from the Pareto set that will reflect, in the best manner possible, the stakeholders' preferences.

3. CASE STUDY

The capabilities of the approach presented are demonstrated through its application to a real case study based on wheat (*Triticum aestivum* L.) production in Spain. Note that this crop is used for illustrative purposes. Our model is indeed general enough to assess any other crop in any other region.

We focus on wheat production because it is one of the most widely used cultivated grain cereals with a major role in feeding people and livestock. Furthermore, we select the Spanish territory because it is the driest country in Europe, with a high climate variability along its territory located in one climate change hotspot (Giorgi, 2006).

Wheat dominates the Spanish cropping system and it is one of the crops most critically affected by water scarcity and climate change (Karrou and Oweis, 2012; Ortiz et al., 2008). Agronomic practises differ largely along the Spanish territory owing to the different climate, topography, soil and social conditions (Rharrabti et al., 2003). In Spain, rainfed wheat land has traditionally occupied more than 85% of the total wheat arable land, while irrigated land produces more than 20% of the nation's wheat grain. Further details on historical wheat production data over Spain can be found in the Agriculture Statistics of Spanish Ministry of Agriculture, Food and Environment (MAGRAMA, 2014).

Considering as base case the spatial location of the wheat harvested in Spain for 2011, the goal is to apply the proposed approach to optimise wheat rainfed and irrigated cropping areas along the Spanish territory. The region of interest (i.e., the whole area of Spain) is divided into a number of watersheds (regarded as autonomous regions of environmental management and economic development). Fig. 2 shows the 16 Spanish watersheds considered in this study, 15 in the Peninsula and one in the Balearic Islands.

Fig. 2 Study area divided into 16 watersheds.

Two areas of environmental protection are considered: ecosystem quality and resources. We consider the environmental characterization factors estimated by Pfister et al. (2009)

based on the Eco-Indicator-99 LCA method (Goedkoop and Spriensma, 2001) (for further details on these metrics refer to (Pfister et al., 2009)). The characterization factors for each Spanish watershed are shown in Table 1. Higher values of the characterization factors imply greater levels of vulnerability in the watershed concerning the effects of water consumption.

Table 1 Characterization environmental factors for ecosystem quality and resources depletion specific for each watershed (Pfister et al., 2009).

Watershed	Ecosystem quality ($m^2 year \cdot m^{-3}$)	Resource depletion ($MJ \cdot m^{-3}$)
Galicia Costa	0.115	0.000
Miño-Sil	0.107	0.000
Cantábrico Occidental	0.159	0.000
Cantábrico Oriental	0.121	0.000
Ebro	0.270	0.000
Cuencas internas de Cataluña	0.314	2.605
Duero	0.271	0.000
Tajo	0.348	0.000
Júcar	0.545	0.000
Guadiana	0.638	0.000
Tinto, Odiel y Piedras	0.240	0.000
Guadalquivir	0.496	2.978
Guadalete y Barbate	0.112	0.000
Cuenca Mediterránea Andaluza	0.398	3.301
Segura	0.574	9.651
Islas Baleares	0.276	0.000

The current wheat rainfed and irrigated surface and yield parameters corresponding to each watershed (Table 2) were estimated using historical data regionalised at the province level sourced from the Agricultural Statistics Yearbooks of the Spanish Ministry of Agriculture, Food and Environment for the year 2011 (MAGRAMA, 2014). The province data were aggregated at the watershed level using conversion factors, as shown in Eqs.13-16.

$$\mathrm{SR_j^{DRY}} = \sum_k \left[\mathrm{CS_k^{DRY}} \cdot f_{k,j}\right] \quad \forall \mathrm{j} \tag{13}$$

$$\mathrm{SR_j^{IRR}} = \sum_k \left[\mathrm{CS_k^{IRR}} \cdot f_{k,j}\right] \quad \forall \mathrm{j} \tag{14}$$

$$\mathrm{Yield_j^{DRY}} = \sum_k \left[\mathrm{YP_k^{DRY}} \cdot \mathrm{CS_k^{DRY}} \cdot f_{k,j}\right] / \mathrm{SR_j^{DRY}} \quad \forall \mathrm{j} \tag{15}$$

$$\mathrm{Yield_j^{IRR}} = \sum_k \left[\mathrm{YP_k^{IRR}} \cdot \mathrm{CS_k^{IRR}} \cdot f_{k,j}\right] / \mathrm{SR_j^{IRR}} \quad \forall \mathrm{j} \tag{16}$$

where SR_j^{DRY} and SR_j^{IRR} denote the estimated rainfed and irrigated surfaces corresponding to each watershed j; CS_k^{DRY} and CS_k^{IRR} are the real crop harvested surfaces under rainfed and irrigated conditions in province *k*; and $f_{k,j}$ represents the fraction of province *k* in the watershed *j* (i.e., area of province *k* belonging to the watershed *j* divided by the total area of province *k*). $Yield_j^{DRY}$ and $Yield_j^{IRR}$ denote the production rate parameter for each watershed *j*; while YP_k^{DRY} and YP_k^{IRR} are rainfed and irrigated crop yield in province *k*.

We also assume that the wheat demand to be satisfied is equal to 6,888,147 tonnes which corresponds to the total wheat production in Spain for 2011 (MAGRAMA, 2014).

Due to the lack of real data, the wheat water requirements in each watershed (i.e. green, blue and grey denoted by CWU_j^{GREEN}, CWU_j^{BLUE} and CWU_j^{GREY}, respectively) were estimated using the framework proposed by Hoekstra et al. (2011) and the CROPWAT 8.0 software developed by the Food and Agriculture Organization (Allen Richard et al., 1998; FAO, 2010). The wheat water requirements were first estimated for 67 meteorological stations spread across all watersheds, and then aggregated at the watershed level. Climate data for each meteorological station (temperature, precipitation, humidity, sunshine hours and wind speed) correspond to the average value for the period 1981-2010 (AEMET, 2014) (see details on this method and the estimation in Appendix A). We assume that the theoretical wheat water use (Table 2) may be overestimated since farmers may not irrigate at the optimum level.

Table 2 shows the parameters regionalised at the watershed level fed into the model: wheat surface and yield for rainfed and irrigated areas and wheat water requirement for green, blue and grey water. Note that we assume that the rainfed and irrigated yields can be attained with the theoretical water requirements that are estimated. For rainfed areas, CWU_j^{BLUE} is zero (no irrigated water); while for irrigated areas, CWU_j^{GREEN} is equal to the rainfed production, and CWU_j^{BLUE} is the theoretical irrigation needed to achieve the irrigated yield ($\mathrm{Yield}_j^{\mathrm{IRR}}$) assuming that farmers irrigate at the optimum level.

Table 2 Wheat yield ($t\cdot ha^{-1}$), available surface (ha) and water use ($m^3\cdot ha^{-1}$) for green, blue and grey water in each watershed.

Watershed	**Rainfed**		**Irrigated**		**Crop Water Use**		
	Yield	Surface	Yield	Surface	Green	Blue	Grey
Galicia Costa	5.94	2847.70	-	-	3781.75	2495.25	285.00
Miño-Sil	2.51	17548.65	5.65	5302.26	3320.25	4237.75	285.00
Canta. Occidental	2.26	1732.64	5.65	362.91	4037.67	1682.67	285.00
Canta. Oriental	4.67	15040.09	5.34	1884.29	4478.00	1423.50	285.00
Ebro	3.27	453705.38	4.84	96464.47	2620.38	6098.25	285.00
C I de Cataluña	3.88	39787.44	4.98	6734.49	3014.00	4823.00	285.00
Duero	3.80	536016.96	5.24	66792.57	2305.78	6331.89	285.00

Tajo	2.89	144233.87	4.81	12320.69	2049.63	7874.00	285.00
Júcar	2.72	57607.40	5.58	14621.28	2103.50	6968.00	285.00
Guadiana	2.45	140166.92	4.10	12869.88	1885.00	8416.50	285.00
Tinto, Odiel y Piedras	3.41	6247.32	4.68	362.00	1800.00	8178.00	285.00
Guadalquivir	2.62	203516.31	4.29	33060.84	1921.75	7965.75	285.00
Guadalete y Barbate	2.89	45809.96	4.02	4956.49	1824.50	6789.50	285.00
C. M. Andaluza	2.46	33023.85	4.22	3668.76	1345.50	8037.50	285.00
Segura	2.21	25152.56	5.17	10756.00	1538.67	8189.67	285.00
Islas Baleares	3.40	3612.00	5.10	446.00	1934.00	6531.33	285.00

All the parameters employed in the model are assumed to be deterministic, that is, we assume nominal values for them. However, the crop yield and water requirements highly depend on soil conditions, climate and agronomic practises; while the LCA calculations are also affected by several uncertainty sources, particularly concerning the environmental characterization factors. As will be later discussed during the article, to deal with these uncertainties we carry out a sensitivity analysis.

It is assumed that the rainfed and irrigated surfaces cannot be altered by more than 20% from their current values (base case). These lower and upper bounds on the variables can be easily modified, and we can even considering replacing crops by others requiring similar conditions. It is also assumed that the water employed in the base case (i.e., for the real wheat harvested rainfed and irrigated areas in 2011 in Spain), corresponds to the theoretical water requirements shown inTable 2.

4. RESULTS AND DISCUSSION

The LP model was implemented in the General Algebraic Modelling System (GAMS) (Brooke et al., 1998) software version 24.2.1 and solved with the CPLEX 12.6.1.0 solver using an AMD A8-5500 APU with Raedon 3.20 Ghz and 8.0 GB RAM. The model features 55 continuous variables and 42 equations. The solution time varied depending on the instance being solved, but was always within the range 0.5 to 1.3 CPU seconds in the aforementioned computer.

4.1. 3-Dimensional objective space

We first generated the Pareto set for the original problem containing three objective functions, that is, maximising the production while simultaneously minimising the damage to ecosystems quality and to resources. Fig.3 shows the set of 3D Pareto points (depicted in blue colour) produced by running 100 iterations of the epsilon constraint method (Ehrgott, 2009). In each of the iterations, production is maximised as a single objective, while the damage to ecosystem quality and resources are transferred to auxiliary constraints. To generate the ε-constraint bounds imposed on the environmental functions, we first calculated the individual optimum for each objective. Then, we defined the range within which each objective function should fall. Next, we divided this interval into 9 equal intervals, thereby generating 10 ε-constraint bounds for each environmental objective function. Finally, the LP model was recursively solved for each possible combination of the ε-constraint values (i.e., 100 possible combinations).

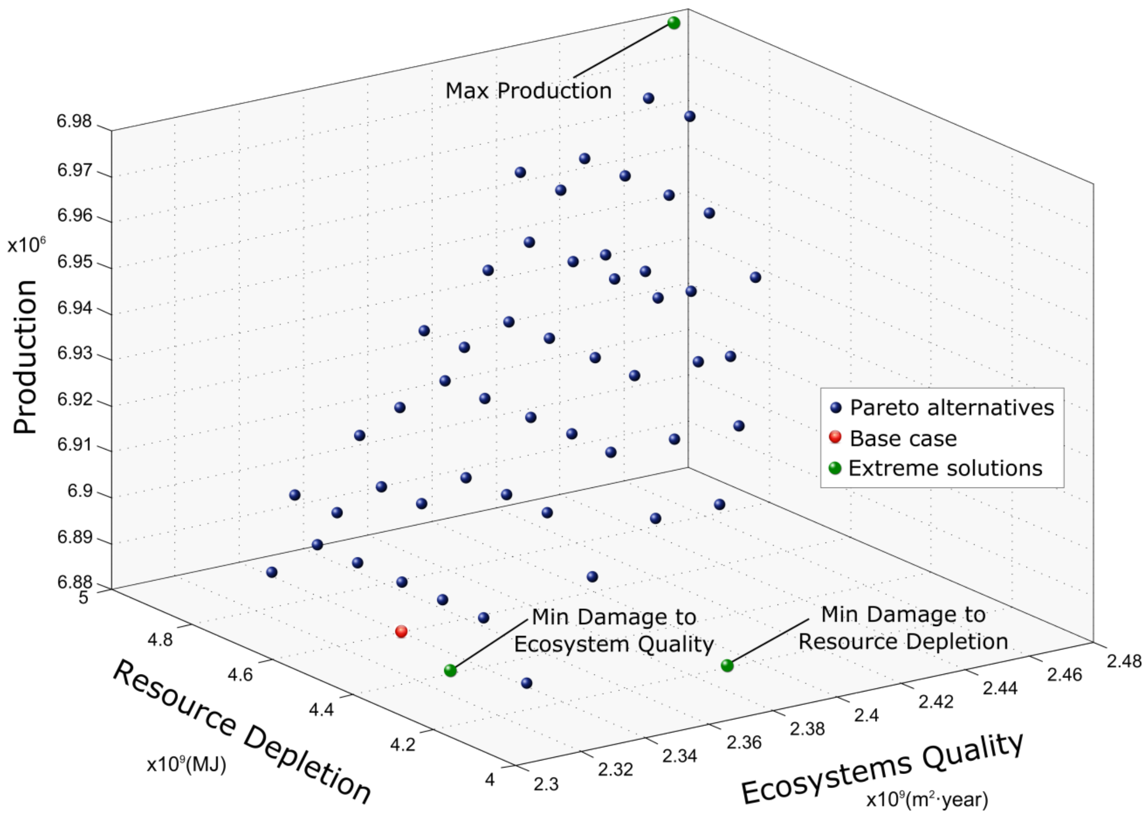

Fig. 3 Pareto set of solutions for the three-criteria multi-objective optimization problem (3-Dimensional visualization).

Each point in the 3D Pareto set represents an optimal alternative achieving a unique combination of objectives values (entailing specific rainfed and irrigated surface areas in each watershed). Therefore, each optimal alternative involves replacing (to a certain extent) rainfed by irrigated surfaces or vice-versa in each watershed (compared to the base case). Additionally, Fig.3 depicts the extreme solutions (in green colour), as well as the base case (in red colour).

The assessment of the 3D Pareto optimal solutions and their comparison with the base case are challenging. To get further insight into the inherent trade-offs between objectives, the solutions are represented in Fig. 4 in the form of a parallel coordinates plot in which each 3D solution is equivalent to a polyline. Each polyline intersects in a specific position the three vertical axes representing the objective functions (production, damage to ecosystem quality and damage to resource depletion). The position where a solution crosses a vertical axis indicates its value in this specific objective. The values were normalised by subtracting the minimum from each element (or by subtracting the value from the maximum, depending on whether the objective is maximised or minimised), and then dividing by the difference maximum-minimum, so that a value of 1 represents the best value for the objective.

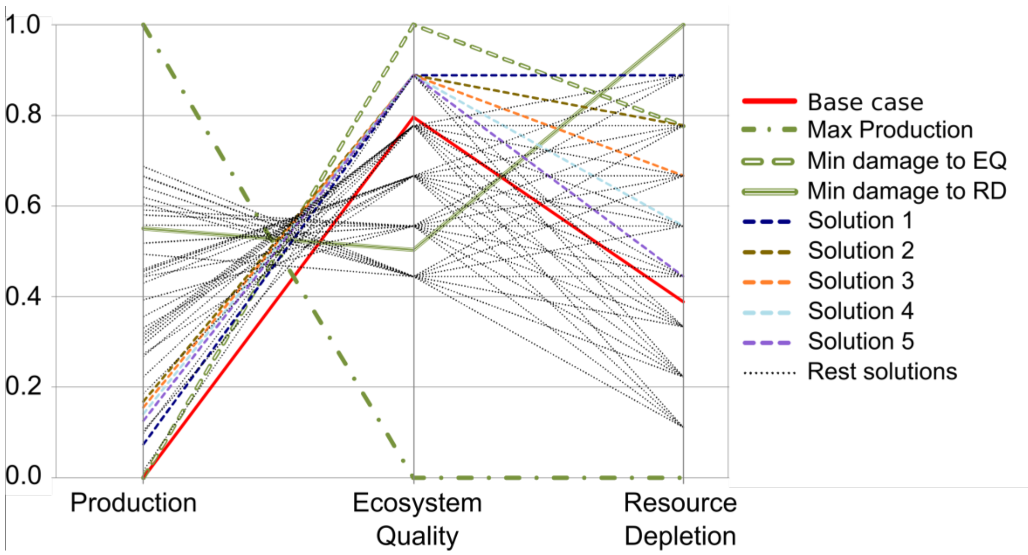

Fig. 4 Parallel coordinates plot of the 3D Pareto set of solutions: extreme solutions for each objective (green polylines), solutions 1 to 5 that improve the base case in the three objectives (dashed polylines), other solutions that improve the base case in at least one objective (dotted polylines), and base case (solid red polyline).

As observed in Fig. 4, the base case (red polyline) is clearly suboptimal, as there are at least 5 Pareto solutions (depicted by dashed coloured polylines) that are better simultaneously in the three objectives. Regarding the extreme solutions, the minimisation of the damage to ecosystem quality leads to a solution showing better performance than the base case in the three objectives. Maximising the production worsens the environmental objectives, while minimising the damage to resource improves the production yield and worsens the damage to ecosystem quality (with respect to the base case). Additionally, Fig.4 shows the remaining 3D solutions (depicted by doted black polylines) that are better than the base case in at least in one objective.

The interpretation of the 3D plot (Fig. 3) and subsequent selection of a preferred Pareto solution are not straightforward. Additionally, the visualization of a large set of solutions in the parallel coordinates plot (Fig.4) may be unclear given the dense nature of the cloud of Pareto points. To facilitate this task and get further insight into inherent trade-offs between pairs of objectives, we projected the Pareto points onto 2D plots. Furthermore, we generated a set of optimal Pareto solutions for subspaces of two objectives and compared them with the points resulting from solving the problem in the original space of three objectives. Note that the solutions generated for the 2D cases are guaranteed to be optimal in the 3D space, while the converse is not true.

4.2. 2-Dimensional Objectives Spaces

The 2D Pareto points were obtained by solving three different bi-criteria LPs, in each of which we minimise each objective against one of the others (*resource depletion vs production*, *ecosystems quality vs production* and *resource depletion vs ecosystem quality*). More precisely, we ran 10 iterations of the epsilon constraint method for each such problem, generating 10 optimal solutions for each 2D space problem.

Figs. 5, 6 and 7 show the projections onto the subspaces *resource depletion vs production*, *ecosystem quality vs production* and *ecosystems quality vs resource depletion*, respectively. The following points are plotted in the figures: the original set of 3D Pareto optimal solutions projected onto the corresponding 2D subspace (unfilled blue points), the optimal points generated in the 2D subspace itself (filled blue points) and the base case (red colour point).

As observed in Fig.5 and 6, there is a clear trade-off between each environmental impact and the production rate (an improvement in the latter implies worsening the former). Furthermore, the base case (depicted in red) is sub-optimal in the space of either pair of two objectives.

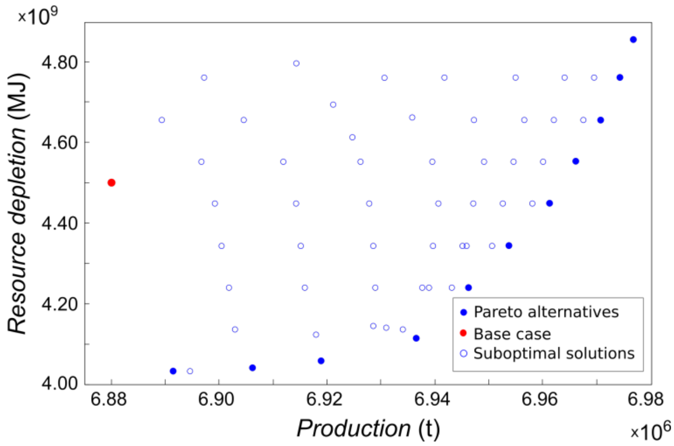

Fig. 5 Set of Pareto optimal solutions for the bi-criteria problem resource depletion vs production.

As can be observed in Fig. 5, there are six optimal solutions in the space *resource depletion* vs *production* (the first ones starting from the left-hand side of the Pareto set) showing lower damage to resources and higher production rates than the base case (i.e., dominating the base case solution). Additionally, the slope of the Pareto curve is small in the first three points and then increases significantly thereafter, implying that larger improvements in production can be attained by increasing marginally the damage to resources depletion (making such solutions appealing for decision-makers).

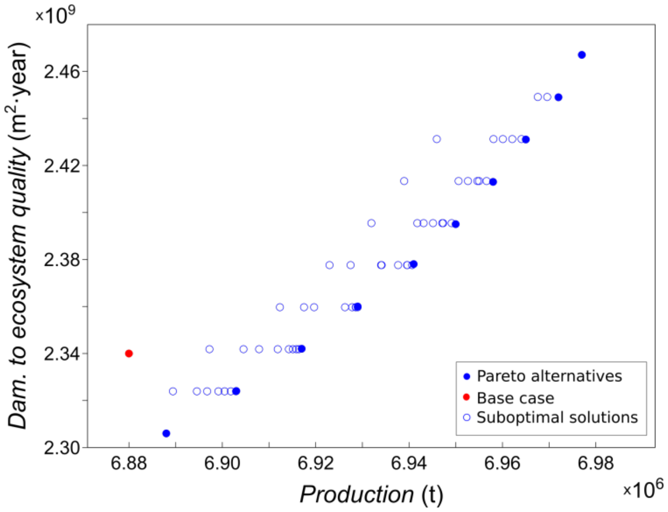

Fig. 6 Set of Pareto optimal solutions for the bi-criteria problem damage to ecosystems quality vs production.

On the other hand, the slope of the Pareto set in Fig. 6 (trade-off between ecosystems quality and production) is almost constant. Again, from point 1 to 3 (starting from the left-hand side of the Pareto set), it is possible to improve the base case simultaneously in both objectives.

Finally, we analysed the trade-off between both environmental objectives (*damage to ecosystem quality vs resource depletion*) (see Fig. 7). As observed in Fig. 7, there is a clear trade-off between both impacts, as an improvement in one criterion is only possible by worsening the other one, that is, reductions in the minimum damage to ecosystem quality are only possible by increasing the minimum damage to resources.

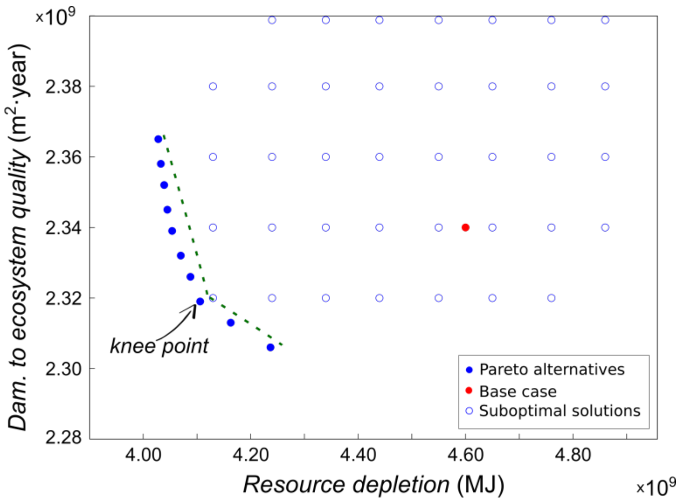

Fig. 7 Set of Pareto optimal solutions for the bi-criteria problem damage to ecosystems quality vs resource depletion.

Remarkably, the base case (depicted in red in Fig. 7) is sub-optimal in the 2D subspace *damage to ecosystems quality vs resource depletion*, as it can be improved simultaneously in both objectives by some points lying in the Pareto front. As observed, all the Pareto solutions generated in the space *damage to ecosystems quality vs resource depletion* show less damage to resources than the base case, and there are six solutions which are also better in terms of damage to ecosystems quality. Starting from the top solution, the slope of the curve decreases sharply, so reductions in damage to ecosystem quality can be attained by increasing the damage to resources depletion marginally, while from point 8 the slope shows a low rate of decrease. Point 8 is identified as a "knee point", in which the slope of the curve changes significantly, and it may be particularly appealing for decision and policy makers.

4.3. Optimal rainfed and irrigated cropping areas

Any Pareto point could be chosen by decision and policy-makers as they all represent optimal alternatives achieving a unique combination of objectives values implying a particular rainfed and irrigated area in each watershed. The selection of the most preferred Pareto solution should be made by an expert panel considering the farmers' and other stakeholders' preferences. A priori and posteriori approaches are available for multi-criteria decision-making (further information on this topic can be found in Figueira et al., (2005)). In this work, we provide the set of optimal alternatives without giving any weight/priority to the objectives (i.e. no ranking of Pareto points is provided), so we avoid subjective value judgements.

For illustrative purposes, Fig.8 shows the surface changes that need to be implemented (with respect to the base case) in the extreme solutions and in the knee point solution identified in Fig.7. Each watershed is coloured according to the change in hectares assigned to the rainfed and irrigated surfaces (yellow colour for rainfed and blue colour for irrigated). Light and dark shades indicate low and high changes, respectively. Note that changes with respect to the base case imply that rainfed areas are replaced by irrigated surfaces or vice-versa, that is, only changes between rainfed and irrigated areas are allowed (Galicia watershed remains unchanged in all of the solutions, since wheat is only grown under rainfed conditions).

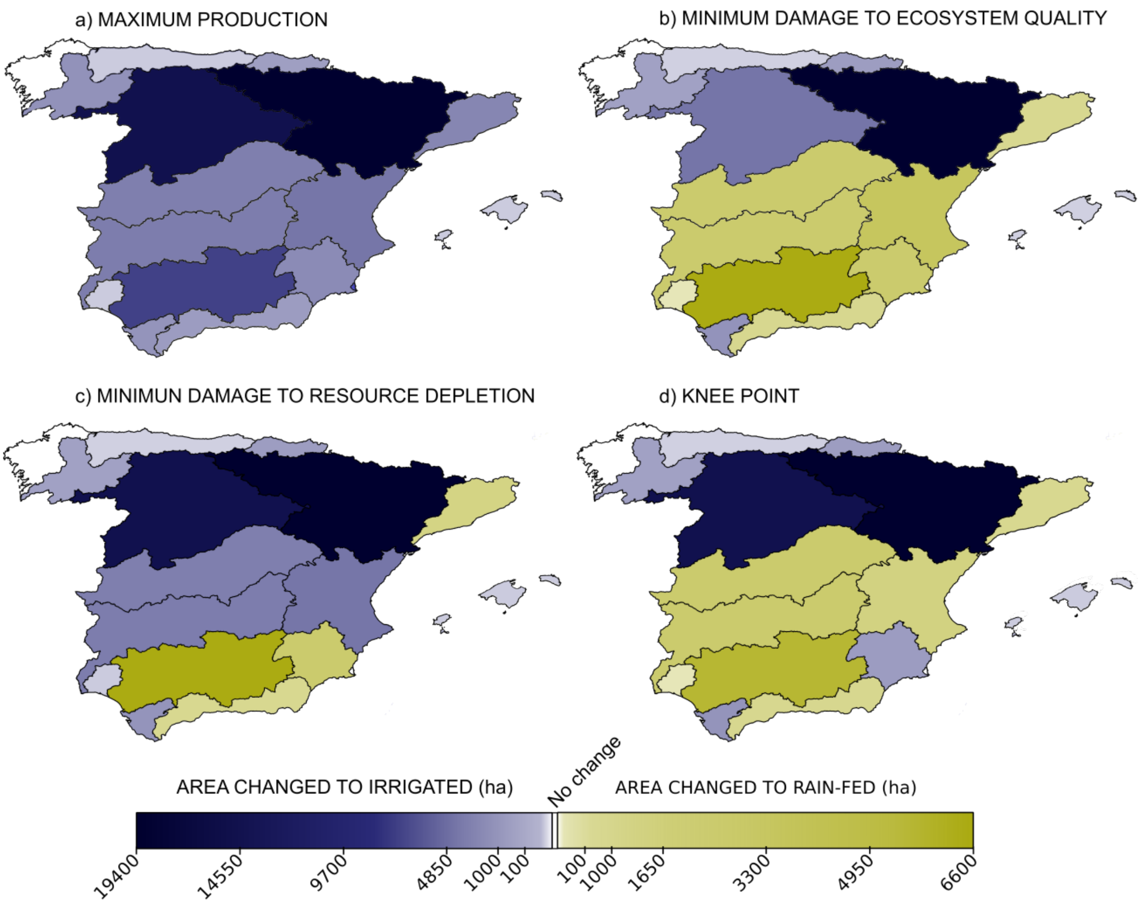

Fig. 8 Optimal changes between rainfed and irrigated areas in each watershed corresponding to the following solutions: (a) maximum production, (b) minimum damage to ecosystem quality, (c) minimum damage to resource depletion and (d) knee point solution identified contrasting ecosystems quality vs resource depletion.

As observed in Fig. 8a, the model maximises the production by increasing the irrigated areas in all of the watersheds, that is, the solution replaces rainfed areas by irrigated ones, since yields are higher in irrigated areas compared to non-irrigated areas that usually suffer water deficiencies. Compared to the base case, the maximum production solution increases the production by 1.1% (92328 t), but this leads to a significant worsening of the environmental objectives, especially in resource depletion (the impact increases by 7.8% in resource depletion and by 4.5% in ecosystem quality).

Fig.8b shows the optimal changes in the minimum damage to ecosystems quality solution. A clear difference between the northern and the southern Spanish watersheds is observed. More precisely, in most of the southern watersheds, with high vulnerability to suffer ecosystem damage due to water consumption, the irrigated areas are replaced by rainfed exploitation. The production deficit generated by implementing this plan is offset by replacing rainfed areas by irrigation systems in the northern watershed as well as in Duero, Ebro, Guadalete and Barbate, and Balearic Islands. Comparing to the base case, the minimum damage to ecosystem quality solution preserves 3263 ha from degradation every year and reduces the amount of water consumed by 1.1 % (in turn, this solution also reduces the damage to resource depletion by 7.9% while maintaining the production).

Fig. 8c represents the optimal changes corresponding to the minimum damage to resource depletion solution. As can be observed in the map (Fig. 8c), the irrigated areas are reduced in Cuencas internas de Cataluña, Guadalquivir, Cuenca Mediterránea Andaluza and Segura watersheds, as these regions show the highest vulnerability to resources depletion (see Table 1). In order to offset the significant production loss taking place when these changes are implemented, the model replaces in the other watersheds rainfed areas by irrigated ones. Compared to the base case, the minimum damage to resource depletion solution decreases by 572 million MJ the energy required to extract water resources in the future (reduction of 12.5%), worsening the impact in ecosystem quality by 2.0% and increasing the production by 0.7%.

Finally, Fig. 8d shows the optimal changes that should be implemented in the knee solution identified in Fig. 7 (trade-off between ecosystems quality and resource depletion). Two clear patterns are identified in the northern and southern Spanish watersheds. More precisely, in many southern watersheds (with high vulnerability in ecosystem damage and resource depletion), the irrigated areas are replaced by rainfed exploitation. However, this reduction of irrigated areas (with higher yields than rainfed ones) generates a production deficit, which is offset by replacing rainfed areas by irrigation systems in other watersheds, including Duero, Ebro, Guadalete and Barbate, Segura and Balearic Islands. Compared to base case, the knee point solution allows decreasing the damage to ecosystem quality and the damage to resource depletion by 0.9% and 10.7% respectively, while the production is maintained at the same level as in the base case.

4.4. Sensitivity analysis

A sensitivity analysis was carried out to investigate the robustness of the deterministic model considering two uncertain parameters: blue water requirements and crop yield. The irrigation requirements may be overestimated in the model, as farmers may not irrigate at the optimum level. On the other hand, the crop yield may be affected by several factors, including weather variations, climate change, soil responses, management practises or pests. Furthermore, we have investigated how the optimal solution changes for different lower and upper bounds imposed on the surfaces.

The results of the sensitivity analysis are summarised in the form of heat maps (Figs. 9 and 10), which show how the extreme solutions (those obtained in the scalar optimisation of each separate objective) change when the irrigation requirements and crop yields are modified. Each heat map cell is coloured according to the percentage change in the objective function with respect to the nominal case. Red colours indicate worse values, while green colours indicate better values. The x-axis corresponds to different bounds on variables from 0% (no change allowed) to 100% (all rainfed areas can be substituted by irrigated or vice versa). Note that we consider that each uncertain parameter is modified simultaneously in all of the watersheds to the same proportion. The base case (BC) and the nominal case (NC) are also shown to facilitate comparisons.

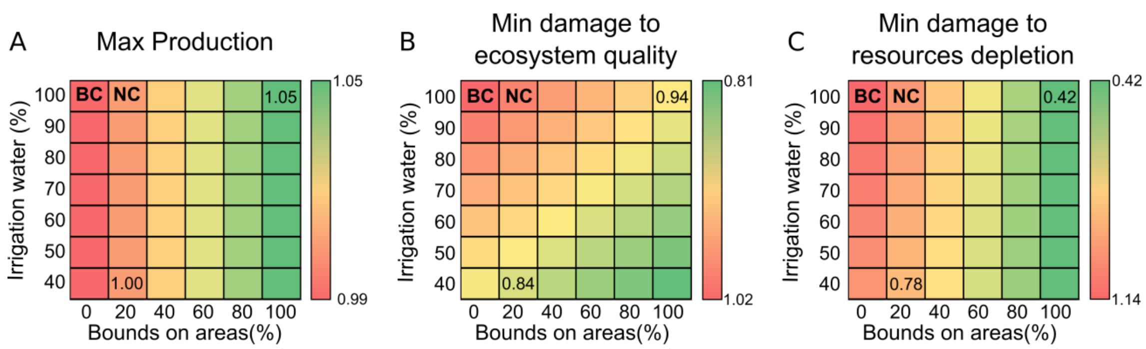

Fig. 9 Sensitivity analysis of the extreme optimal solutions to changes in the irrigation parameter. BC stands for base case and NC for nominal case. The value of each cell represents the percentage change with respect the nominal case.

Changing the irrigation water requirements from 100% to 40% for a fixed yield: As observed in Fig. 9, when maintaining the irrigation as in the nominal case (100% case, as shown in the vertical axis) and changing the bounds on the areas from 20% to 100% (horizontal axis), the production can increase by 5% at most (Fig.9a, cell 1.05), the damage to ecosystems can decrease by no more than 6% (Fig. 9b, cell 0.94) and the damage to resources can drop by as much as 58% (Fig. 9c, cell 0.42). On the other hand, when the dose of irrigation is reduced to 40% of its value in the nominal case (vertical axis) and bounds on areas are fixed to 20% (as in the nominal case), the maximum production remains constant, while the damage to ecosystems and the damage to resources can be reduced by as much as 16% (Fig. 9b, cell 0.84) and 22% (Fig. 9c, cell 0.78), respectively, compared to the nominal case.

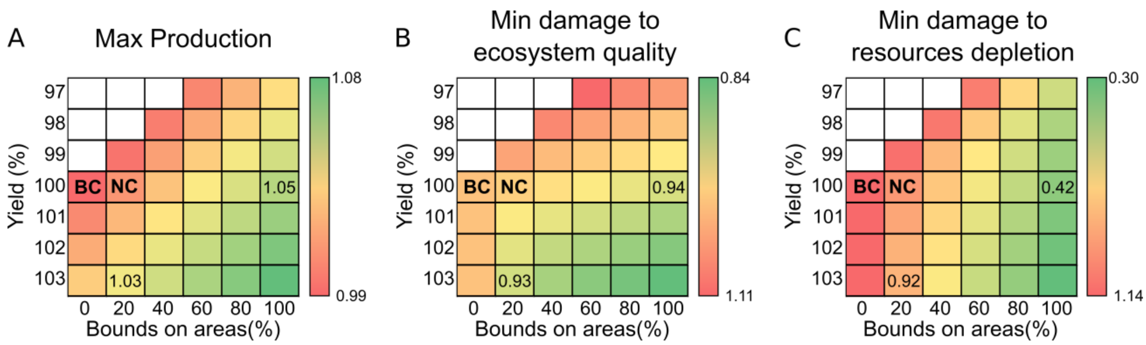

Fig. 10 Sensitivity analysis of the extreme optimal solutions to changes in the crop yield parameter. BC stands for base case and NC for nominal case. The value of each cell represents the percentage change with respect the nominal case.

Changing the yields from 103% to 97% for fixed irrigation requirements: As seen in Fig. 10, when maintaining the yield equal as in the nominal case and changing the bound on areas from 20% to 100%, the production can increase by 5% at most (Fig. 10a, cell 1.05), the damage to ecosystems quality can decrease by 6% (Fig. 10b, cell 0.94) and the damage to resources can decrease by no more than 58% (Fig. 10c, cell 0.42). On the other hand, when the wheat yield is increased by 3% (103% with respect to the nominal case) while maintaining the bounds fixed to 20% (like in the nominal case), the crop production increases in the same proportion (Fig. 10a, cell 1.03), the damage to ecosystems can be reduced by 7% (Fig. 10b, cell 0.93), and the damage to resources can decrease by 8% (Fig. 10c, cell 0.92). When the yield is decreased by 3% and the bounds on the areas are the same as in the nominal case, then the problem renders infeasible (non-coloured cells appearing in the heat map indicate infeasible solutions), since the demand satisfaction constraint is violated. This is because the demand is kept as in the nominal case and even increasing the irrigated areas until they hit their upper bound is not sufficient to offset the decrease in production.

The changes in the optimal areas are summarised in Figs. 11 and 12 in the form of radar charts in which each axis corresponds to a watershed (see watersheds codes in Fig. 2) and the ring with value 1 represents the nominal case.

Changes in the irrigation requirements: As seen in Fig 11, when the irrigation is reduced to 40% and the bounds fixed to 20% (like in the nominal case), the optimal rainfed and irrigated areas remain the same as in the nominal case in the three objectives regardless of the dose of irrigation. When the production is maximised (Fig. 11a), the irrigated areas are increased in all of the watersheds until they hit the bound imposed (20% of change); and when the damage to ecosystems (Fig.11b) and the damage to resources (Fig. 11c) are minimised, the optimal areas are allocated based on the vulnerability of watersheds to the water consumption (i.e., based on the environmental characterization factors specific for each watershed), which remains the same. Therefore, these changes have no impact on the optimal areas.

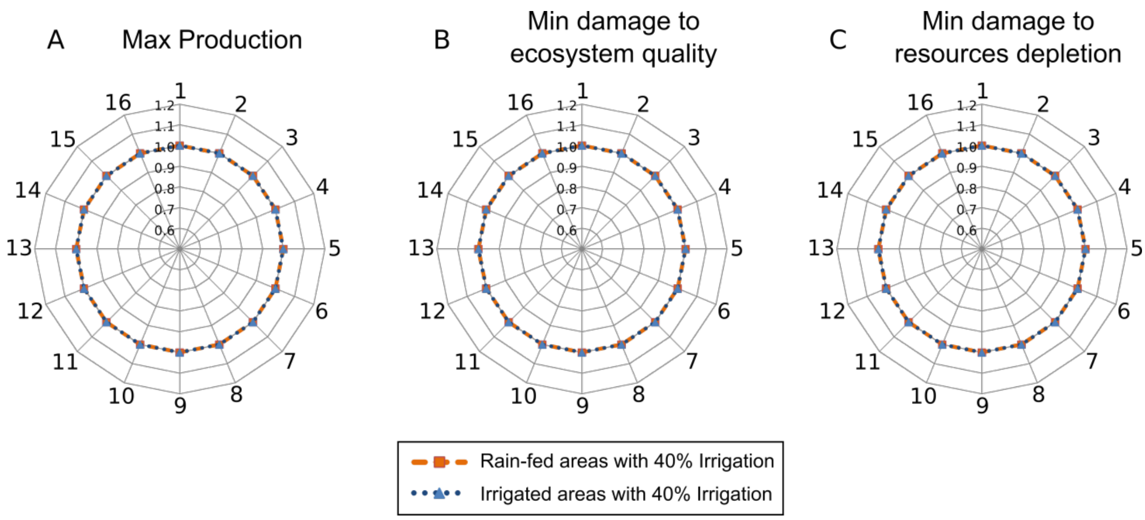

Fig. 11 Sensitivity analysis of the optimal rainfed and irrigated areas to changes in the irrigation.

Changes in the yield: Fig. 12 shows how the optimal areas change for a 3% increment in the yield maintaining the bounds as in the nominal case. When the production is maximised, the optimal cropping areas remain the same regardless of the value of the yield (Fig. 12a), since irrigated areas (which present higher yield) are increased until they hit their upper bound. When the damage to ecosystems quality is minimised (Fig. 12b), the optimal rainfed and irrigated areas vary greatly in many of the watersheds comparing with the nominal case (from 8% increase in rainfed area in Ebro, to 33% reduction in irrigated areas in Ebro, Guadalete y Barbarte and Islas Baleares). On the other hand, when the damage to resources is minimized (Fig.12c), the irrigated optimal areas remain the same as in the nominal case in all of the watersheds, while the rainfed areas are decreased in Cuenca Mediterránea, Guadalquivir and Cuencas internas de Cataluña.

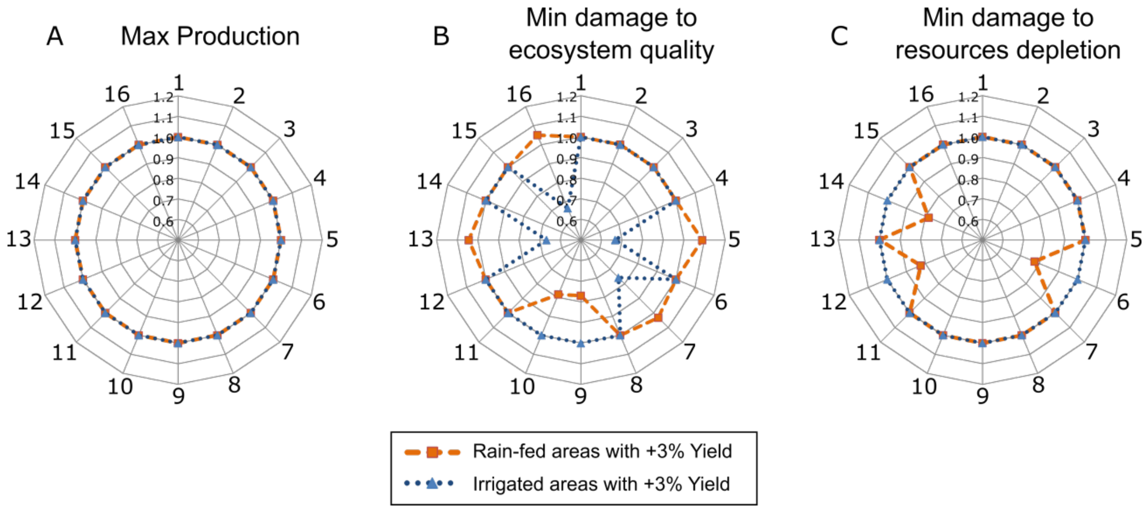

Fig. 12 Sensitivity analysis of the optimal rainfed and irrigated areas to changes in the yield.

5. CONCLUSION

An optimized allocation of rainfed and irrigated cropping areas is identified as a potential pathway to reduce the environmental impact of water consumption in the transition towards a more sustainable agricultural production system. To address this problem, we have developed a novel systematic decision-support tool that integrates WF and LCA principles with mathematical programming techniques. The task of identifying optimal rainfed and irrigated areas in a watershed was mathematically formulated as a multi-objective linear programming problem that seeks to optimise simultaneously the production and environmental impact of water consumption.

The capabilities of our approach were tested through its application to a case study based on wheat production in Spain. Results show that significant reductions in environmental impact can be attained by properly allocating the rainfed and irrigated cropping areas while still maintaining or even increasing the current production. We found that some of the optimal solutions identified by the optimization algorithm represent win-win scenarios that improve the base case (current scenario identified as sub-optimal) simultaneously in all of the objectives (i.e., production targets and environmental impacts). Unlike rules of thumb or heuristics, our approach avoids sub-optimal solutions by guaranteeing convergence to the global optimum. The analysis indicates that the systematic tool presented here, which combines MOO with LCA and WF, can be potentially employed for optimally allocating rainfed and irrigated crops in order to reduce the environmental impact of water consumption in agriculture while enhancing food availability.

Concerning the robustness of the model, the sensitivity analysis performed shows that: (i) water requirements have a significant impact on the environmental objectives (changes in blue water requirements from 100% to 40% can reduce the damage to ecosystems quality by no more than 16%, and the damage to resources in 22%); (ii) changes in the yield can also affect significantly all of the objectives and can even make the model unfeasible for some values (a 3% increment in the yield can increase the production in 3%, and reduce the damage to ecosystems by 7%, and the damage to resources by 8%); (iii) the impact of the bounds on areas is also significant, making it possible to attain larger economic and environmental improvements by widening them (i.e., small lower bounds and bigger upper bounds); (iv) concerning the optimal areas in each watershed, they are sensitive to small changes in yields, which may lead to quite different solutions in each case. The results of the sensitivity analysis highlight the opportunity to extent the deterministic model proposed herein by integrating the uncertainties related to potential changes in climate conditions.

Our systematic decision-support tool is intended to support decision and policy making by providing a set of optimal alternatives and useful guidelines to formulate appropriate regulations and policy responses for the challenge of sustainable agriculture. Note, however, that these policies can only succeed if social and economic costs associated with the transition process are compensated through a set of effective incentives (farmers need to be compensated for the extra costs and income losses incurred). Our framework can contribute to the development of more sustainable agricultural production patterns, enhancing food security and mitigating the problems of water scarcity and environmental degradation.

ACKNOWLEDGEMENTS

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Nomenclature

Indices

J	set for watersheds indexed by *j*
K	set for provinces indexed by *k*

Parameters

Demand	Minimum demand satisfaction level of the crop (t)
$\mathrm{Yield}_{\mathrm{j}}^{\mathrm{DRY}}$	productivity in rainfed farmland in watershed *j* ($t \cdot ha^{-1}$)
$\mathrm{Yield}_{\mathrm{j}}^{\mathrm{IRR}}$	productivity in irrigated farmland in watershed *j* ($t \cdot ha^{-1}$)
$\mathrm{CF}_{\mathrm{j}}^{\mathrm{EQ}}$	characterization factor for ecosystem quality in watershed *j* (m^2 year$\cdot m^{-3}$)
$\mathrm{CF}_{\mathrm{j}}^{\mathrm{RD}}$	characterization factor for resource depletion in watershed *j* ($MJ \cdot m^{-3}$)
$\mathrm{Surface}_{\mathrm{j}}^{\mathrm{AVA}}$	surface available in watershed *j* (ha)
$\mathrm{SR}_{\mathrm{j}}^{\mathrm{DRY}}$	current harvested rainfed surface in watershed *j* (ha)
$\mathrm{SR}_{\mathrm{j}}^{\mathrm{IRR}}$	current harvested irrigated surface in watershed *j* (ha)
$\mathrm{CWU}_{\mathrm{j}}^{\mathrm{GREEN}}$	green water crop requirements in watershed *j* ($m^3 \cdot ha^{-1}$)
$\mathrm{CWU}_{\mathrm{j}}^{\mathrm{BLUE}}$	blue water crop requirements in watershed *j* ($m^3 \cdot ha^{-1}$)
$\mathrm{CWU}_{\mathrm{j}}^{\mathrm{GREY}}$	grey water crop requirements in watershed *j* ($m^3 \cdot ha^{-1}$)
$\mathrm{CS}_{\mathrm{k}}^{\mathrm{DRY}}$	real crop harvested area under rainfed conditions in province *k* (ha)
$\mathrm{CS}_{\mathrm{k}}^{\mathrm{IRR}}$	real crop harvested area under irrigated conditions in province *k* (ha)
$f_{\mathrm{k,j}}$	area fraction of province *k* in the watershed *j* (dimensionless)
$\mathrm{YP}_{\mathrm{k}}^{\mathrm{DRY}}$	real rainfed crop yield in province *k* ($t \cdot ha^{-1}$)
$\mathrm{YP}_{\mathrm{k}}^{\mathrm{IRR}}$	real irrigated crop yield in province *k* ($t \cdot ha^{-1}$)

Variables

$Surface_j^{DRY}$	rainfed surface in watershed *j* (ha)

$Surface_j^{IRR}$	irrigated surface in watershed (ha)
Production	total production of the crop (tonnes)
EQ	damage to ecosystem quality (m^2 year)
RD	damage to resources depletion (MJ)
CWR_j	crop water requirement in the watershed j (m^3)
W_J^{GREEN}	volume of green water consumed by the crop in each watershed j (m^3)
W_J^{BLUE}	volume of blue water consumed by the crop in each watershed j (m^3)
W_J^{GREY}	volume of grey water consumed by the crop in each watershed j (m^3)

REFERENCES

AEMET, 2014. Valores climatológicos normales - Agencia Estatal de Meteorología - AEMET. Gobierno de España [WWW Document]. URL http://www.aemet.es/es/serviciosclimaticos/datosclimatologicos/valoresclimatologicos (accessed 1.27.14).

Alcamo, J., Döll, P., Henrichs, T., Kaspar, F., Lehner, B., Rösch, T., Siebert, S., 2003. Development and testing of the WaterGAP 2 global model of water use and availability. Hydrol. Sci. J. 48, 317–337. doi:10.1623/hysj.48.3.317.45290

Aldaya, M.M., Martínez-Santos, P., Llamas, M.R., 2009. Incorporating the Water Footprint and Virtual Water into Policy: Reflections from the Mancha Occidental Region, Spain. Water Resour. Manag. 24, 941–958. doi:10.1007/s11269-009-9480-8

Allen Richard, G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop Evapotranspiration, Guidelines for Computing Crop Water Requirements., Edición: R. ed. Fao, Rome.

Azapagic, A., 1999. Life cycle assessment and its application to process selection, design and optimisation. Chem. Eng. J. 73, 1–21. doi:10.1016/S1385-8947(99)00042-X

Azapagic, A., Clift, R., 1999. Life cycle assessment and multiobjective optimisation. J. Clean. Prod. 7, 135–143. doi:10.1016/S0959-6526(98)00051-1

Azapagic, A., Perdan, S., 2005. An integrated sustainability decision-support framework Part II: Problem analysis. Int. J. Sustain. Dev. World Ecol. 12, 112–131.

Berger, M., Finkbeiner, M., 2010. Water Footprinting: How to Address Water Use in Life Cycle Assessment? Sustainability 2, 919–944. doi:10.3390/su2040919

Boulay, A.-M., Bayart, J.-B., Bulle, C., Franceschini, H., Motoshita, M., Muñoz, I., Pfister, S., Margni, M., 2015. Analysis of water use impact assessment methods (part B): applicability for water footprinting and decision making with a laundry case study. Int. J. Life Cycle Assess. 20, 865–879. doi:10.1007/s11367-015-0868-9

Branke, J., Deb, K., Miettinen, K., Słowinski, R., 2008. Multiobjective Optimization. Interactive and Evolutionary Approaches. Springer, Verlag Berlin Heidelberg.

Brooke, A., Kendrick, D., Meeraus, A., Raman, R., 1998. GAMS—A User'sManual. GAMS Development Corporation, Washington, DC.

Chankong, V., Haimes, Y.Y., 1983. Multiobjective Decision Making: Theory and Methodology. Elservier-North Holland, New Yoek.

Chapagain, A.K., Orr, S., 2009. An improved water footprint methodology linking global consumption to local water resources: a case of Spanish tomatoes. J. Environ. Manage. 90, 1219–28. doi:10.1016/j.jenvman.2008.06.006

Chen, Z.J., Cheng, Z.J., Yan, X.Q., 2013. Multiobjective Optimization Problem of Multireservoir System in Semiarid Areas. Math. Probl. Eng. 2013, 1–8. doi:10.1155/2013/354206

Dury, J., Schaller, N., Garcia, F., Reynaud, A., Bergez, J.E., 2011. Models to support cropping plan and crop rotation decisions. A review. Agron. Sustain. Dev. 32, 567–580. doi:10.1007/s13593-011-0037-x

Ehrgott, M., 2000. Multicriteria optimization. Springer.

Ehrgott, M., 2008. Multiobjective optimization. AI Mag. 29, 47–57.

Ehrgott, M., 2009. Multiobjective Optimization. AI Mag. 29, 47. doi:10.1609/aimag.v29i4.2198

FAO, 2010. "CROPWAT 8.0" Water Development and Management Unit - Information Resources - Databases [WWW Document]. URL http://www.fao.org/nr/water/infores_databases_cropwat.html

FAO, 2014. AQUASTAT-FAO's information system on water and agriculture [WWW Document]. Organ. las Nac. Unidas para la Aliment. y la Agric. URL http://www.fao.org/nr/water/aquastat/main/index.stm (accessed 3.4.14).

Figueira, J., Greco, S., Ehrogott, M., 2005. Multiple Criteria Decision Analysis: State of the Art Surveys. Springer-Verlag New York.

Finnveden, G., Hauschild, M.Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., Koehler, A., Pennington, D., Suh, S., 2009. Recent developments in Life Cycle Assessment. J. Environ. Manage. 91, 1–21. doi:10.1016/j.jenvman.2009.06.018

Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., Tilman, D., Zaks, D.P.M., 2011. Solutions for a cultivated planet. Nature 478, 337–42. doi:10.1038/nature10452

García, N., Fernández-Torres, M.J., Caballero, J.A., 2014. Simultaneous environmental and economic process synthesis of isobutane alkylation. J. Clean. Prod. 81, 270–280. doi:10.1016/j.jclepro.2014.06.016

Garrido, A., Llamas, M.., Varela-Ortega, C., Novo, P., Rodríguez-Casado, R., Aldaya, M., 2010. Water Footprint and Virtual Water Trade in Spain: Policy Implications. La Fundación Marcelino Botín-Sanz de Sautuola y López, New York, NY.

Giorgi, F., 2006. Climate change hot-spots. Geophys. Res. Lett. 33, L08707. doi:10.1029/2006GL025734

Goedkoop, M., Spriensma, R., 2001. The Eco-Indicator 99: a Damage Oriented Method for Life Cycle Impact Assessment: Methodology Report, Publikatiereeks produktenbeleid; nr. 36A; Ministerie van Volkshiusvesting, Ruimtelijke Ordening en Milieubeheer: Den Haag.

Grossmann, I.E., Guillén-Gosálbez, G., 2010. Scope for the application of mathematical programming techniques in the synthesis and planning of sustainable processes. Comput. Chem. Eng. 34, 1365–1376. doi:10.1016/j.compchemeng.2009.11.012

Guillen-Gosalbez, G., Caballero, J. #x ; A., Esteller, L.J., Gadalla, M., 2007. 17th European Symposium on Computer Aided Process Engineering, Computer Aided Chemical Engineering, Computer Aided Chemical Engineering. Elsevier. doi:10.1016/S1570-7946(07)80218-5

Haimes, Y.., Lasdon, L.S., Wismer, D.A., 1971. On a bicriterion formulation of the problems of integrated system identification and system optimization. IEEE Trans. Syst. Man, Cybern. 3, 296–271.

Hoekstra, A.Y., 2003. Virtual water trade: Proceedings of the International Expert Meeting on Virtual Water Trade', 12–13 December 2002, Value of Water Research Report Series No 12, UNESCO-IHE, Delft, Netherlands.

Hoekstra, A.Y., Chapagain, A.K., Aldaya, M., Mekonnen, M.M., 2011. The water footprint assessment manual: setting the global standard. Earthscan, London ; Washington, DC.

Hospido, A., Núñez, M., Antón, A., 2012. Irrigation mix: how to include water sources when assessing freshwater consumption impacts associated to crops. Int. J. Life Cycle Assess. 18, 881–890. doi:10.1007/s11367-012-0523-7

Jefferies, D., Muñoz, I., Hodges, J., King, V.J., Aldaya, M., Ercin, A.E., Milà i Canals, L., Hoekstra, A.Y., 2012. Water Footprint and Life Cycle Assessment as approaches to assess potential impacts of products on water consumption. Key learning points from pilot studies on tea and margarine. J. Clean. Prod. 33, 155–166. doi:10.1016/j.jclepro.2012.04.015

Karrou, M., Oweis, T., 2012. Water and land productivities of wheat and food legumes with deficit supplemental irrigation in a Mediterranean environment. Agric. Water Manag. 107, 94–103. doi:10.1016/j.agwat.2012.01.014

Khoshnevisan, B., Bolandnazar, E., Shamshirband, S., Shariati, H.M., Anuar, N.B., Mat Kiah, M.L., 2015. Decreasing environmental impacts of cropping systems using life cycle assessment (LCA) and multi-objective genetic algorithm. J. Clean. Prod. 86, 67–77. doi:10.1016/j.jclepro.2014.08.062

Liu, J., Zehnder, A.J.B., Yang, H., 2009. Global consumptive water use for crop production: The importance of green water and virtual water. Water Resour. Res. 45, n/a–n/a. doi:10.1029/2007WR006051

MAGRAMA, 2014. Agriculture Statistics [WWW Document]. URL http://www.magrama.gob.es/es/estadistica/temas/estadisticas-agrarias/agricultura/

Milà i Canals, L., Chenoweth, J., Chapagain, A., Orr, S., Antón, A., Clift, R., 2008. Assessing freshwater use impacts in LCA: Part I—inventory modelling and characterisation factors for the main impact pathways. Int. J. Life Cycle Assess. 14, 28–42. doi:10.1007/s11367-008-0030-z

Núñez, M., Pfister, S., Antón, A., Muñoz, P., Hellweg, S., Koehler, A., Rieradevall, J., 2013. Assessing the Environmental Impact of Water Consumption by Energy Crops Grown in Spain. J. Ind. Ecol. 17, 90–102. doi:10.1111/j.1530-9290.2011.00449.x

Ortiz, R., Sayre, K.D., Govaerts, B., Gupta, R., Subbarao, G.V., Ban, T., Hodson, D., Dixon, J.M., Iván Ortiz-Monasterio, J., Reynolds, M., 2008. Climate change: Can wheat beat the heat? Agric. Ecosyst. Environ. 126, 46–58. doi:10.1016/j.agee.2008.01.019

Pacetti, T., Lombardi, L., Federici, G., 2015. Water–energy Nexus: a case of biogas production from energy crops evaluated by Water Footprint and Life Cycle Assessment (LCA) methods. J. Clean. Prod. 101, 278–291. doi:10.1016/j.jclepro.2015.03.084

Pfister, S., Bayer, P., 2013. Monthly water stress: spatially and temporally explicit consumptive water footprint of global crop production. J. Clean. Prod. doi:10.1016/j.jclepro.2013.11.031

Pfister, S., Koehler, A., Hellweg, S., 2009. Assessing the Environmental Impacts of Freshwater Consumption in LCA. Environ. Sci. Technol. 43, 4098–4104. doi:10.1021/es802423e

Pieragostini, C., Mussati, M.C., Aguirre, P., 2012. On process optimization considering LCA methodology. J. Environ. Manage. 96, 43–54. doi:10.1016/j.jenvman.2011.10.014

Postel, S.L., Daily, G.C., Ehrlich, P.R., 1996. Human appropriation of renewable fresh water. Science (80-.). 271, 785–788.

Rharrabti, Y., Royo, C., Villegas, D., Aparicio, N., García del Moral, L.., 2003. Durum wheat quality in Mediterranean environments. F. Crop. Res. 80, 123–131. doi:10.1016/S0378-4290(02)00176-4

Ridoutt, B.G., Pfister, S., 2010. A revised approach to water footprinting to make transparent the impacts of consumption and production on global freshwater scarcity. Glob. Environ. Chang. 20, 113–120. doi:10.1016/j.gloenvcha.2009.08.003

Rijsberman, F.R., 2006. Water scarcity: Fact or fiction? Agric. Water Manag. 80, 5–22. doi:10.1016/j.agwat.2005.07.001

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F.S., Lambin, E., Lenton, T.M., Scheffer, M., Folke, C., Schellnhuber, H.J., Nykvist, B., de Wit, C.A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P.K., Costanza, R., Svedin, U., Falkenmark, M., Karlberg, L., Corell, R.W., Fabry, V.J., Hansen, J., Walker, B., Liverman, D., Richardson, K., Crutzen, P., Foley, J., 2009. Planetary boundaries: Exploring the safe operating space for humanity. Ecol. Soc. 14.

Sarker, R., Ray, T., 2009. An improved evolutionary algorithm for solving multi-objective crop planning models. Comput. Electron. Agric. 68, 191–199. doi:10.1016/j.compag.2009.06.002

Singh, A., 2012a. Optimal Allocation of Resources for the Maximization of Net Agricultural Return. J. Irrig. Drain. Eng. 138, 830–836. doi:10.1061/(ASCE)IR.1943-4774.0000474

Singh, A., 2012b. An overview of the optimization modelling applications. J. Hydrol. 466-467, 167–182. doi:10.1016/j.jhydrol.2012.08.004

Steffen, W., Richardson, K., Rockstrom, J., Cornell, S.E., Fetzer, I., Bennett, E.M., Biggs, R., Carpenter, S.R., de Vries, W., de Wit, C.A., Folke, C., Gerten, D., Heinke, J., Mace, G.M., Persson, L.M., Ramanathan, V., Reyers, B., Sorlin, S., 2015. Planetary boundaries: Guiding human development on a changing planet. Science (80-.). 347. doi:10.1126/science.1259855

UNEP, 2007. Global Environment Outlook – Geo 4: Environment for Development. United Nations Environment Programme. Valletta, Malta.

Xevi, E., Khan, S., 2005. A multi-objective optimisation approach to water management. J. Environ. Manage. 77, 269–77. doi:10.1016/j.jenvman.2005.06.013

Yue, D., Pandya, S., You, F., 2016. Integrating Hybrid Life Cycle Assessment with Multi-objective Optimization: A Modeling Framework. Environ. Sci. Technol. 50, 1501–1509. doi:10.1021/acs.est.5b04279

Zeng, X., Kang, S., Li, F., Zhang, L., Guo, P., 2010. Fuzzy multi-objective linear programming applying to crop area planning. Agric. Water Manag. 98, 134–142. doi:10.1016/j.agwat.2010.08.010