Trade-offs Associated with Changing Cropping Patterns in Semi-arid Areas of Morocco

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HIGHLIGHTS

- We use data and models to explore ecosystem trade-offs in an irrigated perimeter.
- This includes a new stochastic version of the Rothamsted Carbon model.
- We consider the impacts of changing crop systems and irrigation technologies.
- We used multi-objective optimisation to explore trade-offs and synergies in outcomes.
- Uncertainties in predictions are communicated to end users through tested methods.

ABSTRACT

We developed a comprehensive framework for investigating the trade-offs associated with choices about cropping systems and irrigation technology. The outcomes that we considered relate to agricultural production, soil carbon dynamics, water use efficiency and environmental impacts. To inform our predictions, we used data and models, including the IPCC models to describe nutrient losses, the Rothamsted carbon model to predict soil organic carbon and Cornel's Environmental Impact Quotient model to predict outcomes from pesticide use. To account for uncertainties in input data and model parameters, we used Monte Carlo simulations. We used tested means of visualisation to communicate the uncertainties to end users of the framework. We parameterised our framework to explore outcomes for an irrigated agricultural area (known as R3 perimeter) in a semi-arid region to the east of Marrakesh city in Morocco. We used the framework to explore outcomes that relate to recent policies on the expansion of olive cultivation and the adoption of more efficient irrigation technologies. We considered the impacts of more diversified cropping, as informed by our stakeholder consultation. We found that, for the outcomes we considered, there were clear trade-offs associated with cropping system choice. Compared to the baseline scenario of rotated crops, olive production led to greater carbon sequestration, increased water use efficiency, and reduced emissions, but was less profitable and provided fewer edible calories. Additionally, olive cultivation was associated with potentially higher environmental impacts from pesticide use. Diversified systems, while also less profitable, were associated with less harmful pesticide use. Across all systems, drip irrigation was associated with positive outcomes in terms of profit, water use efficiency and reduced nitrogen leaching with negligible changes in other metrics. However, we did not account for factors associated with increased groundwater depletion. We conclude that frameworks such as the one we produced are a useful means for policy stakeholders to explore the potential outcomes of their decisions (including accounting for uncertainties), thereby, helping to minimise unintended consequences. We emphasise the importance of iterative framework development involving ongoing stakeholder consultation to ensure continued relevance.

Keywords: Agroecosystems modelling, trade-offs, irrigated crops, RothC, Pareto fronts, communicating uncertainty.

1. Introduction

The impact of land use and poor decision-making on the management of natural capital has been well characterised at numerous scales, from national, regional and at the farm and field level (Guerry et al., 2015; World Resources Institute, 2005). The decision-making process around land use and management, and their impacts on natural capital remains a complex and at times fraught process. This is particularly the case under conditions of extreme resource limitation, which is the case in arid and semi-arid regions. In these cases, the quantity and condition of natural capital can be limited and degraded, and decisions around its use and management must be taken with particular care. This is often compounded with a particular scarcity in the evidence base as these areas, or the underlying natural processes, can be poorly characterized (O'Donnell & Manier, 2022). Africa has compounding challenges around increasing the production of food to support its growing population, whilst maintaining and improving the natural capital on which this depends. Africa is also particularly exposed to the effects of climate change (Diffenbaugh & Giorgi, 2012), with significant degradation expected in land suitable for agricultural use and yield potential (Ramos & Kahla, 2009).

Optimal land use, and its management, is intrinsically a consideration of a set of trade-offs between the different functions the land currently performs or may potentially perform in the future. Encapsulating those trade-offs and understanding and developing a cost basis for decision-making is a historic and ongoing significant area of research. The optimal use and management of land entail understanding and quantifying what a particular geographic area is currently providing in terms of benefits (e.g. water retention, food, fibre production, etc) but also what it potentially may provide when it is put to alternative use, and how to best manage the land given a certain use. The current benefits of any given geography can be quantified as its natural capital. This quantification should reflect the potential of any geography to deliver ecosystem services and associated societal benefits. Tools with which to characterise these trade-offs can range from spatially explicit and graphical representations (Zawadzka et al., 2017) to tools such as multi-criteria analysis (Kaim et al., 2018) and others (e.g. bundles (Karimi et al., 2021)). For any of these tools to be useful, we require them to have a robust and sound quantitative assessment of the potential and current benefits of any given system (evidence base for decision-making), with the inclusion of its' associated uncertainty.

The evidence base on which decisions are made around land use and management is often developed from numerous information and data sources; from existing data on the area (e.g. soils, climatic conditions, etc.), surveys (e.g. environmental and/or social surveys on use and utility, etc.) but also from biophysical models which can describe the functioning of a particular component of the biome in the area (e.g. water quality and quantity, C sequestration, etc.), or are often inferred from the type of land use and management through comparable studies where data is scarce. Each of these approaches will contribute uncertainty to the evidence base, and each will do so in different ways. For instance, the appropriateness of a particular biophysical model type, and the success in its parameterisation, will determine the uncertainty that is contained in its predictions of natural capital or ecosystem services. Error quantification, and propagation into a decision tool, or an environment which enables trade-offs is not straightforward but has been extensively used in, for instance, IPCC modelling around the impact of different C pathways on degrees of warming (Knutti et al., 2017). There is generally less evidence that it has been robustly incorporated in natural capital/ecosystem service assessments or in the subsequent process of determining the impact of particular decisions around land use and its management on natural capital and services this provides.

Decisions around land use and its management, in areas where there is severe resource limitation such as water scarcity, and in which the underlying natural capital is sparse, need to be made judiciously. However, often the evidence base (e.g. data) is sparse and the models used to determine how these natural capital stocks may respond to management interventions are not specific to these areas of interest (often developed for temperate climatic conditions). In arid and semi-arid regions, critical decisions on land management —including crop type, water management/irrigation approaches, tillage practices, and implementation of regenerative agriculture are predominantly based on experiential knowledge and/or aspirational expectations of the decision-makers, with little evidence-base to support the likely outcomes from these decisions.

Decision-making occurs at multiple scales, from field- and farm-scale levels to broader policy levels. At the policy level, incentives are often implemented to promote the adoption of practices perceived as beneficial. For instance, the Moroccan government has recently developed a strategy to expand olive cultivation (Silva & Filho, 2007). At the same time, policy incentives have been introduced to increase the adoption of localised irrigation technologies, such as drip irrigation (Molle & Tanouti, 2017) aimed at enhancing water use efficiency and reducing agricultural water losses. However, such policies are often instigated to address a shortfall and issues with one or two specific outcomes, and so may fail to take a more holistic view and consider trade-offs among various outcomes and so may have unintended consequences. As well as this, it is important that adaptations are relevant to the farmers who are called upon to implement them, and so engagement with farming stakeholders is a critical part of any scenario exploration.

A transparent framework that explores co-designed adaptations to potential policy changes and in which available data, models and associated uncertainty arising from their use is clearly represented presents a significant, and robust improvement on current approaches to decision-making around land use and its management. This is particularly critical in areas with very low levels of natural capital (e.g. water, soil organic matter, biodiversity), where the success of a particular policy or programme is built on this natural capital base (e.g. regenerative farming, agroforestry, etc).

Here we develop a novel tool to explore scenarios of future change in the extent and intensity of agricultural land use for an irrigated perimeter in a semi-arid region of Morocco. The tool aims to allow the user to better understand the range of potential outcomes at the catchment scale, should land use and management change. The tool allows the user to explore trade-offs between different responses, accounting for inherent uncertainties, thus providing a valuable method for engaging policymakers and stakeholders (Audsley et al., 2006; Redhead et al., 2020; Tompkins et al., 2008).

To facilitate the trade-off analysis, we used multi-objective optimisations. This approach determines Pareto optimal fronts of multiple objectives, describing the trade-offs between objective variables such as yield and environmental impact. The Pareto front represents scenarios where it is not possible to improve outcomes for one variable without impacting another adversely (A. E. Milne et al., 2020). Presenting a set of optimal solutions in this way enables decision-makers to understand the key drivers of trade-offs and how improving one objective might degrade another. This helps in making balanced decisions that align with priorities and constraints (Todman et al., 2019) of land management. Whilst communication of uncertainty is particularly important in resource-scarce areas such as semi-arid and arid regions, such a framework could be adapted to any scenario-based analysis where uncertainties in underlying methods and data may critically influence decision-making processes and their associated outcomes.

2. Methods

2.1 Methodology Overview

To analyse the impacts of crop choice and management on production and sustainability metrics, we use a synthesis of data and models. Our variables of interest were chosen to be production, profit, water use, soil carbon, nitrous oxide emissions, nitrogen leaching, and pollution in terms of environmental impact quotient (Kniss & Coburn, 2015). Each model component is described below. In each case, the uncertainties in the model parameters and variables were described using probability density functions (PDFs) and Monte Carlo simulation was used to propagate the uncertainties through to the simulated outputs.

The scenarios that we considered related to recent Moroccan agricultural policies, specifically addressing changes in cropping systems (notably the expansion of olive production and adoption of more diversified farming systems) and the implementation of more efficient irrigation practices. Importantly, we engaged with local stakeholders to derive crop rotations that were viewed as relevant to the case study area that we considered. We compiled data for each crop considered in the framework, accounting for both flood and drip irrigation management techniques. The data were derived from various sources. We collated data on ranges of expected yields for primary crop types typical to the area (see Section 3.1) under both flood or drip irrigation (Table S1). These data were obtained from the databases of SONACOS (National Company for the Marketing of Seeds in Morocco), which provided detailed records of average yields per crop. To validate this information and ensure its relevance to our study area, we conducted discussions with local farmers actively cultivating these crops (see El Fartassi et al., 2024). Next, data on fertilizers and phytosanitary product and their application rates were collected through consultations with extension agents from

ONCA (National Office of Agricultural Advice who shared their expertise and provided data specific to the crop types and farming practices prevalent in the area. Lastly, we obtained data on irrigation amounts for each irrigation technology from ORMVAH (Regional Office for Agricultural Development of Haouz). Models were coded in Python.

2.2 Framework components

2.2.1 Production metrics

It is not straightforward to compare the yields of different crops in a meaningful way. Therefore, we used edible calories produced and profitability as metrics of production. For each crop type identified as typical for the area (wheat, barley, maize, forage crops (typically alfalfa), vegetables (typically potatoes, beans and onions) and olives, (see also Section 3.1) we assumed the variation in expected yield was described by normal distribution where the range defines the 2.5th and 97.5th percentiles.

To estimate calories produced it is important to allow for losses associated with waste, milling, and holding-back seed for planting (Sharp et al., 2024). The calories, c (kcal ha^{-1}), associated with a given crop were therefore calculated by:

$$c = 1000\ y\ \varrho\ k\#(1)$$

where y, is the yield (t ha^{-1}), k is the number of calories obtained from consuming a kg of this crop, and ϱ is the proportion of the yield that reaches the plate once losses have been accounted for. This proportion is calculated from:

$$\varrho = (1 - w)(1 - s)m(1 - f)\#(2)$$

where w, is the proportion that is lost between harvest and processing, s is the estimated proportion of the yield that is taken for seed, m is the percentage that remains after processing (e.g. after milling), and f is the proportion lost during food preparation. The estimates used for the losses between the farm gate and plate are summarised in Table S2.

To estimate profit, P (Moroccan Dirham – MAD, ha^{-1} year^{-1}), we accounted for the selling price of the crop (Dh t^{-1}) and the costs associated with fertilizer (calculated by the amount applied, F, (kg ha^{-1}) multiplied by the fertiliser price, p_f, (Dh kg^{-1})), water costs p_w (Dh ha^{-1}) and pesticide costs p_D (Dh ha^{-1}):

$$P = p_c y - p_f F - p_w - p_D.\#(3)$$

Similar to the above, ranges were available for each component in the equation (Tables S3 and S4). In each case, we assumed the variation was normally distributed where the range defines the 2.5th and 97.5th percentiles.

2.2.2 Water use

To estimate water use (m^3 ha^{-1}), we used data on the crop water requirement (mean value and range) and then calculated the irrigation water applied by dividing by the efficiency of the irrigation technology used (Table S4). For flood irrigation, we assumed 60% efficiency and for drip irrigation we assumed 90% efficiency (Bouaziz & Belabbes, 2002). As above, we assumed the variation in water use was described by a normal distribution where the range defines the 2.5th and 97.5th percentiles.

2.2.3 Nutrient loss model

Farmers in the case study area regularly interact with agronomists whom fertilizer companies sponsor to give appropriate fertilizer recommendations. Therefore, we assume that fertilizer is generally well-managed by farmers in this area and that recommended rates are adopted for each crop. These were used to derive PDFs describing the expected fertilizer inputs. We estimated N losses by using the IPCC calculations for greenhouse gas emissions and nitrogen leaching (Eggelston et al., 2006). These calculations estimate both direct and indirect losses of N that come from both fertilizer inputs and plant residues. The full set of equations can be found in the IPCC guidelines. The IPCC publishes uncertainties in model parameter values, which were included in the Monte Carlo simulation (Eggelston et al., 2006).

2.2.4 Soil carbon

To estimate soil carbon, we used the Rothamsted Carbon Model (RothC) (Coleman, Milne, et al., 2024; Coleman, Prout, et al., 2024; Coleman & Jenkinson, 1996) run using Monte Carlo simulation to quantify estimates of uncertainty in predictions of soil carbon. The RothC model partitions Soil Organic Carbon (SOC) into an inert organic pool (IOM) and four active compartments which decompose according to first-order kinetics. Plant residues and farmyard manure (FYM) can be introduced into the soil, with carbon from the plant residues allocated to the decomposable plant material (DPM) and resistant plant material (RPM) compartments, and carbon from FYM allocated to the DPM, RPM and humified organic matter (HUM) pools. These decompose to produce microbial biomass (BIO), humified organic matter (HUM) and CO_2 (which is lost to the atmosphere). The clay content of the soil determines the proportions that decompose to BIO and HUM or are lost as CO_2. Decomposition rates of each active compartment are affected by soil moisture, temperature and plant cover through rate-modifying factors (for details see Coleman, Milne, et al., 2024; Coleman, Prout, et al., 2024; Coleman & Jenkinson, 1996). The IOM was calculated using the equation proposed by Falloon et al. (1998).

The model operates on a monthly time step and requires monthly weather data (average air temperature, total monthly precipitation and total monthly open-pan evaporation) and the monthly volume of irrigation water, which was added to the monthly precipitation. Weather data were obtained from three sites close to the study region. The data comprised half-hourly measures of temperature (°C), precipitation (mm), relative humidity (%), radiation (W m^{-2}) and wind speed (ms^{-1}). These data covered various time periods (Table S5) and were subject to missing observations. First, daily measurements of minimum temperature (°C), maximum temperature (°C), precipitation (mm) and evapotranspiration (ET0, mm) were derived from the half-hourly measurements. For ET0, we used the Penman-Monteith equations as described by FAO (Allen et al., 1998). We prioritized data from the weather station nearest to our study area (see Section 2.8) and filled gaps using data from the other two stations. Full details are given in SI. The final data set spanned February 2003 to June 2022. These daily data were used to calculate the monthly averages and sums required by RothC with associated standard errors describing the uncertainty in these estimates.

The model also requires monthly information on carbon input from plant residues or farmyard manure, as well as monthly information on soil cover. Expected plant residues, R, (t ha^{-1} $year^{-1}$) for rotational crops were computed using the equations from the IPCC (Eggelston et al., 2006). We assumed uncertainties of $\pm 50\%$ which is the conservative estimate used by the IPCC (Eggelston et al., 2006).

For olive orchards, we used estimates by Fantin et al., 2022 and Torrús-Castillo et al., 2023 to calculate a mean and standard error for plant inputs to soil. According to Fantin et al. (2022), the values associated with residues from tree pruning and falling leaves are estimated to be 1.98 t ha^{-1} $year^{-1}$. Torrús-Castillo et al. (2023) gave slightly lower estimates for plant inputs from olives, equating to 1.416 t ha^{-1} $year^{-1}$. In our analysis, we assume these values represent ± 1 standard deviation from the mean value. We assume no inputs from cover crops or compost reflecting local practice.

The soil cover variable is Boolean taking a value of zero when the crop does not provide soil cover and one when it does. For rotated crops, we assumed a value of one between a month after sowing to harvest (see Table S6). For olives, we assume a value of one throughout the entire year.

2.2.5 Pesticide impacts

We identified typical pesticide programmes for each crop that we modelled. These programmes consist of the most commonly used combination of products. In consultation with agronomists working in or near the study region, we determined the products typically used and their application rates (see Table S7). For crops where a range of similar products could be applied, we selected one representative product that covered all commonly included modes of action. For each active ingredient (since one pesticide product may contain multiple active ingredients), we calculated a field use rating (f, g ha^{-1}) according to the concentration of the active ingredient within the product and the application dose.

For each active ingredient, we calculated environmental impact quotients (EIQ) by following the methods established by Kovach et al., 1992 for groundwater, fish, birds, bees, and beneficial arthropods. As we were looking at typical products and therefore active ingredients used in Morocco, not all products were available within the EIQ database provided by (Kovach et al., 1992). Thus, we adapted these scores to use data from the 'Pesticide properties database' (Lewis et al., 2016) following the method described by Sharp et al. (2024) and Metcalfe et al. (2024). We also computed a comprehensive EIQ for an active ingredient by summing the individual EIQs for groundwater, fish, birds, bees, and beneficial arthropods.

For each product used (which is comprised of one or more actives) in the standard pesticide programs, we multiplied the field use rating for each active ingredient by the EIQ. We then summed the values across all active ingredients applied to a crop to determine the typical environmental impact of pesticide use for that crop (Total EIQ).

We did not have specific information on variations in products applied, only on the amount spent on pesticides. The ranges for these variables suggested a positive skew, so we characterised the variation with a lognormal distribution. To account for variation in pesticide use, we scaled the EIQ values by the value sampled from the distribution of pesticide costs divided by the mean pesticide cost.

3. Aggregation of results

We quantified variation in model variables $\boldsymbol{\zeta}$ (crop yield, fertilizer application rates, volumes of water used, and costs associated with fertilizer, water and pesticides) and uncertainties in model parameters $\boldsymbol{\lambda}$ (e.g. emission factors). The former captures the variation in farm management and environment. For any particular outcome (except soil carbon), we, therefore, calculated perimeter-scale outcomes by summing over the average predicted outcome for each field, where farm-scale consistency is assumed for crop inputs, prices and costs. For each sample, j, in the Monte Carlo simulation, a single parameter set is drawn and applied to calculate the outputs across the perimeter. These parameter sets are consistent across scenarios to retain the uncertainty structure. Therefore, any single sample of an outcome is calculated as:

$$\omega_k = \sum_{j=1}^{N} \frac{\sum_{i=1}^{n(j)} \sum_{t=1}^{T} A_{i,j}\Theta\left(c_{i,j,t}; \boldsymbol{\zeta}_{j,t}, \boldsymbol{\lambda}_k\right)}{T} \#(5)$$

where Θ is the field scale outcome of interest, $c_{i,j,t}$ is the crop grown in year t in field i on farm j, $A_{i,j}$ is the area of field i on farm j, T is the number of years we average over, $n(j)$ is the number of fields on farm j and N the number of farms.

For soil carbon, we followed a similar approach as above, but instead of considering average values across years, only considered the predicted values for soil carbon at the end of the simulation period. This approach was adopted to is because we wanted to predict the long-term impacts of adopting each rotation type.

4. Study area

The study region is situated in the Al Haouz plain, which is in the centre of the Tensift basin, 40 km East of Marrakech, Morocco (Fig. 1). The site is an irrigated area called “Perimeter R3” and covers approximately 3100 ha. It lies approximately 7°330’ to 7°390 West longitude and 31°370’ to 31°420 North latitude at an altitude of between 466m to 600m (Sebbar et al., 2020).

The climate is of semi-arid continental climate type. Large Inter- and intra-annual variability in rainfall (average annual rainfall of 250 mm) and drought events are the natural phenomena associated with this climate. Under these dry climatic conditions, 70% of the erratic rainfall distribution occurs during winter and spring. The evapotranspiration (ET0) is relatively high and can reach 1500 mm year-1. An average lowest temperature of 4°C was recorded during the winter season and an average highest temperature of 37°C during summer. The soil type is clay to loam.

The crops grown in the wider Al Haouz basin region include cereals such as wheat and barley (61.71%), olives (22.58%), forage crops, typically alfalfa (4.3%), fruit trees (3.91%) and vegetables, typically potato (3.3%). The remaining 5% of the cropped area is dedicated to citrus, almonds, legumes and sugar crops (see Table S8).

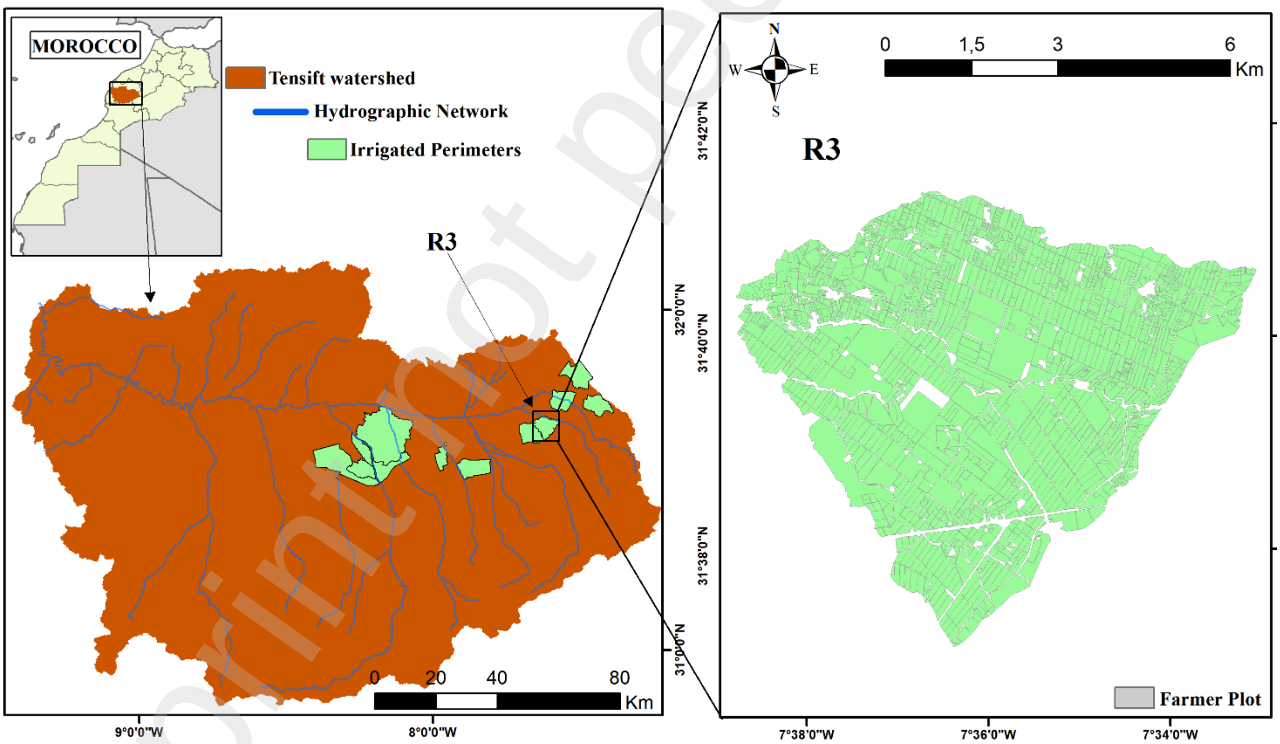

Fig. 1. The location of the R3 irrigated perimeter within the Tensift basin in Morocco, North Africa

2.4.1 Digitisation of the study area

To characterise the study region, we used *ArcGIS Pro* to build a symbolic representation of Very High-Resolution (VHR) satellite images from March, April and May 2022, with a spatial resolution of 2m. These images were selected because they covered the most recent crop season, capturing canopy growth and decline, and thus provided a current state of the study region. The VHR images were segmented into homogeneous areas based on various attributes (see Table S9). Cropped areas were assigned to either "orchards" or "rotated crops".

2.5 Scenarios

In line with the Moroccan government's policy to increase olive production (Serghini et al., 2010), our scenarios explored varying the proportions of arboriculture (specifically olives) and rotated crops across the study area. Our aim was to explore a typical "conventional rotation" along with a more diversified rotation designed to be more sustainable.

To determine these rotations, we held a workshop with farming stakeholders to derive a set of realistic crop sequences and elicit their views on what changes might be needed to make these rotations more sustainable. The workshop was held on the 11th of May 2023 at Mohammed VI Polytechnic University, Morocco. Ten stakeholders attended the event. They comprised farmers from the study area, agronomists and representatives from the Haouz Agricultural Development Regional Office (ORMVAH), which is the local agricultural office in charge of the management of irrigation water in the Al Haouz basin. The workshop was conducted in French as this was a language in which all participants were fluent, although parts of the discussion naturally evolved intermittently into Arabic and English.

To initiate the discussion, stakeholders were presented with three alternative crop sequences that had been derived previously from interviews held in 2020 (El Fartassi et al., 2024). These are shown in Table 2. Participants were asked to consider these sequences and propose alternatives if desired. Then, divided into two groups, they were asked to select one rotation and discuss its perceived sustainability using predefined metrics (Table 3). These rotations became the basis for our "conventional rotation scenario". To ensure a common understanding of sustainability, stakeholders were asked to view themselves as custodians of the farmed land, which they would pass down to future generations, and indeed, in the group conversations that followed they reflected on the farmed land being like a "child to be nurtured".

Once the stakeholders had discussed current rotations in the context of sustainability metrics, they were asked to consider what changes they might make to improve their sustainability. We refer to these rotations as "Diversified Rotations". Based on these two rotation types we explored the following two scenarios under both flood and drip irrigation:

i. "Conventional rotations" with varying proportions of olives and uncultivated areas.
ii. "Diversified rotations" with varying proportions of olives and uncultivated areas.

For each scenario, we ran the Monte Carlo simulation for ten thousand samples. We compared the outcomes against a baseline with a conventional rotation and area allocated to olives reflecting that observed in the satellite imagery.

2.6 Multiple objective optimisation

In addition to exploring the various scenarios, we used multiple objective optimisations to explore the trade-offs between outcomes that result from varying the areas that are dedicated to conventional rotations, diversified rotations and olives (in terms of optimisation these are the control variables). This was done using the 'PARETOSEARCH' directive in MATLAB (The Mathworks, 2022). The PARETOSEARCH algorithm identifies combinations of control variables that result in the 'best' objectives, i.e. those that are non-dominated. A point is considered dominated if another point is better in every single objective. The set of non-dominated solutions defines a Pareto front of optimal solutions.

3. Results

3.1 Quantification of fields, farms and land use

A total of 2140 agricultural parcels were delineated in the R3 perimeter (Fig. 2), with an average parcel of 1.88 ha. Approximately 28% of the cultivated area was dedicated to olive trees, a value we used as our baseline proportion of olive cultivation. The remaining area appeared largely uncultivated, which could be due to various factors such as crops being already harvested or that the land was not cultivated that year. Lower-resolution images which were freely available, indicated that in previous seasons, crops were more widely grown. This suggests that recent drought conditions have led farmers to cultivate smaller areas. We note that our interpretation of geographic features allowed us to capture parcel boundaries but does not necessarily delineate farm boundaries.

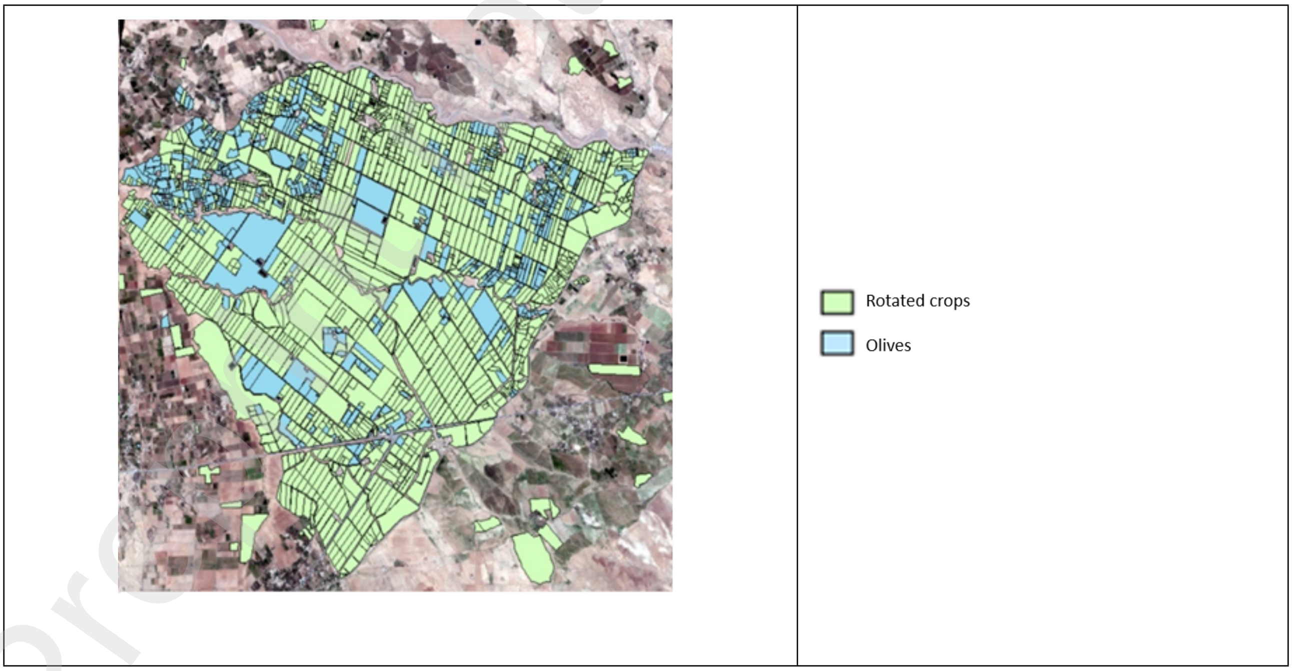

Fig. 2 Delineated field boundaries for the R3 irrigated perimeter, Al Haouz, Morocco. The delineation is based on satellite imagery from March to May 2022.

3.2 Derivation of scenarios

During the workshop, participants naturally formed groups by choosing their seats, with stakeholders from the same establishment tending to sit together. Group A comprised three experts in agronomy, and three farmers from the study region (one conventional, and two that grew more alternative crops such as aromatics, medicinal crops, roses and quinoa, one of which had an agriculture-based degree). Group B comprised three representatives from ORMVAH and a conventional farmer.

3.2.1 Conventional rotations

For the purposes of the discussion a "year" was defined as the period from October to September. The conventional rotations identified were based around wheat and potato, with maize also included in many rotations, though it was reportedly less common. Fallow periods, alfalfa and beans featured intermittently in these rotations. Potatoes and bean are frequently grown in the same year, with beans following potatoes. Stakeholders explained that alfalfa and maize were grown as animal fodder. Although alfalfa was not a profitable crop, once chosen, it was usually not replaced for three to five years. It did however increase soil fertility, which can benefit subsequent cereal crops.

The conventional rotations chosen by each group for further discussion were similar (Table 2) and so it was not surprising to see that opinions broadly accorded across the two groups (Table 3). For soil health, Group B argued that the fallow periods in conventional rotations allow soil regeneration and prevent erosion by promoting vegetation with strong root systems. However, they cautioned that continuous cultivation of wheat and maize without proper nutrient management could cause nutrient imbalances in the soil leading to reduced soil fertility. Within Group A, opinions on the sustainability of soil carbon differed. The conventional farmer agreed with Group B's consensus, whereas the university-educated farmer argued that bare fallow would not lead to healthy soil in which carbon was sequestered. The rest of Group A was split in their opinions. Notably, Group A did not consider soil erosion to be an issue in the study region.

Table 2. The crop sequences presented to the stakeholders (rows 1 – 3) and those proposed by stakeholders as alternatives to consider (rows 4 – 10). The rotations marked by the superscript letters were the ones chosen by the two groups to discuss (Group A and Group B). Years are assumed to run from October to September.

	Year 1		**Year 2**		**Year 3**	
1	Wheat	Maize	Barley	Maize	Fallow	Beans
2	Wheat	Fallow	Barley	Fallow	Alfalfa	Alfalfa
3	Wheat	Potato	Wheat	Alfalfa	Alfalfa	Alfalfa
4A	Fallow	Wheat	Maize	Fallow	Wheat	Maize
5	Fallow	Wheat	Maize	Beans	Wheat	Maize
6	Wheat	Fallow	Wheat	Maize	Wheat	Fallow
7	Potato	Fallow	Potato	Maize	Maize	Fallow
8	Potato – Beans	Potato	Maize	Maize	Fallow	Wheat
9	Potato – Beans	Wheat	Maize	Wheat	Fallow	Wheat
10B	Wheat	Beans	Wheat	Potato	Maize	fallow
11	Wheat	Fallow	Potato – Beans	Fallow	Alfalfa	Alfalfa

Table 3. The sustainability metrics and the opinions of each group on whether the chosen conventional rotations were sustainable with respect to each.

Sustainability indicators	**Group A**		**Group B**	
	Sustainable/ Beneficial	Not sustainable/ Not beneficial	Sustainable/ Beneficial	Not sustainable/ Not beneficial
Soil				
Soil Carbon	*	*	*	
Soil Erosion	*Considered not applicable given soil texture*		*	
Soil Fertility	*		*	*
Water				
Clean Water			*	
Abundant Water		*		*
Biodiversity				
Species diversity		*	*	
Pollinator abundance		*		*
Habitat quality		*		*
Production				
Consistent resilient yields		*		*
Economically sustainable		*	*	

Both groups agreed that the water supply would not be sustainable under typical rotations. They noted that farmers in irrigated perimeter R3 had not received water from the dam since May 2021. Group B noted that allowing the land to rest during fallow periods reduces the risk of agricultural chemicals leaching into groundwater, resulting in cleaner water and minimizing pollution from agricultural activities.

Group B noted that conventional crop rotation can have both positive and negative effects on species diversity and pollinator abundance. On one hand, it promotes diverse plant species and creates habitats for various insects and birds increasing overall species diversity. However, the specific rotation pattern in this case may not provide a continuous supply of pollen throughout the growing seasons, potentially decreasing the overall number of pollinators. Whilst species diversity was not viewed as a potential issue by Group B, Group A were more critical and noted that the rotation was part of a wider ecosystem. Both groups agreed that their chosen rotations were not ideal for pollinators. Stakeholders suggested that growing trees and certain vegetables would better support pollinator populations.

Yields were not considered sustainable for the chosen rotations, primarily due to challenging climatic conditions and water scarcity. The region faces environmental constraints such as aridity and limited water resources, which can negatively impact crop productivity.

Group B noted that the conventional crop rotation was not economically sustainable when the country imported cereals from Ukraine. However, after the war in Ukraine disrupted the cereal supply, Moroccan farmers prioritized cereal production to fill the gap in the national market and earn profitable incomes. By focusing on cereals, farmers were able meet local demand and take advantage of higher market prices. This shift ensured economic sustainability by aligning production with market needs.

3.2.2 Proposed diversified rotations

When asked how to improve the sustainability of crop rotations, both groups focused their discussion on improved crop management strategies. Group A suggested that switching from rotated crops to olives and introducing drip irrigation offered a potential mitigation of issues related to water scarcity. For more sustainable rotated crops, they suggested increasing crop diversity both in time and space. They noted the importance of the sequence of crops, such as legumes preceding cereals. Additionally, they suggested using cover crops like sorghum as green manure to avoid bare fallow periods, stating that this practice would reduce soil degradation and improve water retention during the critical June to September period. The potential to grow more drought-resistant crops was also highlighted. Group B focused their discussions on improving soil fertility, emphasizing the importance of legumes in crop rotations. They also recommended growing alfalfa for several years at the end of a rotation cycle to improve soil quality and facilitate nitrogen fixation.

Based on these discussions and in consultation with a local agronomist, we derived the crop sequences shown in Table 4 to represent our “Sustainable rotations”. We note that we chose not to include sorghum as there was no evidence that it was currently grown in R3, indicating it may not be a viable option.

Table 4. “Sustainable rotations” used in our scenario modelling. These rotations were derived from stakeholder engagement.

	Year 1		**Year 2**		**Year 3**	
1	Wheat	Beans	Wheat	Alfalfa for the next three years		
2	Barley	Beans	Wheat	Alfalfa for the next three years		
3	Wheat	Vegetables (e.g., onion)	Barley	Beans	Wheat	Alfalfa for the next three years

3.3 Model-based scenario analysis

3.3.1 Impacts of changing land use

There are synergies and trade-offs associated with converting more of R3 to olive cultivation (Fig. 3). The results indicate that as the area dedicated to olive cultivation increases, water use decreases, suggesting that olive cultivation is more water-efficient compared to the baseline scenario of growing two arable crops annually. While expanding olive cultivation appears to be environmentally beneficial in terms of water conservation, the economic implications show a different trend. Specifically, while halving the area currently allocated to olives may slightly improve profits over variable costs, expanding the area further —by doubling or tripling it— leads to a decline in profits. This indicates that beyond a certain threshold, the costs involved in olive cultivation, including inputs and management, outweigh the economic benefits. Moreover, there is significant uncertainty regarding profit increases, largely due to the variability in fertilizer application rates and associated costs.

Increasing olive is associated with reduced nutrient losses and enhanced soil carbon sequestration. The downside is that as the area of olive production expands, food production decreases, and the environmental impact of pesticide use potentially increases.

3.3.2 Impacts of changing rotations

Diversifying rotations can lead to reduced production and profitability metrics compared to the baseline **(Fig. 4)**. The introduction of diversified rotations is coupled with increased water use efficiency, with the reduction becoming more pronounced as the area of diversified rotations expands. Based on the results, diversified crop rotations improved soil carbon and reduced environmental impact. Under flood irrigation, diversified rotations also contribute to a reduction in nutrient losses.

3.3.3 Impacts of Irrigation Technologies

Adopting drip irrigation technology yields benefits across all metrics and cropping systems considered **(Fig. 5)**. We note that in our diversified systems, it is impractical to drip irrigate alfalfa, as this crop is typically flood-irrigated.

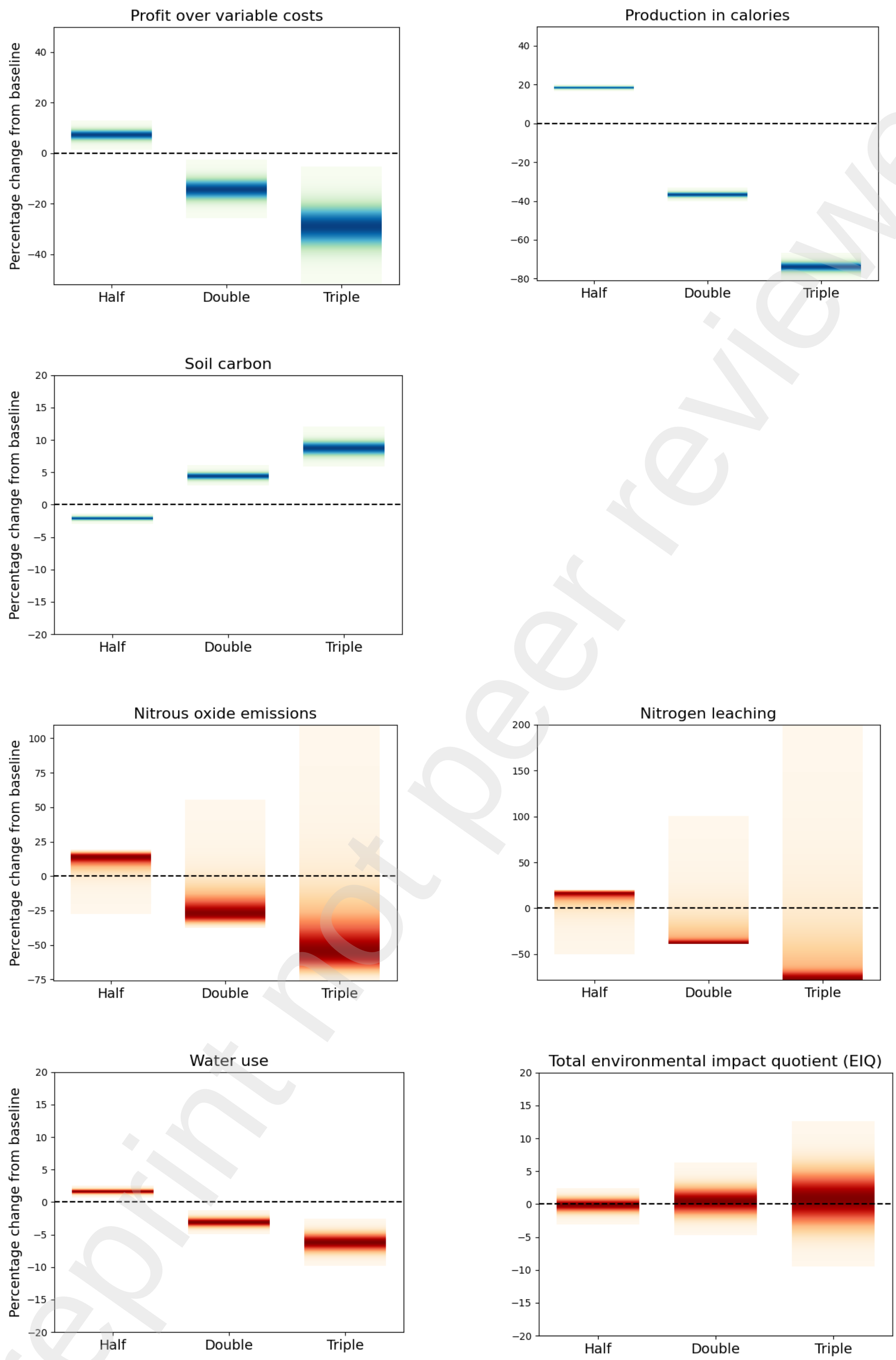

Fig. 3: Predicted percentage changes resulting from converting half, double and triple the area to olive cultivation, compared to the baseline of 28%. The shaded bars indicate distribution generated from ten thousand realisations. In all cases, flood irrigation is assumed. Blue shading

is associated with metrics where a positive percentage change from the baseline is desirable and red metrics where a negative percentage change is desirable.

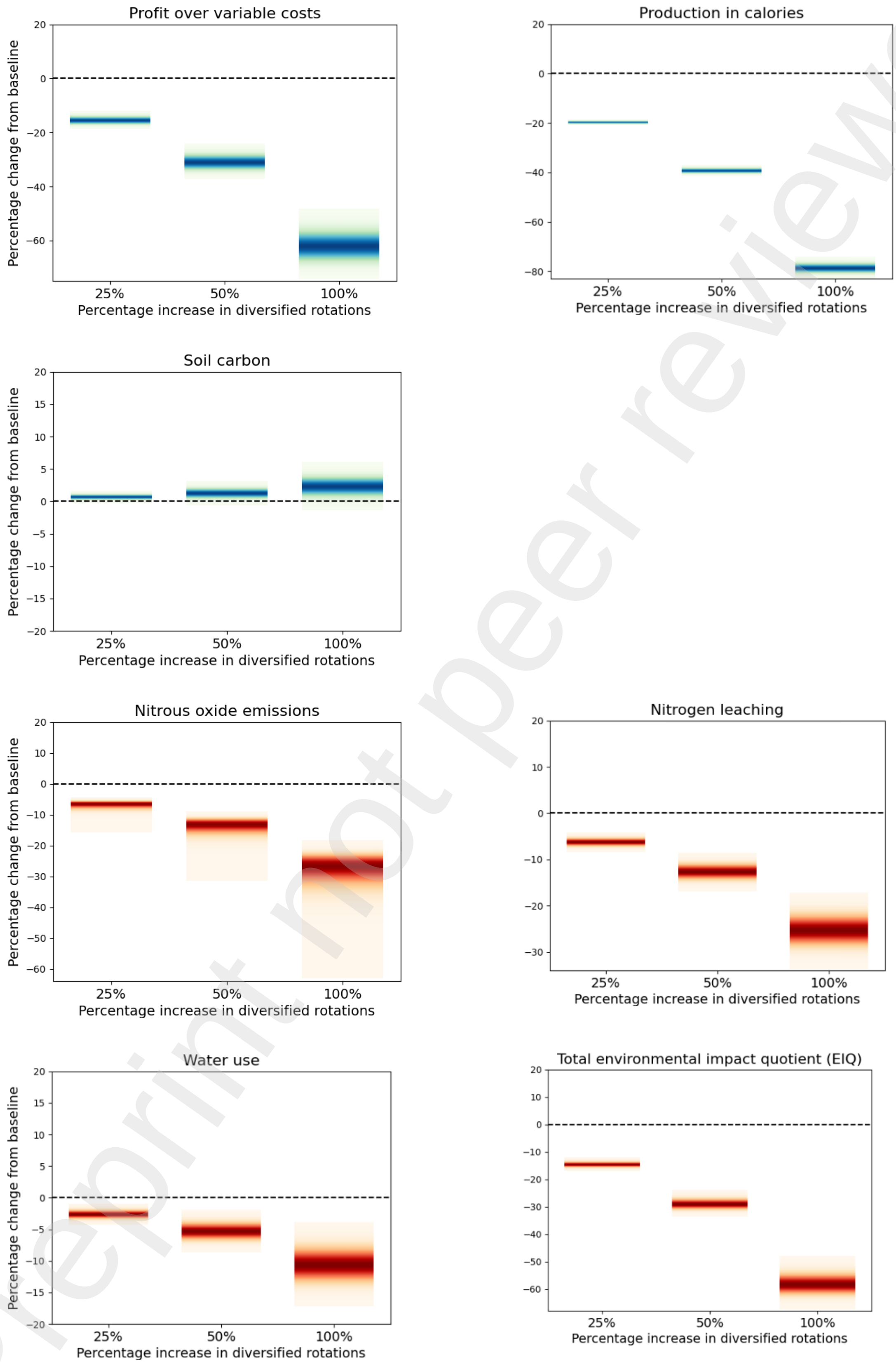

Fig. 4: Predicted percentage changes resulting from increasing the land area under more diverse rotations from a baseline of zero. The shaded bars indicate distribution generated from ten

thousand realisations. In all cases, flood irrigation is assumed. Blue shading is associated with metrics where a positive percentage change from the baseline is desirable and red metrics where a negative percentage change is desirable.

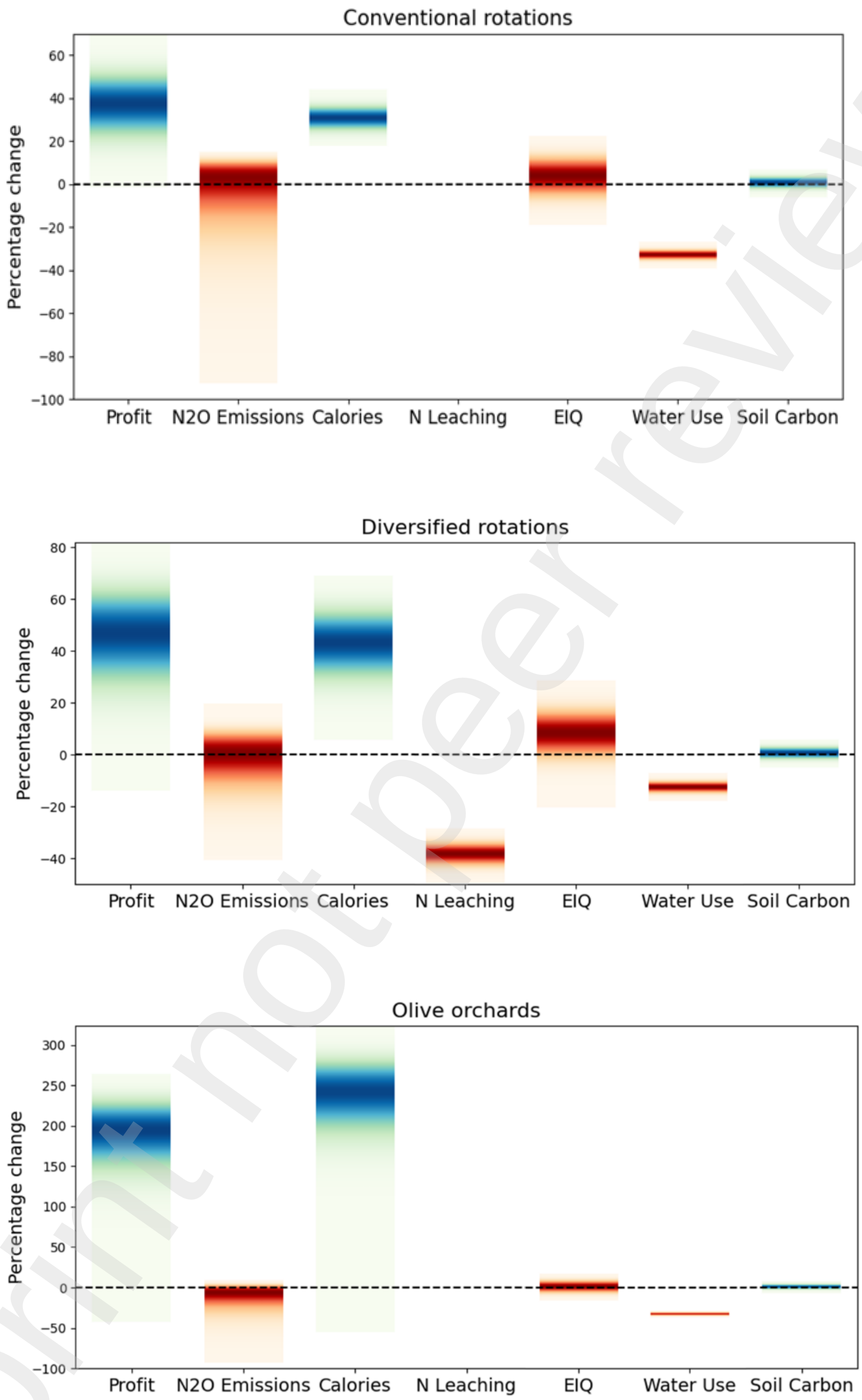

Fig. 5 Predicted percentage changes resulting from adopting drip irrigation. We note that in the diversified rotations, we assume that alfalfa is always flood-irrigated. The shaded bars indicate distribution generated from ten thousand realisations.

3.3.4 Impacts of Irrigation Technologies

As flood irrigation performed relatively poorly across all the objectives considered, it has been excluded from the optimised solutions. The multi-objective optimisation showed that there is no single optimal solution, indicating inherent trade-offs between objectives **(Fig. 6)**. Notably, there were strong correlations between increased profit and reduced N leaching, as well as between increased soil carbon and reduced nitrous oxide (N_2O) emissions. The correlation between increased profit and reduced nitrogen leaching is largely attributable to the characteristics of the diversified cropping system, which includes alfalfa—a crop that is less profitable and relies on flood irrigation. Flood irrigation is less efficient at managing N, leading to higher rates of N leaching. Therefore, scenarios that minimize or exclude alfalfa tend to show both higher profits and lower N leaching. Similarly, the correlation between increased soil carbon and reduced N_2O emissions is driven by the fact that practices enhancing soil carbon also reduce the need for synthetic N fertilizers, which are a primary source of N_2O emissions. Trade-offs were observed between profit and N_2O emissions, as well as between soil carbon and the EIQ. These trade-offs indicate that improving one objective often comes at the expense of another. For instance, increasing profit might lead to higher N_2O emissions, or enhancing soil carbon might involve practices that increase pesticide use.

We note that the extremes of each axis (i.e. where the standardised metric takes a minimum or maximum value) were associated with complete dominance of one production type. For example, when olive production dominated, calories and N_2O emissions were minimised while soil carbon was maximised. This suggests that olive groves, though less productive in terms of edible calories, offer significant benefits in terms of reducing greenhouse gas emissions and increasing soil carbon sequestration.

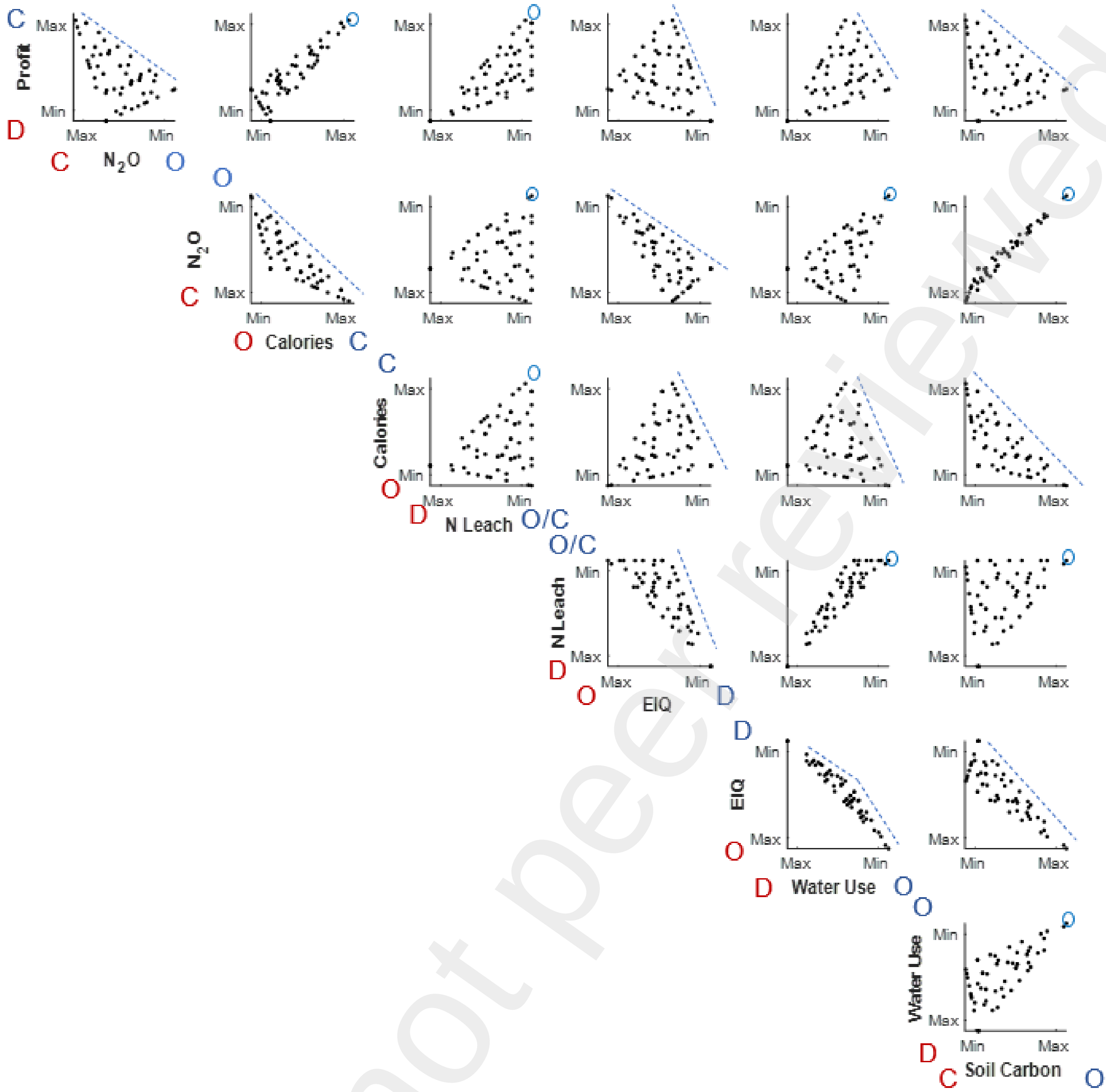

Fig. 6 Pareto fronts for standardised objectives. Each point represents a scenario (proportion of land allocated to convention rotations, diversified rotations and olive groves) that lies on the Pareto front for the multidimensional space. For purposes of visualisation, the metrics have been standardised between a minimum and maximum value. Objectives viewed as positive (e.g. soil carbon) have axes that go from Min to Max. Those viewed as negative (e.g. N_2O emissions) have axes that go from Max to Min. The blue dotted lines/discs indicate the front/optimal point for the two objectives considered in each subplot. Extremes of each metric are associated with a dominance of one land management type as indicated by C=convention rotations, D=diversified rotations and O=olive groves.

5. Discussion

Our results show trade-offs and synergies associated with changes in crop-system choices. These are illustrated most poignantly by the optimisation analysis where the extremes of each outcome (min or max value) are associated with the dominance of a single land management system. For instance, converting extensive areas to olive orchards yielded positive outcomes in terms of soil carbon sequestration, and reduced nutrient losses, but significantly lowered the production of edible calories. The analysis also shows that the expansion of olive cultivation results in a significant decrease in profitability. This indicates that beyond a certain threshold, the economic benefits of further increasing olive cultivation are outweighed by the costs associated with inputs and management. In contrast, a complete shift to conventional agriculture maximized edible calorie production but was suboptimal for carbon sequestration.

Among the systems examined —conventional agriculture, olive orchards, and diversified rotations— the latter was predicted to have the lowest profit and environmental impact. Diversified rotations were more favourable for carbon sequestration and nutrient losses were generally more favourable than for conventional rotations. Alfalfa's substantial water requirement stems from its high evapotranspiration compared to other crops, primarily because of long periods of transpiration (Sheaffer et al., 2015). Studies have been undertaken to understand the impacts of deficit irrigation on alfalfa yields (Hanson et al., 2007). These found that although alfalfa yield could be substantially impacted, the yield of subsequent crops was not significantly affected. So, there is scope to reduce this impact. Stakeholders in our study emphasized the benefits of alfalfa for soil health and advocated for the broader use of cover crops and drought-resistant varieties to enhance water use efficiency. Although our study did not include these crops due to data limitations, future research incorporating these variables could leverage our proposed tools to evaluate broader impacts.

For the metrics we considered, drip irrigation emerged as a superior technology compared to flood irrigation, offering significant benefits in water use efficiency and climate change mitigation. This method is particularly critical in arid and semi-arid regions where water scarcity is exacerbated by climate change, ensuring resilient agricultural systems (Dawit et al., 2020). One limitation of our study is that we did not account for the fact that the study area currently lacks a shared drip irrigation infrastructure. This means that individual farmers must install their own drip irrigation systems if they have access to groundwater resources. Drip irrigation requires a reliable water source, which may be difficult for individual farmers to secure without a communal irrigation system (Kuper et al., 2018). They would need to invest in their own wells or water storage facilities, increasing costs substantially. Without community infrastructure, only those who can afford to install their own equipment and have enough groundwater on their land will be able to use this irrigation method. Farmers who cannot afford to install their own systems or who lack access to groundwater may be unable to take advantage of the technology, potentially widening existing disparities within the agricultural community. Plus, the individual installation of drip irrigation systems without proper oversight and regulation could result in unsustainable groundwater extraction (Meinzen-Dick, 2014), and in some cases degradation of the soil by increasing salinity (Salman et al., 2020).

Our EIQ analysis indicates that increasing olive production would be the most harmful of the scenarios we explored, in terms of the environmental impact of pesticides. This is due to the substantial volumes of chemical application required to maintain the phytosanitary health of olives. However, whilst this metric considers the toxicity and risk associated with agrochemical use, it does not consider other impacts of olives on the environment and biodiversity. For example, olive groves serves as an important breeding habitat for migratory turtle doves (Hanane & Baamal, 2011) and a source of pollen for honeybees (Giovanetti, 2018). Furthermore, we assumed the use of a typical pesticide program, including both herbicides and fungicides with insecticide application being more sporadic and targeted. It is important to acknowledge that not all producers will adhere to this program. In disadvantaged rural communities, as few as 3.8% of farms use chemical pesticides (Serghini et al., 2010). These farms may benefit from shared protection afforded by their neighbours' use of pesticides or alternatively, the lack of herbicide-use may promote increased diversity of understory vegetation which can provide habitat and food resources for other beneficial taxa.

As part of this research, we consulted with stakeholders about their perceptions of sustainable solutions to adapt to an increasingly drought-stricken region. Traditional farmers advocated for fallow period to aid soil regeneration, whereas those with more formalised training proposed cover crops for improved water and nutrient management. We did not explore in depth how fallow periods were managed by the farmers that we interviewed and the true impacts of these, so have no evidence to support or dispute their claims. We note, however, that the literature documents several instances where traditional management and local farmer adaptations have demonstrated sustainability benefit (Chuma et al., 2022; Fairhead & Scoones, 2005; Occelli et al., 2021). In particular, Osbahr & Allan (2003) highlighted how Indigenous knowledge of soil fertility management in southwest Niger enabled farmers to make complex decisions, suggesting that integrating Indigenous knowledge with scientific evidence could yield significant benefits. The tool that we have produced could be used to facilitate discussions between various groups of stakeholders by elucidating the trade-offs inherent in agricultural systems and fostering a collaborative approach to sustainable agricultural practices.

Our results are presented as percentage changes from a baseline to provide a straightforward means to interpret whether the given metrics are likely to improve, despite their differing associated units. As is common in agroecosystems modelling, there are uncertainties related to these predictions that result from model and data input uncertainties. For tools such as the one we present here, it is important to communicate these uncertainties to the end user (Chagumaira et al., 2022; A. E. Milne et al., 2015; Spiegelhalter et al., 2011). Effective communication of uncertainty allows users to better weigh the risks and benefits, thereby facilitating informed decisions. Without communicating uncertainty, users might interpret model predictions as absolute truths, leading to misinterpretation and potentially harmful decisions based on overly confident predictions.

Acknowledging uncertainty ensures that both model developers and users alike take responsibility for the potential errors in predictions. This accountability encourages continuous improvement of the model and its application and fosters trust by being transparent about the limitations of the predictions (Chagumaira et al., 2022).

There are several numerical and visual ways in which uncertainties can be communicated including confidence intervals, IPCC-calibrated phrases, box plots and frequency plots (A. Milne et al., 2015). These types of visualizations can effectively communicate uncertainties to diverse audiences, including non-experts or stakeholders who may not have a strong background in statistics or mathematics. They can bridge the gap in understanding between technical experts and end-users. We chose to use shaded arrays to communicate the uncertainty in predictions as, of the methods listed above, these were shown to be generally the easiest to interpret by non-technical stakeholders (A. E. Milne et al., 2015). What is not explicitly presented to the user are the underlying assumptions of the data inputs and models. For sound policy guidance or elicitation exercises, these assumptions need to be clearly communicated. In some instances providing the capability to adjust certain setting for more advanced scenario analysis can be beneficial.

The framework we present integrates models and data to explore trade-offs associated with decision-making. This tool supports decision-making by encouraging end user to consider the potential unintended consequences of their actions. Here we used relatively simple models and considered a limited range of outcomes. Future enhancements of this framework could include additional models and increased complexity. We recommend that this is done in consultation with expert stakeholders so that the choices of what to include can be guided by knowledge of what outcomes and systems are most relevant to the environment of interest.

6. Conclusion

We developed a framework for investigating the trade-offs associated with cropping system choices. In total, we considered seven objectives that are relevant to stakeholders and presented predictions of the impacts of these variables, including associated uncertainties. Despite our relatively constrained set of management choices, the results become complex to navigate as no single solution is optimal for all objectives. This highlights the importance of stakeholders using tools such as the one we developed to explore outcomes and challenge preconceptions. Conversely, stakeholder involvement in the development process can ensure that the management options and objectives considered are relevant. We propose an iterative process of system development and exploration involving stakeholders to improve the utility of frameworks like ours and improve decision-making.

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CRediT authorship contribution statement

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Helen Metcalfe: Methodology, Software, Validation, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing.

Vasthi Alonso Chavez: Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Supervision.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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