Assessing trade-offs and synergies in climate smart agriculture across timescales

Laura Natalia Arenas Calle

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The candidate confirms that the work submitted is her own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

The work in Chapter 2 of the thesis has appeared in publication as follows: Arenas-Calle, L.N., Whitfield, S., Challinor, A.J., 2019. *A Climate Smartness Index (CSI) Based on Greenhouse Gas Intensity and Water Productivity: Application to Irrigated Rice.*Frontiers in Sustainable Food Systems volume 3-105. The candidate designed the Climate-Smartness Index, calculated the CSI for set of studies and wrote the manuscript with comments from all co-authors.

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Abstract

Climate-Smart Agriculture (CSA) aims for the transformation of agriculture -particularly in low- and middle-income countries- into sustainable, food secure and climate-resilient systems by the achievement of its three principles: increasing of sustainable productivity and food security, building climate resilience, and reducing Greenhouse Gas (GHG) emissions. Since strategies addressed in any of CSA pillars can potentially benefit (synergies) or hinder (trade-offs) the others, CSA focus on identifying such relations to enhance synergies and minimise trade-offs in each context. This holistic approach of CSA is widely accepted, and its uptake has been going faster than the availability of official methodological frameworks and metrics for its assessment. The lack of alignments for climate-smartness results controversial given its increasing relevance in agriculture policy.Moreover, several organizations have been raising concerns that CSA may narrowly address agronomic issues and overlook social issues like the underrepresentation of minorities, inequality, and resources access that constraint agricultural development.

In this thesis, two CSA metrics are developed and assessed using existing data sets and process-based modelling simulations. The Climate-Smartness Index (CSI) and Soil-based Climate-Smartness Index (SCSI) were built from agronomic/biophysical indicators of mitigation, adaptation, and productivity to their represent trade-offs and synergies. The CSI represents the synergy between water use efficiency and GHG mitigation by the implementation of water-oriented adaptation practices in irrigated rice. The SCSI represents the synergy between the progressive improvement of soil and crop productivity under soil-oriented practices. CSI was first calculated for a dataset of existing experiments that assessed several irrigation strategies, and second, for output from a process-based model. SCSI was calculated for a dataset of conservation agriculture experiments.

The CSI and SCSI are useful tools to identify and compare climate-smartness across spatial-temporal contexts. The CSI captured the temporal and spatial variability climates-smartness and evidenced the context-dependency of this attribute in so-called “climate-smart practices” (e.g., Alternate Wetting and Drying). SCSI results evidenced the temporal dynamic of climate-smartness in treatments under Conservation Agriculture management. The indices showed the potential to summarised information regarding the performance of soil and water adaptation strategies in cropping systems from existing evidence, both alone and when used with model output. The indices can help to monitor CSA interventions and be complementary in socio-economics assessments or scaling up projections. The results of this thesis contribute to the call to

generate reliable and transparent measures of climate smartness. The results of this thesis contribute to the call to generate reliable and transparent measures of climate smartness.

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Chapter 1

Introduction

1.1 Motivation and overview

The challenges of agriculture under climate change are two-fold: agriculture and land-use change contribute to 25% of the GHG emissions but at the same time production is sensitive to climate change (Smith et al., 2014). there are increasing calls for transformation in agriculture and food systems to simultaneously address climate change mitigation and adaptation challenges. This idea of co-benefits has become mainstreamed within agricultural policies.

Organizations like FAO and the CGIAR consortium encourage the holistic addressing of climate change issues through initiatives such as, Climate-Smart Agriculture (CSA). Central to the CSA movement is the principle of transformation of current agricultural systems towards sustainable, climate-resilient, and low-carbon agriculture (Campbell, 2017). CSA has been implemented through plans and practices in agriculture, generating different responses and achieving CSA objectives to different extents. Given that climate-related challenges in agriculture are context-specific it is unsurprising that CSA technologies and techniques (such as conservation agriculture and alternate wet and dry irrigation) are associated with a mixed evidence base. This is relevant in the context of the current push (from CGIAR, FAO and others) for the upscaling of CSA approaches.

In recent years, a large body of evidence related to the benefits of CSA implementation has expanded to include analyses of the trade-off and synergies among CSA pillars. The research agenda around CSA aim for the collection of evidence related to successful CSA interventions, the identification of trade-off and synergies between CSA pillars and how this information can be used. The communication of such findings uses well-known agronomic, economic, and biophysical indicators used in agriculture; however, there is still a knowledge gap regarding how to measure climate smartness and quantitative metrics that integrate the CSA pillars (Rosenstock et al., 2016; Thornton et al., 2018).

It is important to generate replicable and comparable criteria that support the decision to accept or re-address agronomic management based on the pros and cons identified in the trade-off and synergies (Lankoski et al., 2018).

This thesis assesses the trade-off and synergies between mitigation, adaptation, and productivity in agriculture across spatial and temporal scales. The analysis uses as a reference the adoption of two well-known agronomic practices promoted from CSA: Alternate wetting and Drying (AWD) and Conservation Agriculture. The thesis contributes to the discussion of climate-smartness meaning in different spatial and temporal contexts, aiming to reduce the ambiguity around the concept. The thesis uses the analysis of climate-smartness to propose metrics and modelling-based assessments that reduce the gap between site-specific analysis and replicable assessment methods.

This chapter provides an overview of agriculture in the climate change context, introduces the CSA approach, describes the three CSA pillars (mitigation, adaptation, and productivity) and their trade-offs and synergies. The chapter starts by framing the challenges of agriculture under climate change (Section 1.2). The overall contribution of agriculture to Greenhouse Gas emissions is described in Section 1.3, as well as the sources of CO_2 and sinks of Carbon (Section 1.3.1) and non-CO_2 GHG such as methane (Section 1.3.2) and nitrous oxide (Section 1.3.2).

The impacts of climate change on agriculture are discussed in Section 1.4, and the global and regional impacts are described in (Section 1.4.1). The role of agriculture in climate policy is outlined in Section 1.4.2. This section discusses global climate policy related to agriculture and as the recent emphasis on Climate Smart Agriculture. Section 1.5 introduces the concept of the Climate-Smart Agriculture (CSA) approach and its three pillars of CSA: sustainable production (Section 1.5.1), climate resilience (Section 1.5.2), and GHG mitigation (Section 1.5.3). The trade-off and synergies between the three CSA pillars are described in Section 1.5.4

Section 1.6 introduces two well-known climate-smart agricultural practices: Alternate Wetting and Drying (Section 1.6.1) and Conservation Agriculture (Section 1.6.2). The scaling up of these climate-smart practices and the metrics used to assess their performance in terms of the CSA objectives are described in Section 1.7. The potential for modelling CSA metrics is discussed in Section 1.8 The thesis objectives are outlined in Section 1.9

1.2 Agriculture in changing climate

The evolution of agriculture in the coming decades will be decisive for humankind: The Food and Agriculture Organization (FAO) projects that by 2050 agricultural production must increase by 60% to meet future food demand (Gomiero, 2016). Since the suitable land for agriculture is limited and much of this land is already in use, achieving the future food demand will depend on the intensification and efficiency of agricultural systems (Davis et al., 2016).

So far, agricultural production has grown through intensive practices that progressively degrade the soil and deplete non-renewable resources, making food production unsustainable in the long term (Kuzyakov and Zamanian, 2019; Obalum et al., 2017). Thus, projected food demand clashes with an accumulation of environmental issues that already represent a constraint for food security in several regions (Tilman et al., 2011).

Environmental concerns associated with agriculture like deforestation, soil degradation, and pollution of water resources demand immediate actions. For instance, the expansion of agricultural land generated more than 50% of the total deforestation in humid tropic forests of South America and Southeast Asia (Armenteras et al., 2017; Ordway et al., 2017), representing a threat for the wildlife and the loss of ecosystem services such as climate and air quality regulation, carbon storage, nutrient recycling, and water balance (Foley et al., 2007).

At a local scale, farmers copes with the progressive land degradation by intensive agronomic management. The use of machinery and overgrazing affect soil properties such as water retention, gas diffusion and biological activity (Pires et al., 2017). Besides, the overuse of agrochemicals and manure deposition in grasslands contaminates groundwater and alter soil nutrient recycling, generating atypical Carbon dioxide (CO_2) and non-CO_2 Greenhouse Gas (GHG) emissions rates (Savci, 2012).

Among the environmental issues associated with agriculture, GHG emissions have rising concerns. The scientific community agrees that the rise of anthropogenic GHG emissions has been accelerating climate change; being agriculture an important contributor to these gases (Li, 2007). Thus, agriculture not only must cope with multiple climate-related stresses but also must reduce its GHG contributions and become more efficient to meet the future food demand.

1.3 Greenhouse Gases emissions from agriculture

The Agriculture, Forestry, and Other and Land Use (AFOLU) sector contributes 24% of the global GHG emissions (Smith et al., 2014). The countries with the largest GHG contributions from agriculture are Brazil, China, India, and the United States, counting with 39% of global GHG emissions from agriculture (Figure 1.1a). However, the GHG emissions from agriculture sector at national level are highly variable across the countries (Figure 1.1b). The national contribution of agriculture to GHG ranging from 0 to 98%, and 42 countries reported that agriculture represent more than 50% of their national contributions (Richards et al., 2015a).

From the AFOLU sector, 44% of the emissions come from deforestation of native forests for its conversion to agricultural lands and 56% from agriculture activities. The different sources of GHG in agriculture generate 52% of global methane emissions and 84% of global nitrous oxide (Smith et al., 2014).Thus CO_2, CH_4, and N_2O are the three gases generated in agriculture; their emissions will depend on the type of agricultural activity and its impact on the nitrogen and carbon cycles in the ecosystems.

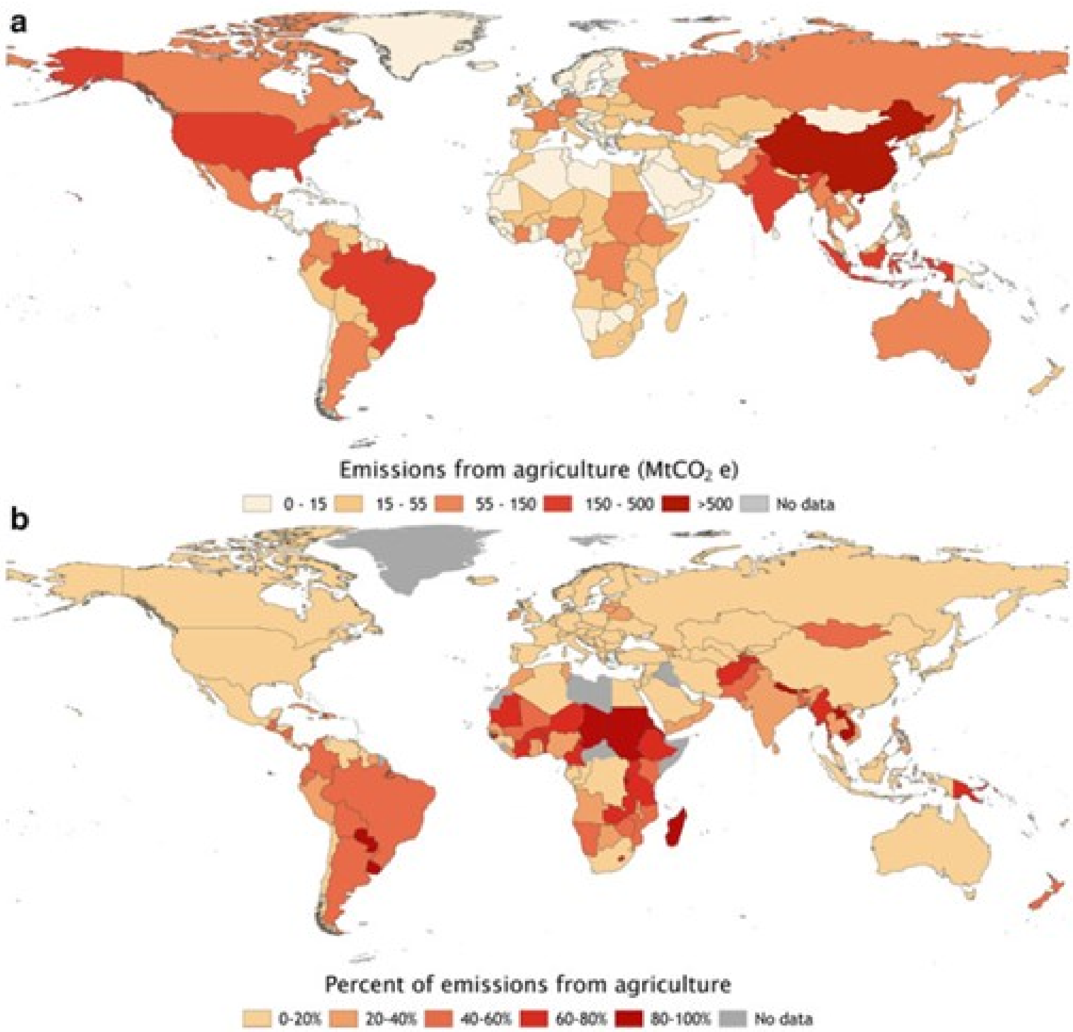

Figure 1.1: Total agricultural GHG (N_2O and CH_4) emissions (Gt CO_2-e yr^{-1}) by country (a) and percent of national emissions from agriculture, (excluding land-use, land-use change and forestry; b) (Taken from (Rosenstock et al., 2016)

1.3.1 Carbon cycle: Carbon Dioxide (CO_2) emissions and carbon pools

ASeveral a griculture activities alter the carbon cycle generating changes in CO_2 and soil carbon recycling (Figure 1.2). The loss of biomass by deforestation represents 15% of global anthropogenic emissions. Moreover, agricultural soils have lost up to 75%

of their native SOC content by the imbalance between organic matter turnover and biomass return to the soil (Lal et al., 2007; Schlesinger, 2000). Additionally, agricultural practices generate indirect CO_2 emissions associated with fossil fuel use and production of synthetic inputs such as fertilizers and pesticides (Marland et al., 2003; Xu and Shang, 2016).

Agriculture also has a high potential to sequester carbon. When Soil organic matter is turnover, increases the Particulate organic Matter (POM). The Carbon in POM is mineralized to labile carbon pools which, with short turnover periods (from weeks to years), while recalcitrant fractions are more stable and resistant to biochemical activity, remaining in the soil for more than 1000 years (Laganière et al., 2010). In natural conditions, the NPP and soil carbon pools tend to be higher than carbon loss by soil and plant respiration.

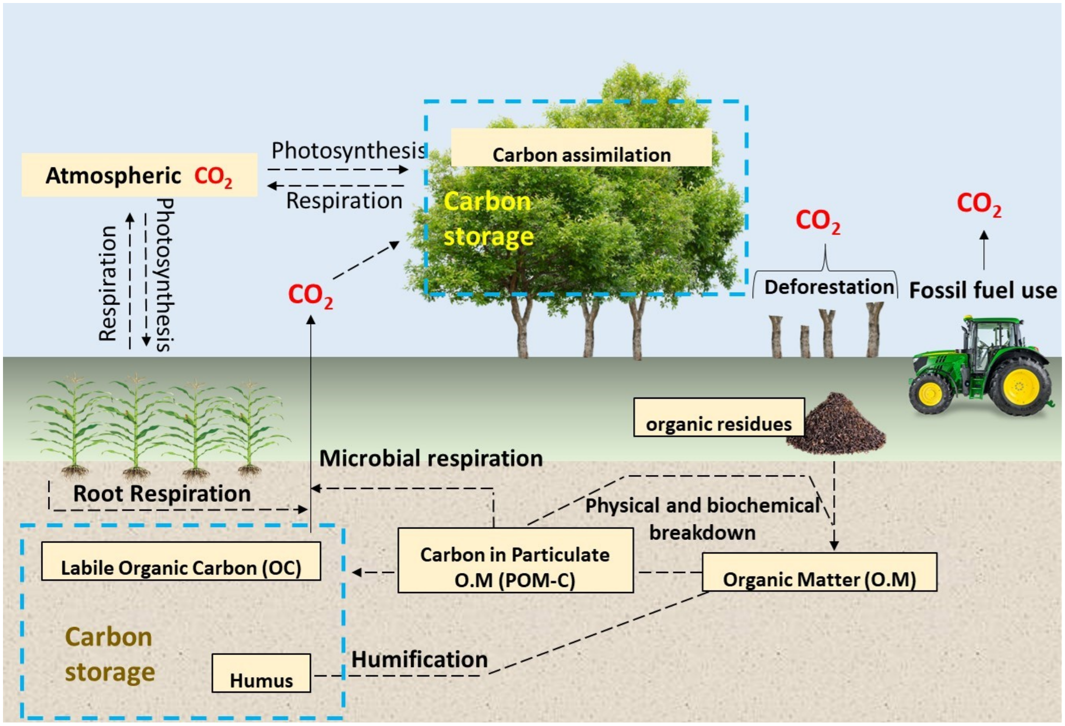

Figure 1.2: Sources and sinks of CO_2 in agricultural lands

1.3.2 Non-GHGs from Agriculture: methane (CH_4) and nitrous oxide (N_2O)

Methane is produced from different agricultural activities associated with livestock and cropping systems. In livestock systems, enteric fermentation generates 64% of CH_4 emissions and manure management 36% (Smith et al., 2014). In cropping systems, flooding conditions in rice fields are the main source of methane, responsible for approximately 10% of emissions from agriculture. Decomposition of organic matter under anaerobic conditions is the principal driver of methane production in soils (Banger et al., 2012; Fazli et al., 2013). For its part, nitrous oxide results as a sub-product of the biological oxidation/reduction of N substrates (organic matter, Chemical fertilizers, manure) when ammonium is transformed to nitrate (nitrification) and the nitrate to nitrite (denitrification), in a crucial soil process for plant nitrogen uptake (Grahmann, 2013).

Agronomic management influences the emissions of both non-CO_2 gases. The interaction of continuous flooding conditions and organic amendments application can increase CH_4 emissions; while the use of the different type of N fertilizers under intermittent irrigation can either inhibit or promote the methane production in soils (Serrano-Silva et al., 2014; Yu and Patrick, 2004). Moreover, N_2O emissions depends on the amount of N present in the native organic matter, organic amendments, manure deposition, or synthetic fertilizers (Beauchamp, 1997). Agronomic replaceddecision-saspects like type of fertilizers, use of nitrification inhibitors or cover crops can influence the amount of N_2O emitted (Charles et al., 2017; Derpsch et al., 2010).

1.4 Climate change and its impacts on Agriculture

The accelerated accumulation of GHGs in the atmosphere has been leading to changes in the global climate dynamic. Since the 18th century, the global temperature was 0.68°C warmer, representing the highest temperature change in the last 1000 years (IPCC, 2013). As a result of this global warming, the planet has experienced a reduction of cold days and nights, an increase of warm days, and an increment of heatwaves in Europe, Asia, and Australia. From 1901 to 2010, the sea-level has risen by 0.19 m, and the IPCC project an increase of 0.19 to 0.59 m by 2100, which will affect the agriculture in coasts and river deltas (Church et al., 2013).

The occurrence of heavy precipitations increased in the high-altitude regions of North America and Europe. On the contrary, subtropic areas have experienced shorter and less intense precipitations, affecting agricultural lands in southern Asia, Africa, Central America, and the Mediterranean (IPCC, 2013; Trenberth, 2011). Moreover, the temperature rise will change the intensity of the natural modes of climate variability at different timescales (e.g., El Niño-Southern Oscillation (ENSO) and the Asian monsoon), which largely determine the rainfall regimes in the tropics (Loo et al., 2015; Yun et al., 2021).

Rising atmospheric CO_2, warmer temperatures and changing rainfall patterns interact at different scales generating significant impacts on agricultural systems. Climate-related stressors like heat waves, drought, or floods affect crop physiology and trigger environmental problems that conflict with agricultural activities. In the table 1.1 are summarised the main direct and indirect impacts of climate change on crop and soil.

Table 1.1: Direct and indirect climate impacts on cropping systems

Climate impact	Plant response	Direct impacts on crops	Indirect impacts
Elevated atmospheric CO_2	Accelerated photosynthetic rate in C3 plants (CO_2 fertilization effect) and increase of stomata closure.	Increase accumulation of biomass and yields. Reduction of transpiration in C3 and C4 plants.	Water use efficiency increase but the concentration of micronutrients can be reduced by "carbohydrate dilution".
Increased temperature	Reduce stomata closure and increase vapour pressure deficit. Heat-induce stress reduce CO_2 assimilation and accelerate phenological stages.	Shortening of the time to maturity with subsequent reduction of biomass accumulation.	Increase evaporation and organic matter decomposition in soil. Longer frost-free and warmer seasons in cold regions. Pest-relocation.
Changes on rainfall patterns	Reduce stomata closure and increase the vapour pressure deficit as a response of drought-induced stress.	Reduced rainfall generates poor crop establishment and impaired germination. Reduces the specific leaf area index,increases pollen sterility, and generates poor grain quality.	Excessive rainfall increases water erosion and nutrients leaching while lack of rainfall reduces soil moisture and nutrients mobilization.

Sources: Elevated atmospheric CO_2: Dong et al. (2018); Müller et al. (2014); Soares et al. (2019); Increased temperature: Deutsch et al. (2018); Gornall et al. (2010); Gregory et al. (2009); Changes on rainfall patterns: Alqudah et al. (2011); Barnabás et al. (2008); Farooq et al. (2009)

1.4.1 Global and regional climate impacts on agriculture

The impact of combined climate stressors reviewed in table 1.1 progressively affects food production worldwide. According to FAO, the annual occurrence of economic losses in agriculture associated with climate-related disasters increased by 122% during the 04'-14' decade compared with the 80'-90' decade (FAO, 2016a). In time-series analysis, Ray et al. (2015) analyzed global crop statistics over the 1979-2008 period and found that climate variability explained about 32 to 39% of yield fluctuations of major cereal crops.

CThe nature of the climate impacts differs across regions. Lesk et al. (2016), reported that global extreme weather events during 1964–2007 reduced the global cereal production by 9-10%, with a difference in the impact magnitude among developed and developing countries. According to climate projections, agricultural land in temperate regions could increase its suitability (Balkovič et al., 2018), while tropical and subtropical regions will experience negative shocks (Hatfield et al., 2011; Wiebe et al., 2015).

Crop models project that moderate warming willwould enhance yields and expand suitable crop area in the north of Europe, Russia, and Central Asia, and North of America (Motha and Baier, 2005; Tubiello and Schmidhuber, 2016). In their meta-analysis, Knox et al. (2016) reported an average increase of 14% in projected yields for seven major crops in Northern Europe and 5-6% in central and southern Europe.

The subtropical zone of Europe and Asia have been experiencing an increase in temperature and droughts, affecting agricultural activities in the Mediterranean (Iglesias and Garrote, 2015; Iglesias et al., 2011) and rainfed crops in the north and northeast of China (Tao et al., 2003). Water scarcity issues affect the river deltas in South and Southeast Asia, where 23 million hectares of rainfed rice are affected by changes in rainfall patterns and increasing salt intrusion (Li et al., 2015; Pandey et al., 2007; Schlesinger, 2000). An example is Bangladesh, where rice production decreased by 15-31% in the last 15 years in coastal areas affected by salinity (Rabbani et al., 2013; Rahman et al., 2019).

Agriculture in the tropical and subtropical regions offrom Africa is considered highly vulnerable to climate change (Connolly-Boutin and Smit, 2016; Niang et al., 2014). Approximately 97% of food production in Sub-Sahara Africa comes from rainfed crops, relying entirely on temporal and spatial rainfall dynamics (Kotir, 2011). Moreover, 70% of cropland are drylands (dry sub-humid, semi-arid and arid lands) that are intrinsically nearly to sub-optimal conditions for agriculture (World Bank, 2015).

The temperatures in Sub-Saharan Africa are projected to increase about +2.0 to 4.5 by 2100, and rainfall is expected to decrease in southern Africa but increases in East Africa (Kotir, 2011; Niang et al., 2014; Serdeczny et al., 2017). Warmer environments will increase the risk of desertification of drylands, threatening rainfed agriculture in these areas. The crop projections show an overall negative effect on yields of major crops in Africa (Knox et al., 2012), with a few exceptions in Eastern Africa, where moderate warming in highlands can increase the productivity of crops like the maize (Lobell and Burke, 2008).

Although agriculture in sub-tropical and tropical regions of America presents high heterogeneity, rainfed farming for subsistence purposes is the most representative system in the region (Vergara et al., 2014), which implies high vulnerability to climate change. This vulnerability was reported by Lachaud et al. (2017), in their Total Factor Productivity (TFP) analysis developed for Latin America and the Caribbean (LAC) for the 1961-2012 years. The study showed climate variability was responsible for -22.7 to -0.02% of negative impact on agriculture in 20 of the 28 countries of LAC.

Central America is perhaps the most vulnerable region to climate change in the continent given the combination of extreme seasonal events as floods and extended droughts across the dry corridor of Central America that comprised areas in El Salvador, Guatemala, Honduras, and Nicaragua (Restrepo and Alvarez, 2006). In Central America, agriculture depends on a bimodal rainfall regime, influenced by the ENSO phenomenon- the main driver of rainfall patterns in the region (Imbach et al., 2018). The drier conditions projected for Central America going to affect the yields of subsistence crops such as maize and beans that could decrease 4% in Nicaragua, 22% in Belize, and up to 34% in the dry corridor (Gourdji et al., 2015; Hannah et al., 2017).

Agriculture in tropical/equatorial regions and the sub-tropical zone of South America will face contrasting climate impacts. Climate models project an increase in temperature and decrease in rainfall in the north of South America, the tropical Andes, and northeast of Brazil (Magrin et al., 2009). Without adaptation measures, countries such as Colombia might face an impact on 80% of their crops (Ramirez-Villegas et al., 2012). For its part, warmer conditions could reduce maize and potato productivity in andean regions in Peru and Bolivia (Jones and Thornton, 2003; Tito et al., 2018), while crops like coffee could have to migrate to higher altitudes in Brazil (de Camargo, 2010).

Warmer temperatures might increase sugarcane yields in southern Brazil (Marin et al., 2009; Walter et al., 2010). In contrast, warmer nights might reduce the wheat and barley yield in Argentina (García et al., 2018). Similar results were reported by Magrin et al. (2009), who estimated that wheat yield could reduce 7.5% for each °C in the Pampean region (western Argentina); however, the authors remarked CO_2 fertilization effect could offset the negative impact of temperature, even increasing rainfed wheat yields up to 14%. The projected climate conditions also might extend the suitable land for tropical livestock in Argentina (Rolla et al., 2019).

1.4.2 The role of agriculture in the climate change policy context

Governments -warned by the scientific community- became aware about the need to articulate efforts to tackle climate change. A global climate policy started with the first World Climate Conference in 1979. By the late 80s, the Intergovernmental Panel on Climate Change was established and was held the first UN General Assembly Resolution on Climate Change. This first decade of climate policy was defined by Gupta (2010) as "problem framing", which closed with the publication of the First Assessment Report (FAR) of IPCC in 1990 (Newell and Taylor, 2018). The key messages in the FAR were the urgency to reduce the GHGs from all the sectors including agriculture. The report pointed out the need to research the regional impacts of climate change on crops and livestock, and the identification of mitigation opportunities in agriculture (IPCC, 1990).

A global climate policy was consolidated during the 90's decade with the UN Framework Convention on Climate Change (UNFCCC) and posteriorly with the compromises established in the Kyoto protocol in 1997 Gupta (2010). In the Kyoto protocol, several mechanisms were created to finance mitigation projects in developing countries (non-Annex countries) by Annex I countries (developed countries) as an offset alternative to achieve their GHG reduction compromises. Given the multiple mitigation opportunities that represent agriculture in developing countries, agriculture became a key sector with a portfolio of projects on sustainable agriculture, sustainable forestry, and soil carbon sequestration (Lipper et al., 2018).

The climate policy approach changed Since 2009 when developing countries acquired their own mitigation compromises. These mitigation compromises have to be submitted through mechanisms as the Nationally Appropriate Mitigation actions (NAMAs) established in the COP18 in 2011 and then, the Intended Nationally Determined Contributions (INDCs) in 2014 during the COP20 (Boos et al., 2015). In the COP21-when the Paris Agreement was signed- 119 countries pledge to reduce their emissions from agriculture. The submitted INDCs and the NAMAs showed that 85% of developing countries compromised to reduce GHG emissions through agriculture and land-use change, having 90% of the commitments related to mitigation and adaptation in agriculture (Richards et al., 2015b).

International community is aware of the numerous mitigation opportunities in agriculture and, at the same time, in the challenges that represent the climate adaptation for agricultural systems (Burton and Lim, 2005). The need for a holistic perspective is reflected in the submitted INDCs that integrate adaptation measures and aim for simultaneous achievement of adaptation and mitigation, taking advantage of their synergies (Lipper et al., 2018). This new paradigm replaces the mitigation-centric climate policy with approaches that consider mitigation and adaptation in an integrative way.

In this sense, initiatives that aim to transform agriculture according to current needs-like Climate Smart Agriculture- have been gaining attention in the past years and become mainstream in the climate and agriculture policy agenda at the national and international level (Newell and Taylor, 2018).

1.5 Climate-Smart Agriculture

The concept of Climate-smart agriculture (CSA) was presented during the Hague Conference on Agriculture, Food Security, and Climate Change by FAO, as a response to the need to re-interpret the relation between mitigation, adaptation, and sustainable food production (Lipper et al., 2018). The CSA concept has been summited to a broad discussion since its first mention by FAO in 2009 (See timeline in Figure 1.3), when general framework without specific guidelines to define what is or is not climate-smart was published; since then the concept had a high acceptance and was used to label different plans, programs, and techniques.

Since the CSA presentation stakeholder have been held biannual Global Science Conferences on Climate-Smart Agriculture. These conferences are a focal point for researchers and stakeholders to discuss and identify research needs, and present evidence and methodologies for the monitoring and scaling-up of CSA (Lipper et al., 2018). To date, CSA is presented as a context-dependent approach that supports the transformation of agricultural systems small farmers in low and middle income countries towards sustainable agriculture in the change climate context supported three main principles: 1. Increasing agricultural productivity and incomes by sustainable ways 2. Adapting and building resilience to climate change; 3. Reducing or removing greenhouse gas emissions as much as possible (FAO, 2010; Lipper et al., 2014). The three principles represent the productivity, adaptation and mitigation pillars and their interactions represent the core of CSA (Figure 1.4)

Although CSA aims to achieve all three goals, this is unlikely in all cases; the idea is to consider the particularities of three goals in different temporal and spatial scales (Lipper et al., 2014). Thus, CSA should be considered more than a set of specific practices that deliver "triple wins", given the broad range of processes and actors in which CSA can operate (Karlsson et al., 2018).

It is precisely the complexity to address the interaction of actors within different contexts where CSA is considered a contested approach. Taylor (2018), pointed out that "triple wins" scenarios promoted in CSA often assume an absence of conflict of interest between productivity, adaptation and mitigation goals among social groups. Moreover, CSA planning may encourage the potential asymmetric representation of stakeholders (e.g., gender or ethnic minorities under-representation) and uneven researcher-stakeholders relations that overlook the needs of unrepresented groups.These

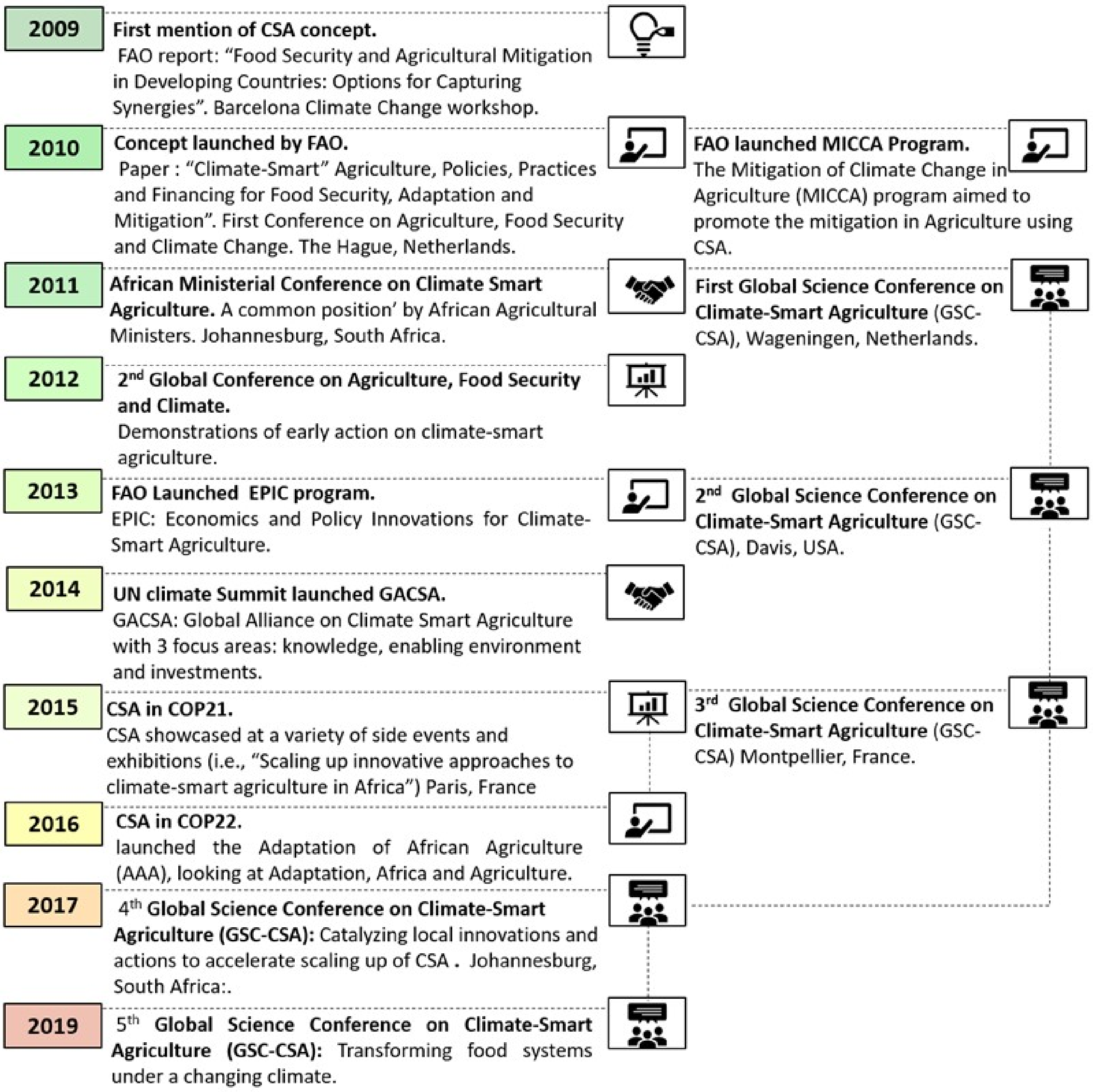

Figure 1.3: Timeline of main events on the development of Climate-Smart Agriculture (CSA). (Sources: (Lipper et al., 2018; Newell and Taylor, 2018)

issues could constrain social inclusion and reinforce inequity (Eriksen et al., 2019; Howland et al., 2021; Newell and Taylor, 2018).

In this sense, the priorities and representations of productivity, adaptation, and mitigation will differ across the contexts and thus the CSA goals. Although the pillars have an intrinsic relation in all agricultural systems, each one addresses several processes that correspond to different nature and therefore need to be defined before identifying the trade-off and synergies between them. The next three subsections describe each of three CSA pillars in turn.

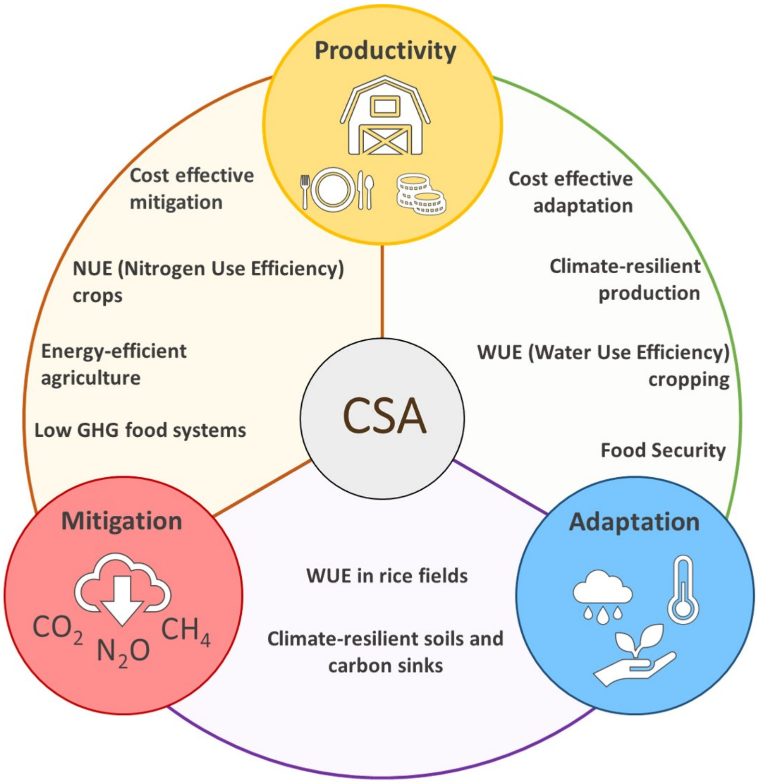

Figure 1.4: Representation different links between the Climate-Smart Agriculture Pillars

1.5.1 Sustainable productivity in a changing climate

Climate change represents a threat to the agricultural production and livelihood of 2.5 billion people worldwide (FAO, 2016b). Climate impacts in regions with agricultural-based economies could constrain their development, as well as a reduce food access and food stability, either by physical unavailability of products or by increasing of poverty. Climate impacts on agro-food systems are an increasing concern, particularly in low-income regions and rural areas where socio-economic context already constrains food access (FAO, 2003), increasing the risk of food insecurity.

The productivity pillar aims to manage agricultural systems from a sustainable approach, which the non-renewable resources are using efficiently while reducing the GHG contributions, relying on the Sustainable Agriculture (SA) principles (Campbell et al., 2014; Tilman et al., 2011). Although the SA concept is subject to be interpreted from different perspectives, all consider the environmental health, economic profitability, and social and economic justice components equally important (Wall and Smit, 2005). Thus, CSA recognises these SA elements interact at different temporal and spatial scales in a changing climate (Ignaciuk and Mason-D'Croz, 2014).

The challenges that suppose the transition towards sustainable agriculture are as diverse as the components and scales in which they interact. At the farm scale, sustainable intensification represents a primary challenge; increase food production without incurring in expand agricultural land or environmental impacts, avoiding GHG emission by land-use conversion, and loss of biodiversity (Pendrill et al., 2019; Pretty and Bharucha, 2014). The adoption of agronomic practices as high-yielding crop varieties, water and soil conservation management, and integrated livestock-crop systems can support the transition towards sustainable agriculture by improving productivity, soil health, and increasing the efficiency of agricultural systems (Pretty et al., 2011).

1.5.2 Strengthening climate resilience and adaptation

Agricultural systems are subject- to some extent-to climate stressors; however, climate change has accelerated the severity, scale, and frequency of extreme climate events. Accelerated climate change increasing the pressure and the impact on the agriculture (Gitz and Meybeck, 2012). Hence, adaptation measures become a priority for agriculture in the future, given the concerns about sustaining stable food production in climate change scenarios (FAO, 2012; Meinke et al., 2009). To understand adaptation needs is necessary to recognise the specificity of climate risks, the adaptive capacity of systems, and their resilience.

Climate resilience is the ability of agricultural systems to perform during climate-stress events and its recovery time afterwards (FAO, 2012). For its part, the term adaptation is used when the systems are transformed as a response to climate threats, increasing its resilience through the modification or improvement of its adaptive capacity (Lobell, 2014; Wall and Smit, 2005).

Adaptation strategies will depend on the type of agricultural systems, geographic distribution, and scenarios of climate change considered (Rosenzweig and Tubiello, 2007). For instance, different adaptation measures are required for rice crops in lowland and rainfed upland rice. At a farm level exist a broad range of alternatives to increase the adaptive capacity of cropping, these adaptations include, (Anwar et al., 2013; Howden et al., 2007):

- **Inputs**: Organic fertilizers, Nitrification inhibitors, use of microbial inoculants to improve nutrients efficiency.
- **Water conservation**: Water harvesting, soil moisture conservation (e.g., crop residue retention), optimization of irrigation systems.
- **Floods control**: soil conservation practices to reduce erosion, nutrient leaching, and waterlogging.
- **Genetic resources**: crop breeding of varieties/species with climate tolerance (drought, submergence, heat, salinity).

Agronomic adjustments made as a response to short-term climate threats may be insufficient against potential future changes; might require more emphasis on output stability and resilience rather than just seasonal productivity. (Figure 1.5, (Stokes and Howden, 2010)). In this case, the adaptation strategies should be able to -over a range of likely climate, social and economic scenarios- minimize the potential climate impacts (Rosenzweig and Tubiello, 2007).

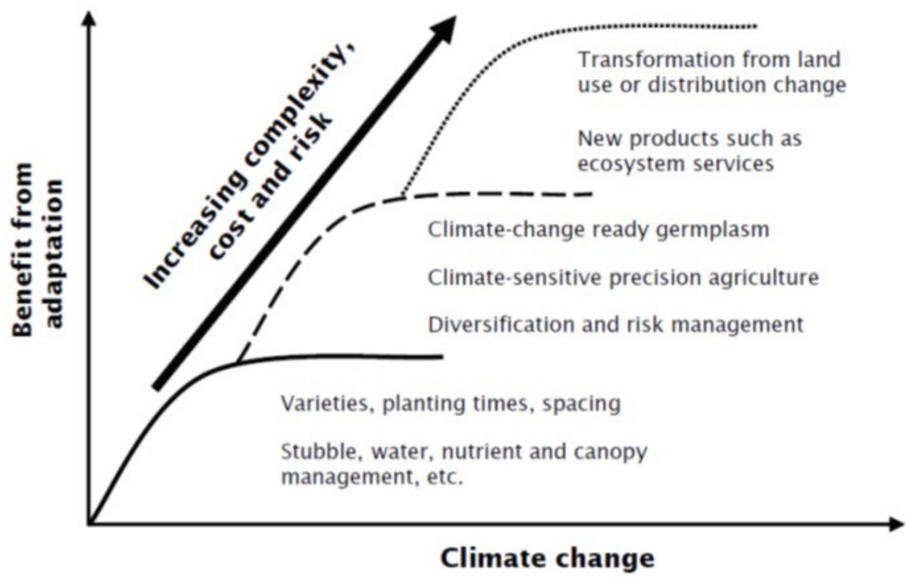

Figure 1.5: Relation between the increasing climate change and the different levels of adaptation measures. Taken from Stokes and Howden (2010)

1.5.3 Mitigation

Agriculture plays a key role in the reduction of global GHG emissions, particularly for the mitigation commitments of developing countries. The Intended Nationally Determined Contributions (INDCs) reported for the countries to the UNFCCC, indicated that 86% of the countries identified mitigation opportunities in the AFOLU sector (FAO, 2016a). These mitigation opportunities in agriculture could happen in three ways: 1) as a direct reduction of the emissions, 2) as an increment in the removals via carbon sequestration, and 3) by the displacing or increasing of agricultural efficiency (Smith et al., 2008). The three mitigation options in agriculture are strongly dependent of the context and the mitigation opportunities are setting by conjoint effect of agro-climatic conditions and socio-economic contexts (Smith et al., 2008).

1.5.3.1 Direct reduction of GHG emissions

The mitigation of direct GHG emissions is associated with the regulation of N_2O and CH_4 production in the soil (Paustian et al., 2016). Given that N_2O is a product of nitrification and denitrification, its mitigation involves the regulation of external N input in the soil (Shcherbak et al., 2014). Lower fertilization rates coupled with an appropriate fertilization schedule synchronizes the N crop demand with the N availability (Venterea et al., 2012). Furthermore, the use of slow-release fertilizers and nitrification inhibitors can reduce N_2O by 35% (Ruser and Schulz, 2015); however, the use of inhibitors can increase the production cost and result in an expensive mitigation strategy.

Given that methane production in the soil occurs in the absence of oxygen, the main opportunity to mitigate methane in cropping systems comes from rice fields. The anaerobic conditions and carbon sources are the main factors that affect methane production in flooding rice fields (Zhao et al., 2011). The mitigation of CH_4 in rice fields involves efficient irrigation management to reduces the periods of anaerobic conditions in the soil, constraining the methanogenesis. In this regard, irrigation strategies as intermittent irrigation, mild-season drainage, or Alternate Wetting and Drying (AWD) have proven to reduce CH_4 up to 60% (Carrijo et al., 2017). Moreover, the combination of irrigation strategies with nutrient management can reduce CH_4 emissions and control N_2O production during drainage periods (Mahal et al., 2018; Maneepitak et al., 2019).

1.5.3.2 Enhancing atmospheric carbon removals

Agriculture represents an important carbon sink because of its potential to store carbon in biomass and soil. Mitigate GHGs emissions by enhancing CO_2 removals means increment of biomass accumulation and soil organic carbon at higher rates than carbon direct and indirect losses (Jose and Bardhan, 2012).

Mitigation potential of agricultural soil resides in the large SOC deficit originated from decades of intensive agriculture (Post and Kwon, 2000). Several authors estimate that it could take over 20 to 60 years to reach a C saturation in croplands; however, this span varies according to agronomic management, initial SOC deficit, and soil properties (Desjardins et al., 2005; West and Post, 2002).

Estimations indicate that croplands worldwide could sequester between 0.90 and 1.85 Pg C/yr (Zomer et al., 2017). Extensive evidence has shown that soil-oriented management practices as the addition of organic manures, cover cropping, mulching, conservation tillage, fertility management, agroforestry, and rotational grazing can increase C stocks on agricultural lands (Paustian et al., 2016; Smith et al., 2008). Besides, land-use change specifically, from croplands to forest, has a promising C sequestration potential (Deb et al., 2015). This was confirmed by Guo and Gifford (2002) in their meta-analysis, where reported that conversion from crop to secondary forest increases the C stock by 59%.

1.5.3.3 Avoiding GHG emission

Another mitigation option is to avoid indirect GHG emissions (Smith et al., 2008). Indirect GHG sources in agriculture are the use of fossil fuel for agronomic operations, the manufacturing of agro-chemicals inputs, and land-use change (Lal, 2004; Schneider and Smith, 2009). Among the indirect sources, land-use change, specifically from native forests to crop and grassland are the largest contributor to GHG emissions. Reducing deforestation is the main mitigation alternative; however, would be needed an increment in the land-use efficiency to discourages agricultural land expansion (Popp et al., 2014).

For its part, several alternatives to the use of fossil fuel in agriculture are available; for instance, solar-powered electric agricultural machinery (Gourdji et al., 2015) and irrigation systems (Mérida García et al., 2018), or use of biofuels (Powlson et al., 2005). Replacement of chemical fertilizers by composts and other organic amendments reducing the dependence on synthetic N fertilizer and their associated GHG emissions. Aside from the reduction of N synthetic fertilizer use at the farm level, a needed off-farm strategy to reduce GHG emissions is to optimize the energy use of the chemical engineering process involved in the N fertilizers manufacturing Chai et al. (2019); Zhang et al. (2012).

1.5.4 Trade-offs and synergies between CSA Pillars

Climate-oriented interventions in agriculture (plans, policies, farm-scales strategies) respond to goals among CSA pillars. Addressing specific challenges can simultaneously achieve mitigation, adaption, and productivity goals (synergies) or, on the contrary, improve some of them at the expense of others generating trade-offs (Figure 1.6). These relations surge because mitigation, adaptation, and productivity goals at the farm level involve -to a different extent- the intervention of carbon and nitrogen cycles at different scales (Smith and Olesen, 2010). Moreover, many of CSA pillars priorities are focused on the same resources such as the soil or hydric resources.

Identifying synergies and trade-offs among CSA pillars helps to outline the scope of interventions and optimize resources. For instance, soil-oriented practices enhance resilience through soil improvement and increase stored carbon in the long term. On the contrary, overlooked trade-offs on adaptation and mitigation measures could lead to low adoption rates; especially, when crop profitability is affected (Locatelli et al., 2015). Several synergies occur across agriculture strategies promoted by CSA. The use of improved varieties or rhizobium inoculants to enhance crop profitability also reduces water pollution and N_2O emissions (Sainju et al., 2020; Smith and Olesen, 2010). Another example is the diet management in tropical cattle livestock reported

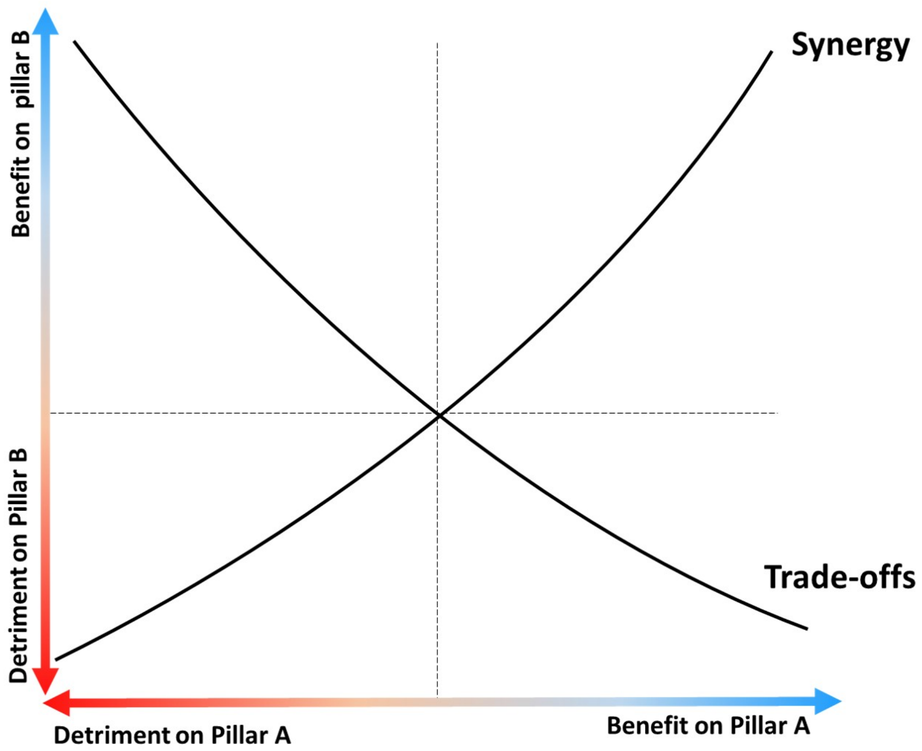

Figure 1.6: Representation of the trade-offs and synergies among CSA pillars (A and B as any combination between adaptation, mitigation, and productivity).

by (Gaviria-Uribe et al., 2020), which reported that legume-based feed reduces CH_4 emissions from enteric fermentation while increase animal weight gains.

For its part, some examples of trade-offs were evidenced in some studies. Paul et al. (2018) showed how some agricultural intensification scenarios using improved seed and inorganic fertilization could increase food availability in Rwanda, but also GHG emissions. Likewise, Sain et al. (2017) reported an increase of labour demand in the adoption of CSA practices in the Dry corridor in Guatemala; increasing the operation and maintenance costs.

Trade-offs and synergies occur simultaneously in agricultural systems, evidencing the complexity of design and implement CSA interventions. The case of irrigation management in rice fields is a good example. Alternative irrigation managements to continuous flooding in rice cultivation enhance water saving and generate a synergy with mitigation by the reduction of CH_4 emissions from soils. However, two trade-offs are often reported: 1) Yield penalties associated with the reduction of water inputs, and 2) in some cases overall increment of GHG contribution by the increasing of N_2O emissions (Carrijo et al., 2017; Kritee et al., 2018).

Such trade-offs and synergies also can occur at different temporal scales, increasing its analysis complexity. For instance, Conservation agriculture (CA) practices increase water and nutrients retention in the short term (Rawls et al., 2003; Thierfelder et al., 2013); however, it needs from 2 to 5 years to reflect the benefits of soil improvement in the yields (Thierfelder et al., 2017). For its part, the mitigation potential of CA is observable after several decades even if improvements in productivity are no longer achieved (Poulton et al., 2018).

1.6 Agricultural technologies aligned with CSA objectives: Climate-Smart Practices

As a response to mitigation, adaptation, and productivity challenges, agricultural research and technological innovations have identified a wide range of farm-level strategies that can contribute to CSA aim according to agro-climatic and social contexts (Meinke et al., 2009). These practices are crucial for any plan or policy framed within the CSA approach and largely determine the achievement of its goals (Rosenstock et al., 2016). Agronomic practices that can support the achievement of several CSA goals in agricultural systems are commonly labelled as "Climate-Smart Practices". The use of CSA tag to define farm-level strategies could suggest a guaranteed achievement of CSA goals under such practices; however, this depends more on the interactions between such agronomic practices with climate and biophysical conditions rather than the practice itself. Researchers are calling to avoid "climate-Smart" label overuse and focus on the particular pathways that will contribute to the achievement of CSA goals in each context (Campbell, 2017).

Thus, "climate-smart practices" can be interpreted as agronomic strategies that generate benefits aligned with the CSA principles in a given context. The practices that are so-called "climate-smart", include land regeneration, improved crop varieties, improved integration of crop-livestock systems, and integrated soil and water conservation strategies (Campbell et al., 2014; FAO, 2018; Rosenstock et al., 2018). Despite the extensive literature that evidences the contribution of CSA practices on CSA goals, research gaps still remain in the prioritization and scaling-up of the CSA practices, as well as trade-off and synergies among CSA pillars at different scales.

Among the most promoted Climate-smart practices, Alternate Wetting and Drying (AWD) and Conservation Agriculture (CA), have gained popularity because of their potential to deliver mitigation, productivity, and adaptation benefits. AWD has been widely promoted in rice producer countries by its potential to save water without yield penalties while reducing methane emissions.For its part, CA is well-known worldwide, especially in Sub-Sahara Africa, where it has been widely promoted to increase soil-oriented climate resilience.

These practices can increase the productivity of important staple crops such as rice, maize and wheat, which provide more than 42% of calories intake worldwide. AWD can -potentially- contribute to improving the water use efficiency of more than 144 million rice farms worldwide, especially in Asia, where 90% of rice is produced (GRiSP, 2013). For its part, 11% of the arable cropland worldwide has been farmed under any of CA principles (Kassam et al., 2014). Given its broad coverage of staple crops and its relevance to improving households of small farmers in low and middle-income countries, both practices were used as study cases during the development of this thesis.

1.6.1 Alternate Wetting and Drying (AWD)

Alternate Wetting and Drying (AWD) is a water-saving strategy for irrigated rice that consists of alternate flood and drained periods during the crop cycle. The AWD is proposed based on the premise that flooding conditions are unnecessary as long as remain water in the active zone of water intake by plants (rhizosphere). Thus, the field can be re-flooded before the water in the soil drops below the rhizosphere (approx. 30 cm) instead of keeping it flooded (IRRI, 2016).

The implementation of AWD requires the monitoring of water depth in the soil during the crop cycle. Bouman et al. (2007) proposed the use of a bottomless PVC pipe of 35 cm long and 20 cm diameter with 0.5 cm diameter holes spaced 2 cm apart (Figure 1.7a). The pipe is inserted 20 cm in the field and the soil should be removed to the bottom. During the irrigation, the water would flow through the holes into the pipe, making visible the water depth level outside the pipe.

The duration of dry periods depends of soil characteristic and climate; thus, it should be carefully monitored to avoid yield penalties. The International Rice Research institute (IRRI) recommend a "safe-AWD" implementation, that consist to re-flood the field once the water drops 15 cm to the surface or when the water potential reaches -5 kPa (Figure 1.7b). The level of water depth should be measure from the top of the pipe using a ruler; to calculate the water level, subtract the 15 cm of the pipe that are above to the ground to the reading.

The drained period of rice fields under AWD represent a reduction of water inputs and an inhibition of methane production. The benefits of AWD adoption are the water-saving (up to 30% less water use) and a significant reduction of GHG emissions, by the reduction of methane emissions up to 60% (IRRI, 2016; Tuong et al., 2005). The percentage may vary among agro-climatic and social conditions.

The meta-analysis reported by Carrijo et al. (2017) showed that AWD performed better in soils with pH $\geq$ 7 and SOC > 1% which present better water retention conditions. These results coincide with the spatial suitability assessment reported by Nelson et al. (2015) who based on the analysis of water balance, climate, and soil proprieties in rice producer regions of Philippines, concluded that AWD will perform

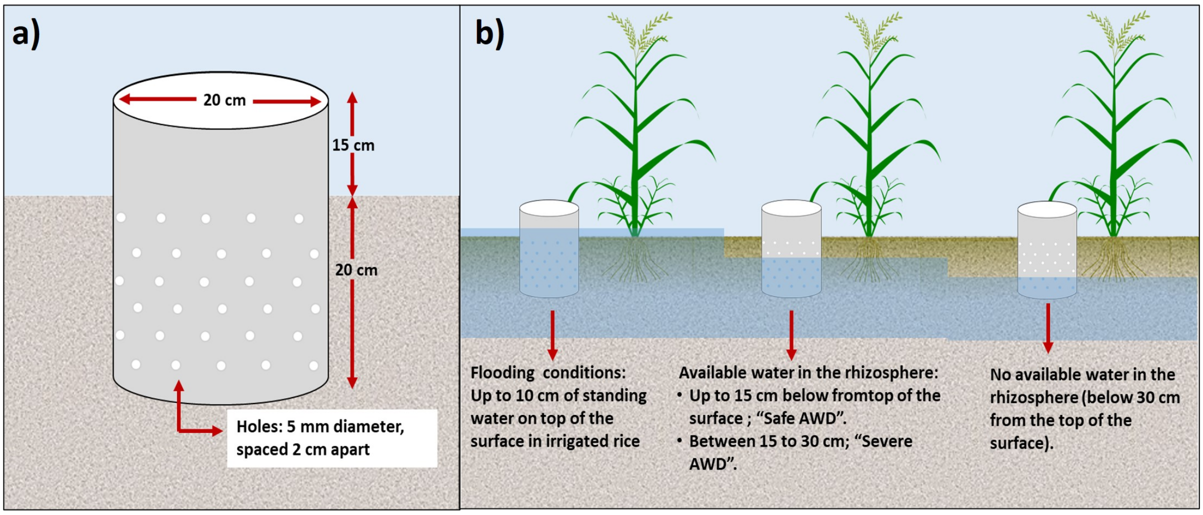

Figure 1.7: Scheme of the PVC pipe dimensions to monitor water level in the soil (a; based on Bouman et al. (2007)). Representation of the different scenarios from continuous flooding, "Safe-AWD", "severe-AWD" to the situation where water level drops below rhizosphere and the irrigation is required (b)

differently in soils with different hydraulic properties such as percolation rate, but also will vary between dry and wet season. The synergy between the water-saving and the reduction of methane represents an opportunity to contribute to mitigation in rice cultivation while increasing resilience (Richards and Sander, 2014), which are presented as the main benefits of its adoption. Other benefits of AWD adoption are the reduction of operational costs of irrigation (Rejesus et al., 2011) and the reduction of rice grain arsenic (Chou et al., 2016; Linquist et al., 2015).

However, studies of AWD present contradictory evidence regarding the impact on productivity. Discrepancies exist regarding the positive impact of AWD on effective tillering and grain fill (Pearson et al., 2018), thus, the main constrain to AWD adoption is the potential yield penalty which has been reported in several studies (Bouman and Tuong, 2001; Yao et al., 2012). Other reported disadvantages are the increase in N_2O emissions during drained periods, which potentially can compensate the reduction in methane (Lagomarsino et al., 2016).

1.6.2 Conservation Agriculture (CA)

Conservation Agriculture (CA) is a farming system that aims to adequate soil functioning by the implementation of three principles: 1) the minimum soil disturbance, 2) crop diversification and 3) permanent soil organic cover (FAO, 2017). The CA adoption generates a positive impact on soil biodiversity (Habig and Swanepoel, 2015), nutrients and water cycling, and overall soil productivity (Figure 1.8).

Within each CA principle, farmers dispose of different practices to adopt according to their agronomic and socio-economic context. Minimizing soil disturbance is possible through the restriction of tillage operations and the implementation of No-till and reduced tillage methods (Hobbs et al., 2008). For its part, the alternatives for a permanent soil cover are the use of cover crops or incorporate, at least 30% of crop residues in the field (FAO, 2017). Finally, crop diversification can be as a rotation or intercropping.

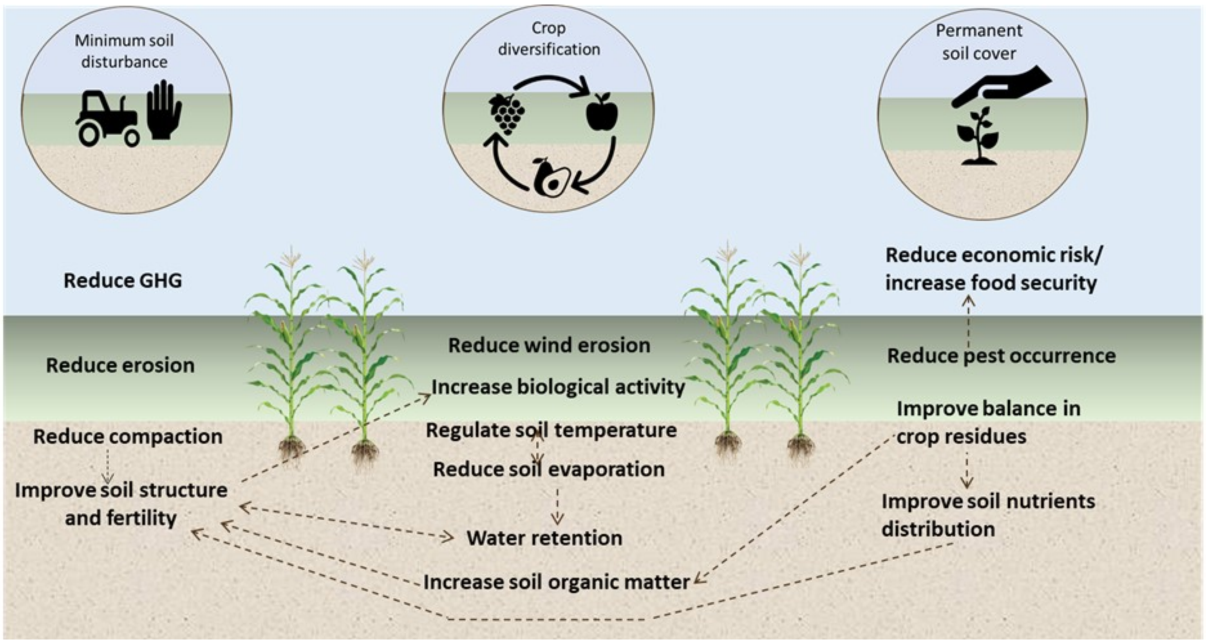

Figure 1.8: Benefits of Conservation Agriculture (CA) principles. Dashed arrows indicate synergies between benefits (Data extracted: CIMMYT)

It is important to mention, the three CA principles have been part of agricultural practices for a long time and have been extensively researched separately (Derpsch, 2004). Thus, instead of being defined as a "new set of practices", CSA proponents recognize the benefits of each CA principle for climate resilience, mitigation, and sustainable production promoting their coordinated adoption to encourage the synergies among them (Kassam et al., 2014).Moreover, CA principles interact with other agronomic practices that can complement their adoption. Practices related to appropriate nutrients management (such as use of compost or organic amendments), use of stress-tolerant varieties or pest and disease control can improve the feasibility of CA and support long term adoption (Thierfelder et al., 2018).

CA can generate changes in the cropping systems aligned with CSA principles, that will depend on the context (Giller et al., 2015). For instance, the two mitigation potential of CA is the removals of CO_2 through the increment of soil C stock, and the reduction on indirect GHG from operations and input use (Pratibha et al., 2016). Regarding to C sequestration, Powlson et al. (2016) reported in their meta-analysis that C stock was approximately 3 times larger in CA experiments. However, not all CA practices have the same C storage potential, as is the case of No-till which influences the distribution of SOC but does not contribute to its accumulation directly (Luo et al., 2010).

The increment of carbon in the soil presents a synergy between mitigation and adaptation; as C is increasingly stored in the soil, soil quality improves (Busari et al., 2015). The increase in SOC enhances the water holding capacity, which in turn, increases crop resilience during periods with low rainfall frequency and reduces water evaporation (Qin et al., 2015). Moreover, SOC activates the biological activity and increases the cation exchange capacity in the soil, enhancing the soil fertility and nutrient retention, both attributes to increasing the adaptive capacity by improving its soil productivity (Van Eerd et al., 2014).

A large body of evidence reported the impact of CA on CSA- relevant indicators. In their meta-analysis of 43 studies, Mahal et al. (2018) reported that CA practices as crop rotation have 44% more Potentially Mineralizable Nitrogen (PMN) than continuous cropping systems. Moreover, the authors found that cover crops increase the PMN by 211% compared with cropping systems without cover crops. In a global meta-analysis, Li et al. (2019) analysed 264 peer-review studies that showed that conservation tillage presents higher available water capacity and aggregate stability. The authors also reported that Soil porosity increased 2.5% under residue retention treatments; however, the authors highlight that such findings varied according to experiment duration.

1.7 Scaling up and metrics of CSA

CSA represents a portfolio of interventions with demonstrated results in the achievement of CSA goals. CSA Practices can be scaled out (horizontal scaling) that consist of transferring local knowledge to increase the adoption in the same spatial scale (e.g., among villages). When the CSA interventions show potential to be implemented on a larger scale, a scaling up (vertical scaling) process is developed. To scaling up CSA, decision-makers use policy instruments to launch successful practices to regional or national programs and plans (Aggarwal et al., 2018). Promoters of CSA such as FAO, CGIAR research centres and international cooperation agencies, seek reliable and transparent methods for scaling up, prioritization, and monitoring of CSA interventions.

Researchers and stakeholders need to do a rigorous appraisal of the implications for adaptation, mitigation, and productivity in both scaling approach. For instance, specific practices can represent benefits at the farm level but detrimental effects at the landscape or community level (Campbell, 2017). In the same way, identify synergies between CSA pillars facilitate the selection of the most suitable interventions and foresee potential adoption constraints. Thus, the analysis of trade-offs and synergies in

CSA are transversal to all prioritization and scaling-up assessments.

Different methodologies exist to assess the suitability of scaling out/up CSA as well as for monitoring its performance. Such assessments use well-known CSA-relevant indicators covering from biophysical to social and economic aspects of mitigation, adaptation, and productivity in agriculture (Christiansen et al., 2018). For instance, Duffy (2017) reported for CCAFS the National level indicators for gender, poverty, food security, nutrition, and health in Climate-Smart Agriculture (CSA) activities. For its part, World Bank, 2016 listed CSA indicators related to policy, technology, and performance that used to report and monitor their funded projects. Given the wide range of these indicators and the need to use the most appropriate to assess the CSA intervention CCAFS design the CSA Programming and Indicator Tool to support stakeholders to select the most suitable indicators according to the scope of the projects, the scale, and the agricultural systems involved.

When those mitigation adaptation and productivity indicators are analysed from a holistic lens promote from CSA, it generated more elaborated analysis (Nowak et al., 2019). Thornton et al. (2018) listed the existing approaches to assess the suitability and prioritization of CSA interventions. The authors mentioned the use of meta-analysis and systematic reviews to summarise and identified the impact of CSA interventions. A novel application of this approach is the Evidence for Resilient Agriculture (ERA); an interactive platform that provides a comprehensive synthesis (built on the last 30-plus years of agriculture research in Africa) of the effects of shifting of agronomic practices on indicators of mitigation adaptation and productivity.

Other approaches develop more complex analyses that include economic and social indicators related to mitigation, adaption, and productivity. Among these tools are the cost-benefits balances, Life Cycle Assessment (LCA), econometrics models, and participatory approaches. These approaches contribute to the overall CSA assessment beyond the agronomic and biophysical aspects. Some of these approaches use own metrics and quantitative rankings for CSA. For instance, the participatory approach has been used in the design of a score-based analysis of the impact of CSA practices on several CSA indicators. Some examples are the Rapid appraisal to prioritize CSA interventions published by Mwongera et al. (2017).

World Bank (2016), developed a set of CSA indices to monitoring the performance of funded CSA projects. These indices are the CSA-Policy Index, CSA-technology Index and CSA Results Index and are based on a set of indicators that assess the progress of projects regarding to the implementation of climate policy, the suitability of practices and the overall impact on CSA priorities. For its part, World Bank, CIAT, and CATIE (2014), presented the CSA countries profiles, which are a country level assessment of the CSA portfolio of practices and the impact of these in the main agricultural activities of the country. These profiles provide a score of each practice based on several CSA-relevant indicators and the adoption rates.

Although CIAT, World Bank, and FAO progress on the design of quantitative metrics of CSA research gaps persist between current metrics and its replicability and comparability across time and spatial scales. Thus, it becomes relevant to develop comprehensive metrics useful for stakeholders to monitor, compare and assess CSA interventions in the most time effective and less cost-demanding way (Neufeldt et al., 2013).

1.8 Modelling CSA metrics

Models are a valuable source of data for climate-smartness assessment and CSA metrics calculation. The use of modelling approach brings the opportunity to assess uncountable combinations of CSA practices, agro-ecological contexts, and climate scenarios (Thornton et al., 2018). Models can simulate biophysical, economic outcomes at the farm and regional scale using different time scales. An interdisciplinary modelling approach is useful to understand agri-food systems and their dynamics (Jagustović et al., 2021). Several studies have been using modelling to assess different indicators under CSA scenarios. de Pinto et al. (2020) uses climate and crop (DSSAT) models to generate an ex-ante analysis of the long-term impact of CSA adoption on global food security and GHG emissions. Bagley et al. (2015) use models to predict the performance of Climate-Smart Agriculture practices on yields in the United States for the years 2049 to 2068.

The model outcomes also allow the analysis of trade-offs and synergies at different spatial and temporal scales. For instance, Tian et al. (2021) explore the trade-offs and synergies between food-water and GHG emissions in Paddy rice in several rice producer regions in China. For its part, Tian et al. (2021) identified short and long-term dynamics of trade-offs and synergies among several biophysical and socio-economic indicators of CSA pillars in a Climate-Smart Village located in Ghana. In a similar analysis, Shirsath and Aggarwal (2021) used the Climate Smart Agricultural Prioritization (CSAP) toolkit to simulate the trade-off and synergies between production, GHG emissions and income for different climate-smart and intensification growth pathways in the next 100 years.

The modelling approach have been using to simulate a wide range of scenarios, time-frames and picture the transversality of CSA pillars. Models can provide a wider perspective of the impact of CSA than field experiment does and can be less time and cost demanding. Additionally, the simulation outcomes can be using to simulate integrated metrics that allow a systematic comparison and monitoring of climate-smart agriculture interventions over different scenarios Neufeldt et al. (2013).

1.9 Research aims and objectives

This thesis aims to design quantitative and replicable metrics to measure climate-smartness from the analysis of trade-offs and synergies in Climate-Smart Agriculture (CSA). With this, the thesis expect to contribute to fill research gaps in the understanding and measuring of climate-smartness in agriculture.

The proposed metrics were applied on secondary data of experiments that assessed two agronomic practices widely promoted under CSA: Alternate Wetting and Drying (AWD) and Conservation Agriculture (CA). The application of the metrics seek to evaluate the feasibility of this approach to measuring climate-smartness and, in turn, contribute to the understanding of climate-smartness as a dynamic temporal and spatial attribute. The second aim was to use the trade-offs and synergies analysis and the CSA metrics to generate a climate-smartness assessment using a modelling approach. This climate-smartness assessment uses the irrigated rice systems in Brazil as a case study.This aim expect to explore the applicability of modelling outcomes and CSA metrics to develop climate-smartness assessments.

- Chapter 2 introduces the Climate-Smartness index (CSI). The CSI summarises the most representative synergies among CSA pillars in cropping systems under water-oriented adaptation priorities. The definition of climate-smartness for this context was discussed and taken as a reference to outline the CSI. The CSI is composed of normalized indicators aggregated in a single way to represent the achievement or the lack of climate-smartness on a quantitative scale. The CSI was calculated for a set of published experiments on rice that evaluated the adoption of several irrigation strategies as Alternate Wetting and drying (AWD). The methodological decisions and the advantage-limitations of CSI were discussed. The CSI results showed the applicability of the CSI to contrast evidence related to the implementation of CSA interventions. The CSI score results useful to differentiate the performance of irrigation strategies according to the geographical location and interaction with other management.

- Chapter 3 presents a climate-smartness analysis using modelling tools to simulate the CSI. The comparison of several irrigation strategies in irrigated rice in Brazil was used as a study case. The modelling process (calibration, parametrization, validation) was described and discussed along with the advantages-limitations of the modelling approach. The use of models for climate-smartness assessments was explored through the discussion of study case results.

- Chapter 4 introduces a second CSA metric using the methodological steps proposed in chapter 2. The Soil-based Climate-Smartness Index (SCSI) is a metric conceived to represent the climate-smartness of cropping systems under soil-oriented practices at different time scales. Since the SCSI incorporated the temporal dimension, the metric was composed from normalized time series. The SCSI was applied to a set of long-term experiments that evaluated the adoption of Conservation Agriculture (CA) practices. The methodological decisions, as well as the definition of climate smartness, were discussed in this chapter. The SCSI scores were analysed and discussed the importance of considering the time dimension in the climate-smartness assessments.

- Chapter 5 summarises the design of CSA metrics. It discusses the novelty of the indices and their contribution to the research priorities in CSA. It discusses the definitions of climate-smartness and the attempt of providing a quantitative measure. It discusses the applications of the indices, their advantages, and their limitations. It provides recommendations for further CSA metrics design that contribute to the monitoring, comparing, and analysing the climate smartness in agricultural systems.

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Chapter 2

A Climate Smartness Index (CSI) Based on Greenhouse Gas Intensity and Water Productivity: Application to Irrigated Rice

[1]**Laura N. Arenas**; [2]Stephen Whitfield and [1]Andrew J. Challinor

[1]*Institute Climate and Atmospheric Science (ICAS), University of Leeds, Leeds, United Kingdom.*

[2]*School of Earth and Environment, Sustainability Research Institute (SRI), University of Leeds, Leeds, United Kingdom*

Abstract

Efforts to increase agricultural productivity, adapt to climate change, and reduce the carbon footprint of agriculture are reflected in a growing interest in climate-smart agriculture (CSA). Specific indicators of productivity, adaptation and mitigation are commonly used in support of claims about the climate smartness of practices. However, it is rare that these three objectives can be optimized simultaneously by any one strategy. In evaluating the relative climate smartness of different agricultural practices, plans and policies, there is a need for metrics that can simultaneously represent all objectives and therefore be used in comparing strategies that have different benefits and trade-offs across this triad of objectives. In this context, a method for developing a Climate Smartness Index (CSI) is presented. The process of developing the index follows four

steps: (1) defining system specific climate smartness; (2) selecting relevant indicators; (3) normalizing against reference values from a systematic literature review; and (4) aggregating and weighting. The CSI presented here has been developed for application in a systematic review of rice irrigation strategies and it combines normalized water productivity (WP) and greenhouse gas intensity (GHGI) The CSI was developed for application to data from published field experiments that assessed the impact of water management practices in irrigated rice, focusing on practices heralded as climate-smart strategies, such as Alternate Wetting and Drying (AWD). The analysis shows that the CSI can provide a consistent judgement of the treatments based on the evidence of water efficiency and reduced GHGI reported in such studies. Using a measurable and replicable index supports the aim of generating a reliable quantification of the climate smartness of agricultural practices. The same four step process can be used to build metrics for a broad range of CSA practice, policy and planning.

2.1 Introduction

Climate-Smart Agriculture (CSA) has been heralded as the basis of transformative changes toward sustainability. As a response to climate challenges, CSA founded on mitigation, adaptation and productivity pillars has been presented as an approach in agriculture aimed at simultaneously achieving three goals: increasing productivity, adapting to climate change, and reducing the GHG emissions (Lipper et al., 2014). To be meaningful, these generic CSA objectives need to be translated into specific properties of agricultural systems according to the relevant spatial and temporal scales and agro-climatic contexts of those systems Rosenstock et al. (2016).

In many agricultural systems, it would not be possible to optimize for all three of these broad objectives simultaneously (Notenbaert et al., 2017; Suckall et al., 2015). The complex compatibilities and trade-offs between mitigation, adaptation and productivity objectives have contributed to ambiguities in how the CSA concept is interpreted in agricultural policy and planning (Thornton et al., 2018). It is not clear, for example, whether a strategy that optimises yield is more or less climate - smart than one that optimises mitigation, or one that opts for a compromise across both. It is also important to recognise that "climate smartness," is a relative concept, and this is part of the reason for its ambiguity (Neufeldt et al., 2013).

The way we define and measure climate smartness should depend on the comparative question that is being asked.We may ask whether one agricultural practice is more or less climate smart than another in a given context or set of conditions, or we may ask whether it is more climate smart to adopt a give practice in context A vs. context B (with these contextual differences being delineated spatially or temporally or both). We may also ask whether you get a larger benefit from switching from one practice to another in context A or context B. In all of these cases, we might adjust our choice of indicators and what we take as reference values, to reflect the contexts/practices against which we are comparing.

Although the productivity objective of CSA is relatively unambiguous, adaptation and mitigation require some system specific interpretation (Wollenberg et al., 2016). Relevant aspects of mitigation include reducing direct emissions from agricultural inputs and machinery, reducing field level emissions related to the anaerobic decomposition of organic matter, or the longer term storage of carbon in soils, for example (Smith et al. 2014; GIZ 2014). The significance of these diverse sources and sinks differs greatly by production system and agro-ecological condition. In the case of adaptation, objectives should be considered relative to predominant climatic risks in a given context and these may relate to varied combinations of water scarcity, precipitation and temperature extremes, flooding, frost and heat stress that might impact the crops development (FAO, 2017; Wall and Smit, 2005).

There is no single replicable measure of climate smartness that captures its three objectives simultaneously and systematically accounts for the trade-offs between them. However, frameworks for monitoring and measure the climate smart properties of agricultural systems are being increasingly developed and utilised Frameworks such as "target CSA" designed by Brandt and Rufino (2017) and Climate-smart agriculture rapid appraisal (CSA-RA) designed by Mwongera et al. (2017) offer a means to quantitatively assessing suitability and priority indices for CSA practices at a regional scale in Africa. The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) have outlined an approach to measuring climate smartness using expert judgement (World Bank, CIAT, and CATIE, 2014).

The impact of adopting a particular climate-smart practice on each CSA pillar is scored separately in a range from 0 ("has no impact") to 5 ("Very high"), and the average of these numbers forms the final score. Whilst the individual scores based on expert judgements have broad application and context-specificity, they are not easily reproducible for the purposes of comparative studies. Similarly, the World Bank uses a group of CSA indices–the CSA Technology Index (CSA-Tech Index) and CSA Results Index (CSA-Res Index). Such indices are used in monitoring the suitability, implementation and progress of agriculture projects and use a large list of indicators of mitigation, adaptation, and productivity, grouped in different categories that are scored based on a specific threshold set accordingly to projected scope of the projects (World Bank, 2016), and so have limited general applicability.

The methodological approaches: rural participatory methods, Principal component analysis (PCA) to select indicators, analytic hierarchy, and expert judgement approach among others] adopted in the design of these CSA assessment frameworks, and the range of indicators drawn on within them, are indicative of the complexity of measuring climate smartness, as well as the importance of the context for its interpretation. However, it should be mentioned that even with the methodological differences among CSA indices and the CSI, there is commonality in their structure. All are derived from some degree of theorization of what CSA is, the translation of these principles into effective proxies, and an approach to weighting and aggregating them This structure is widely used in the construction of composite indicators and explained in detail by Nardo et al. (2005), OECD (2008), Mazziotta and Pareto (2013) and Baptista (2014). For the purposes of planning, monitoring and evaluating CSA, it is important to enrich the pool of CSA metrics with indices and indicators that integrate several dimensions (biophysical, economic, social, and environmental) in different spatial and temporal scales. Such metrics can support the analysis and monitoring of either the performance or the suitability of agricultural practices, or help to identify the climate-smart potential of agricultural systems.

Drawing on guidelines for the development of composite indicators (Baptista, 2014; Mazziotta and Pareto, 2013; OECD, 2008), we present a four-step process that can be applied in developing replicable qualitative indicators of climate smartness for a given context or set of research questions. We illustrate the process by presenting an index constructed for application in the systematic review of rice irrigation systems. A variety of irrigation regimes, such as AWD, are heralded as climate smart technologies within these systems (FAO, 2013; Rosenstock et al., 2016; Wassmann, 2010) By replacing the continual flooding of paddy rice systems, with a carefully managed regime of applying irrigation water only when soil moisture dips below a given threshold, it is thought that water inputs can be reduced by up to 30%, and land-based methane emissions (which are high under the anaerobic conditions that continual flooding creates) can be reduced by 48% (Richards and Sander, 2014). This GHG reduction is meaningful considering that irrigated rice, is responsible for10% of global emissions in the agriculture sector (Smith et al., 2014).

2.2 Materials and methods

2.2.1 Design of Climate Smartness Index (CSI)

To design a composite index that provides a measure of climate smartness, a four-step approach was followed, and applied in the design of a CSI for irrigated rice systems. First, a conceptual definition of climate smartness in irrigated rice systems was developed (in section 2.2.1.1: Defining Climate Smartness in Irrigated Rice System). Second, a set of indicators to represent the critical climate smart trade-offs in these systems were selected (section 2.2.1.2: Indicators of Climate Smartness in Irrigated Rice). Third, these indicators were normalized by reference values (section 2.2.1.3: Normalization and Selection of Literature-Derived Reference GHGI and WP Values). Finally, the normalized indicators were weighted and aggregated (section 2.2.1.4: Weighting and Aggregation).

2.2.1.1 Step One: Defining Climate Smartness in Irrigated Rice System

Among the climate events that affect the rice crop (floods, heat stress, salinity, and droughts), water scarcity-related risks have become a substantial constraint for rice production (Kim and Nishimori, 2019; Pandey et al., 2007; Serraj et al., 2011; Tivet and Boulakia, 2017; Zhang et al., 2018). Several studies reported economic losses in rice crop by drought in north and north-eastern of China (Lin et al., 2013; Sekhar, 2018) and South Asia and southeast Asia (Li et al., 2015; Pandey et al., 2007; Prasanna, 2018), in addition to projected yield losses in some temperate and tropical regions within the next 50 years under “no adaptation” scenarios (Challinor et al., 2014). Added to the concern about water availability in drought-prone regions, GHG emissions from rice also represent a remarkable issue. Rice crop contributes 9–11% to annual total non-CO_2 emissions by agriculture (Smith et al., 2014). The major source of those contributions come from methane production under anaerobic conditions in flooded fields (Bouman and Tuong, 2001; Suryavanshi et al., 2013).

Both, methane emissions and rice yields are highly sensitive to soil water content (Bouman et al., 2007; Singh et al., 2017; van Dasselaar et al., 1998) thus, water management becomes an important aspect of rice production and GHG mitigation (Meijide et al., 2017; Yang et al., 2017). Reductions in soil water content (either by climate events or reduction of irrigation frequency) contribute to reducing the CH_4 production in the soil (Haque et al., 2016; Jiao et al., 2006). However, the relationship between soil water and GHG emissions is not strictly linear since other factors like temperature, pH and carbon inputs may constrain or promote the conditions for GHG production (Gaihre et al., 2016; Han et al., 2016). Furthermore, during soil drainage periods, a trade-off between CH_4 and N_2O could take place. The nitrous oxide produced by nitrification/denitrification process, could offset the potential mitigation of CH_4 during soil draining and re-wetting events, or even increase the carbon footprint since the GWP of N_2O is 9.5 times higher than CH_4 (Johnson-Beebout et al., 2009; Kudo et al., 2014; Liu et al., 2016).

For its part, water reduction may also affect rice yield. Water stress promoted by reduction of soil water moisture can potentially reduce the productivity of the crop by affecting processes like tillering, panicle formation, flowering initiation, grain filling among others (Bouman et al., 2007; Hayashi et al., 2006; Ookawa et al., 2000). To avoid yield losses, continuous flooding conditions are traditionally implemented by the farmers since yield and total water input (TWI) has a positive correlation. However, this relationship has a limit. Beyond an attainable yield, the use of extra inputs will not necessarily lead to an increment in yield and, by the contrary, would reduce water productivity (Wichelns, 2002).

In water constrained conditions, the relationships between GHG emissions and yield and between water inputs and yield are key determinants of the climate smartness of an irrigation strategy. However, it may not be possible to optimize both of these relationships simultaneously, either because of the low capacity of the system to respond to the interventions (e.g., Sandy soils have high infiltration rates and thus water retention strategies are hardly successful) or by cross-effect processes (e.g., crop residue incorporation are beneficial for productivity but might increase GHG emissions by organic matter decomposition processes As such it is the trade-off between GHG emissions/yield and water inputs/yield, a measure of climate smartness that must account for the potential trade-offs between these.

2.2.1.2 Step Two: Indicators of Climate Smartness in Irrigated Rice

To represent the trade-off between water use/yield and /GHG emissions/yield, we constructed an index comprised of water productivity based on irrigation and rainfall (WP) and Greenhouse Gas Intensity (GHGI). Both WP and GHG are listed as performance indicators in the Performance indicators for sustainable rice cultivation published by Sustainable Rice platform (SPR, 2019), The Climate-Smart Agriculture indicators published by the World Bank (World Bank, 2016) and, the Climate-Smart Agriculture Sourcebook (FAO, 2013). WP is defined as the ratio between rice yield (kg grain/ha) and the TWI from irrigation and rainfall, expressed as m^3 (Equation 2.1).

$$WP(kg\ grain/m^3) = \frac{yield\ (kg\ grain/ha)}{TWI_{(irrigation+rainfall)}\tilde{(}m^3/ha)} \tag{2.1}$$

For its part, GHGI (or also called Yield-scaled GWP) is defined as the ratio between the total field-based GHG emissions expressed as Global Warming potential (GWP, kg CO_2-eq /ha /season) per yield rice, expressed as kg grain/ha grain (Equation 2.2).

$$GHGI\ (kg\ CO_2 - eq/kggrain) = \frac{(GWP\ kg\ CO_2 - eq\ /ha/season)}{yield\ (kg\ grain/ha)} \tag{2.2}$$

2.2.1.3 Step Three: Normalization and Selection of Literature-Derived Reference GHGI and WP Values

To transform the indicators into dimensionless and comparable values, GHGI and WP were normalized using the min-max normalization method (Mazziotta and Pareto, 2013; OECD, 2008). This normalization re-scales these indicator values from 0 to 1, giving them an easily associated "more is better" or "less is better" attribute, and thus facilitating the interpretation of each indicators' contribution in the CSI (Pollesch and Dale, 2016). This normalization method, has been used previously in environmental indices like the pollution index and composite environmental impact index (Khanna, 2000; Sabiha et al., 2016) as well as sustainability indices like City Development Index (CDI),Human Developed Index (HDI) among others (Böhringer and Jochem, 2007; Gómez-Limón and Sanchez-Fernandez, 2010; Muthuprakash and Damani, 2019). As a method it has benefits both in terms of the simplicity of its calculation and the scope it offers for adapting the CSI to the context in which it is being applied. When using the CSI in a comparative analysis, it is straightforward to select reference values that are representative of the fixed conditions that are being compared, and to normalize the index against these.

For this type of normalization, minimum and maximum thresholds of WP and GHGI were required. For application in a systematic literature review of the climate smartness of rice irrigation, we derived normalization values from our reviewed literature. The search was made in ScienceDirect and Google Scholar databases using the following keywords searched in the article titles: "rice" and "water productivity"; "rice" and "GWP"; "rice and "GHGI"; "rice" and "agronomic management"; and "water management"; "rice" and "yield"; "rice and "water use." Data from field experiments that reported all or any of the following variables: yield, TWI, GHG emissions (CH_4 and N_2O), GWP (Global Warming potential, expressed in CO_2-eq ha^1 season^1), and Water Productivity based on irrigation and rainfall, were selected. For this search, the studies that reported the use of the closed chamber technique as GHG sampling method were selected, Eddy Covariance and incubations techniques were excluded due to methodological and fluxes calculation differences. GHGI and WP values from 80 studies published between 2005 and 2019 were consulted (see Supplementary Materials 1 and 2). A total of 499 GHGI values were collected from the studies consulted (Figure 2.1a). The average for GHGI was 1.24-kg CO_2-eq/kg grain, and minimum and maximum values were 0.01 and 7.65 kg CO_2-eq/kg grain, respectively. In the case of WP, references values were obtained from a dataset compiled from 33 studies that resulted in 381 WP values (Figure 2.1b). The average WP was 0.79 kg grain/m^3 and the minimum and maximum values 0.12 and 3.69 kg grain/m^3, respectively.

Thus, these reference values were used a GHGI and WP used to calculate the index.

The indicators were normalized on a scale of 0 to 1 as shown in Equations (2.3) and (2.4):

$$GHGI_{(N)} = \frac{GHGI_{obs} - GHGI_{min}}{GHGI_{max} - GHGI_{min}} \tag{2.3}$$

$$WP_{(N)} = \frac{WP_{obs} - WP_{min}}{WP_{max} - WP_{min}} \tag{2.4}$$

$GHGI_{min}$ (= 0.01-kg CO_2-eq/kg grain) and WP_{min} (= 0.1 kg grain/m^3 are the minimum reference values of both variables and, $GHGI_{max}$ (= 7.8 kg CO_2-eq/kg grain) and WP_{max} (= 3.7 kg grain/m^3) are the maximum values.

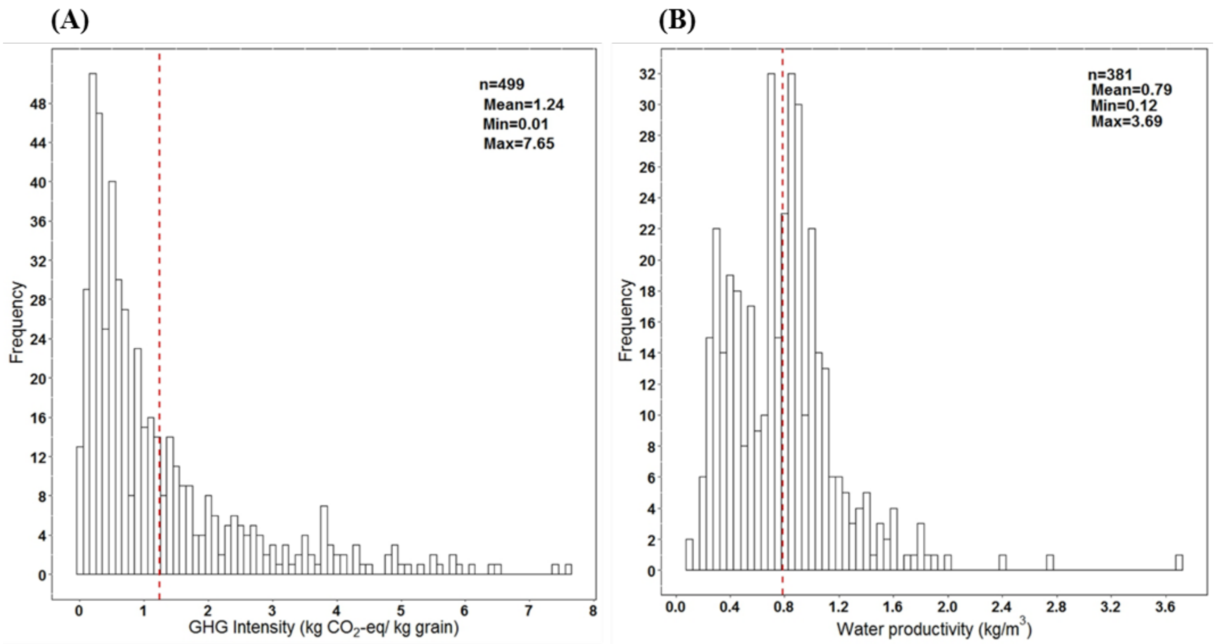

Figure 2.1: Frequency of Greenhouse Gas intensity (A) and Water Productivity (B) data collected from reviewed studies.

The values found in the literature are intended to represent a relevant reference point based on representative agronomic practices of irrigation, N management, tillage, residue incorporation in relevant rice producer regions. These should be adapted for the systems and questions to which a CSI is being applied. It is important to recognize that these reference values are, themselves, not absolute. New studies may report higher or lower max/min values in the future. Given that reference values come from different contexts to which the CSI is being applied (as the case described here), care should be taken not to interpret them as attainable goals. The climate smartness results derived from the index should be interpreted as relative scores that are bounded by ref. values, rather than absolute scores, within which there is a specific climate-smart threshold.

2.2.1.4 Step Four: Weighting and Aggregation

Improvements in individual indicators may be interpreted as climate smart where these represent a particular priority within a given system. For instance a reduction in GHGI contribution may be more of a priority in rice growing environments (i.e., those where there are particular policy incentives to reduce agricultural emissions) than in others. In our case, normalized GHGI and WP (that take values from 0 to 1) were assigned an equal weighting, this type of weighting is commonly used when indicators are considered equally important and there are no statistical grounds for choosing a different weighting (Gan et al., 2017). The equal weighting assignment also corresponds with the CSA principle of the trade-offs between productivity with mitigation or adaptation are equally considered climate-smart since the prioritization of one CSA pillar in specific should be evidenced in the index instead of being induced by the weighting.

To aggregate the normalized indicators, the additive aggregation method was used. This aggregation method provides a compensatory effect on both indicators (Munda and Nardo, 2005). This compensation represents the trade-off between the amount of GHG produced by a unit of grain yield and the amount of water used and allow the possibility of offsetting a disadvantage of an increasing of GHGI by a sufficiently large increasing of WP and vice versa.

The normalized GHGI value was subtracted from normalized WP to represents the compensatory effect of a GHGI increment over the overall climate smartness in a certain rice system. On the contrary, WP contributes positively to the index, representing the climate smartness associated with efficient use of water. Thus, the climate smartness score can progressively increase when WP increases and GHGI decreases. Conversely, the climate smartness could be diminished by an increment in GHGI simultaneously with a decreasing WP (Equation 2.5).

$$CSI = WP_{(N)} - GHGI_N \tag{2.5}$$

Given this configuration, the scale of CSI ranges from -1 to 1. A high CSI score (close to 1) indicates a situation of high water-efficient rice production and low greenhouse gas emissions relative to literature-derived reference values. Conversely, low CSI scores represent conditions where the rice crop has a high GHG footprint and low water efficiency.

2.2.2 Application of the Climate Smartness Index (CSI)

From the database compiled in step three of the material and methods section, studies with available data to calculate the index–those representing controlled experiments comparing continuous flooding with other irrigation management strategies and in which yield, GHG and water input data were available– were selected. This resulted in a subset of 16 studies, which are summarized in Table 2.1. A paired comparisons analysis between AWD and continuous flooding treatments was carried out, using the CSI.

Alternative water management strategies to continuous flooding (CF), take a variety of forms. In furrow irrigation, water saturated soil conditions were maintained along crop cycle while Sprinkler Irrigation used a pivot irrigation system to keep optimal soil water content. For its part, in Controlled Irrigation (CI), the irrigation events are determined by the water requirements at different growth stages (Yang et al., 2014). Finally, AWD promotes the alternation of dry and wet periods, where the dry periods are maintained until the soil water content in the first 20 cm (rhizosphere zone) drops to pre-defined soil water content thresholds. Those thresholds can be conservative–"safe-AWD" (soil water potential > 20 kPa); or more drastic water stress conditions (soil water potential <-20 kPa)).

Table 2.1: Summary of selected studies used to validate the CSI

Reference	Country	Soil		Agronomic management		
		Texture	pH	Planting method	Water management	Organic amendment
Chu et al. (2015)	China	Sandy loam	–	T	CF-AWD	Straw
Chidthaisong et al. (2017)	China	Clay	4.8	PB	CF-AWD	–
Fangueiro et al. (2017)	Spain	Loam	–	DS	SI-CF	–
Jain et al. (2014)	India	Loam	8	TPR-SRI-MSRI	CF-SRI/AWD-MSRI/AWD	–
Lagomarsino et al. (2016)	Italy	Silty clay loam	–	DR	CF-AWD	–
Liang et al. (2017)	China	–	6	T	CF-AWD	–
Linquist et al. (2015)	United States	Silt Loam	5.60	DR	CF-AWD	–
Setyanto et al. (2018)	Java	Loam	–	T	CF-AWD	–
Sibayan et al. (2017)	Philippines	Clay	7	T	CF-AWD	Organic amendment
Sun et al. (2016)	Philippines	–	7.6	T	CF	–
Tarlera et al. (2016)	Uruguay	Loamy clay	5.5-6.3	DS	CF-AWD	–
Tirol-Padre et al. (2018)	Vietnam Indonesia Thailand	Loam–Clay Loam	3.5-5.8	DS-T-PB	CF	–
Tran et al. (2017)	Vietnam	Loam	4.18	DS	CF-AWD	–
Wang et al. (2018)	China	Sandy Loam	–	DS	CF-FI-AWD	Wheat straw
Yang. et al. (2012)	China	–	–	T	CI-CF	–

Studies selected from the dataset in Step Three: Normalization and Selection of Literature-Derived Reference GHGI and WP. T, Transplanted; **DS**, Direct seeding; **DR**, Dry-seeding; **PB**, pre- germinated broadcasting method; **TPR**, conventional puddled transplanted; **SRI**, Conventional System of Rice Intensification; **MSRI**, Modified System of Rice Intensification; **CF**, Continuous Flooding; **AWD**, Alternate Wetting and Drying; **FI**, Furrow Irrigation; **CI**, Controlled Irrigation; **SI**, sprinkler irrigation.

2.3 Results

Across the 16 studies, the range of CSI values for AWD treatments ranged from −0.3 to 0.72, while the range for CF was −0.62 to 0.44. Other water management strategies like FI, SI, CF-30%, CF-70% have a closer CSI range with CF treatments (−0.67 to 0.5).The broad CSI range in the water treatments might be the result of differences in the agro-ecological context of the studies. Due to the lack of representability, a limited geographical analysis of CSI was possible. From the 16 studies, 6 are from China, with a mean CSI ranged from 0.33 to 0.08, that was considerably higher compared with the mean CSI of the other Asian countries represented in the sample like Vietnam, India, Thailand, Indonesia, and Java (mean CSI =−0.27 to 0.20).

At study level, the highest CSI was scored by the treatments assessed by Linquist et al. (2015) (mean CSI = 0.43; n = 12). This average CSI is the result of a high mean WP (1.71 kg/m^3), compared with the mean WP among the studies used to set the references max. and min. WP values (0.79 kg/m^3), combined with a low GHGI (mean GHGI = 0.156 CO_2-eq/kg grain); that was significantly lower than the average GHGI from the dataset of (1.24 kg CO_2-eq/ kg grain). The lowest climate-smartness were evidenced in the treatments reported by Tran et al. (2017) (textminus0.49 to −0.11) and Fangueiro et al. (2017) (−0.67 to 0.23).

Despite high CSI variability within similar water treatments, in all the studies the water management alternatives scored higher CSI than CF treatments (Figure 2.2). According to CSI calculated for the results reported by Yang. et al. (2012), Controlled Irrigation (CI) treatment showed higher climate smartness compared with CF, similarly the results reported by Fangueiro et al. (2017), showed that Sprinkler irrigation (SI) scored higher CSI than CF, although that scored the lowest CSI among the studies (mean CSI = −0.19, n = 15). The CSI also showed differences when was calculated for different seasons. Tirol-Padre et al. (2018), reported results for wet and dry growing seasons in Southeast Asia, where dry season scored higher CSI (mean CSI = −0.04) than the same CF treatment during the wet season (CSI =−0.19).

2.3.1 CSI of Contrasting Water Managements: CF vs. AWD

CSI scores were calculated and compared along paired experimental studies of water saving strategies-categorized as either AWD and Continuous flooding (CF). The overall climate smartness associated with water management practices can be evidenced using the CSI metric. Seventeen paired comparison between CF and AWD were analyzed. The results showed that AWD scored higher than CF in all cases. Those differences could be associated with changes in Water productivity (indicated by the vertical arrows

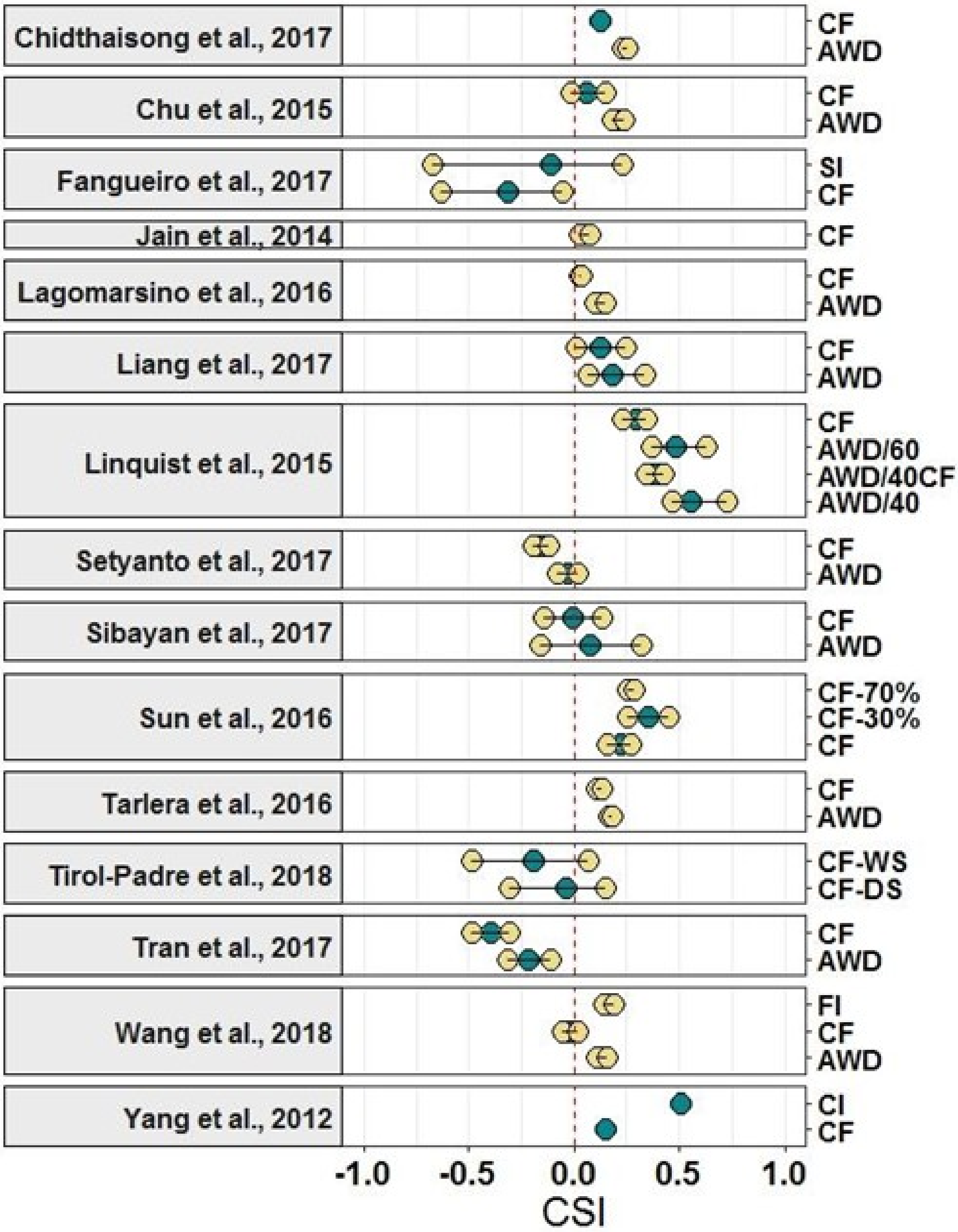

Figure 2.2: CSI scores of the selected studies. Yellow circles represent max and min CSI values in the studies and green circles represent the CSI average.**CF**, Continuous Flooding; **CF-70%**, 70% of normal irrigation; **CF-30%**, 30% of normal irrigation; **AWD**, Alternate Wetting and Drying; **AWD/60**, AWD treatments were irrigated until soil moisture reached 60% of saturated volumetric water–measured at 5 cm depth when the plots were re-flooded; **AWD/40**, AWD treatments were irrigated until soil moisture reached 40% of saturated volumetric water–measured at 5 cm depth when the plots were re-flooded; **AWD/40CF**, AWD treatments were irrigated until soil moisture reached 40% of saturated volumetric water–measured at 5 cm depth when the plots were re-flooded, up until the plants reached the reproductive growth stage; after which a flood was maintained up until the field was drained for harvest; **CI**, Controlled Irrigation; **SI**, Sprinkler irrigation; **CF-WS**, Continuous Flooding during Wet Season; **CF-DS**, Continuous Flooding during Dry Season; **FI**, Furrow Irrigation; **SRI/AWD** and **MSRI/AWD**, Irrigation was given on twice a week to keep soil just moist (3.5 cm).

in Figure 2.3, GHGI (indicated by horizontal arrows in Figure (2.3) or both (arrows with some slope degree). The implementation of AWD in all cases, improved the climate smartness independently of the site. The magnitude of the changes generated by the AWD implementation can be evidenced by the CSI differences between paired comparisons.

The greater differences between paired comparisons were up to 0.5 in treatments reported by Linquist et al. (2015), due to the difference of WP that was double in AWD. These treatments presented a relative low GHGI (below to the average) that did not change between treatments. Paired comparisons with GHGI upper the average and WP below to average, showed CSI differences between 0.12 and 0.19, mainly associated with the reduction on GHGI. The CSI differences provide a quantitative measure of the adoption impact, however, might not inform about what originated those differences.

The study that showed the largest CSI difference between treatments was (Linquist et al., 2015), which showed a CSI difference of 0.26 between CF (mean CSI = 0.22) and AWD/40 (mean CSI = 0.560). It is recalled that this AWD/40 treatment represents the most severe AWD option, in terms of water reduction, that Linquist et al. (2015) assessed for. AWD/40 was the treatment with the lowest TWIs and with a yield penalty of 13%. However, the AWD/40 treatment showed an increase of 63% in irrigation water-use efficiency and a reduction of CH_4 emissions by 86%, in comparison with continuous flooding treatments (Linquist et al., 2015).

In contrast to the CSI results of Linquist et al. (2015), the CSI differences between AWD and CF treatments carried out by Tarlera et al. (2016), showed a closer difference. Although AWD held higher CSI (CSI = 0.17) comparing with CF (CSI = 0.12) this slight difference was the result of a reduction in GWP rather than water savings benefits. It should be noted that even with a difference of 46% in GWP between CF and AWD, the trade-off between water-saving (12%) and yield losses (11%), under AWD, did not represent a gain in water productivity, and consequently did not improve the CSI significant.

Apart from CSI differences between AWD and CF, seasonal differences were evident. In the case of experiments reported by Tran et al. (2017), the winter-spring season trial achieved higher CSI (mean CSI = 0.24) for both AWD and CF treatments compared with the CSI scores in the summer-autumn season trial (mean CSI = −0.14). Those differences resulted from high GWP during the summer-autumn season. According to the authors, this might be due to differences in the air temperature added to the short fallow period between both cropping seasons.

The fallow left in the field during summer-autumn season translates into carbon sources for anaerobic bacteria populations, responsible for methane production. For its part, results reported by Liang et al. (2017) also showed seasonal differences in CSI.

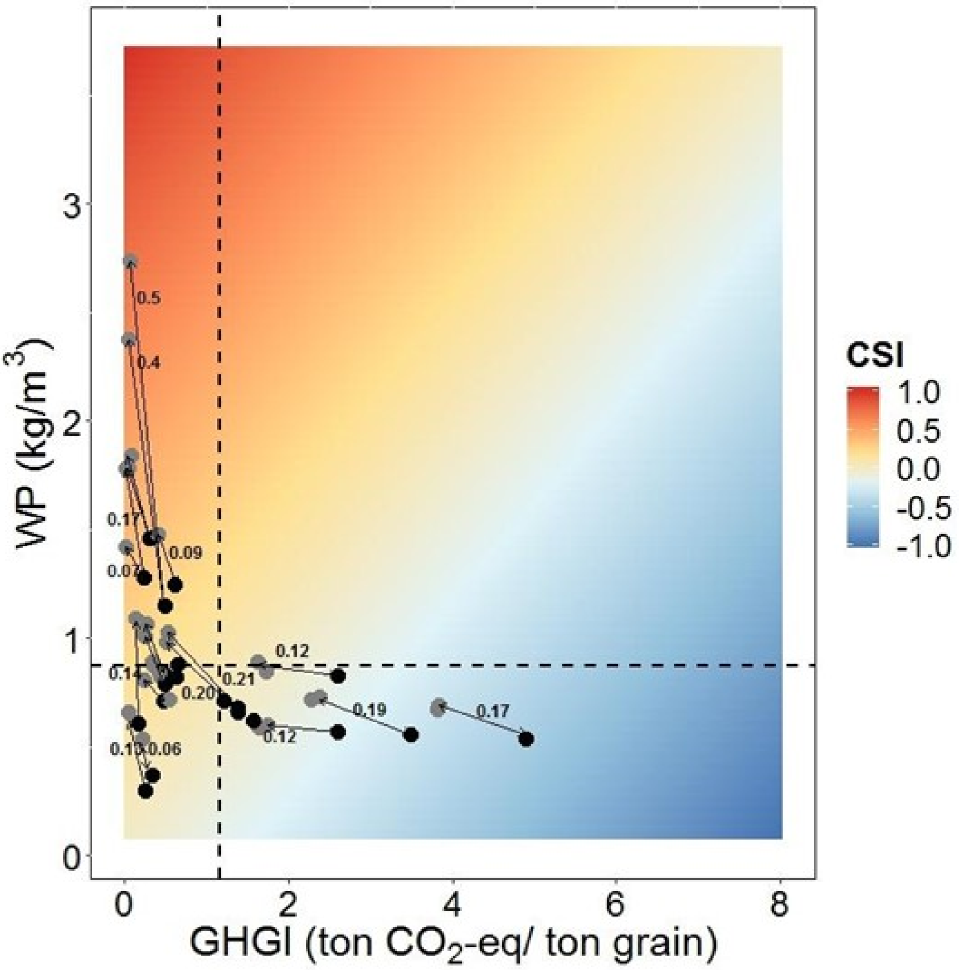

Figure 2.3: Scatterplots of the relationship between Global Warming Potential (GHGI) and Water Productivity (WP) plotted over a heat map indicating CSI values. Gray circles represent AWD treatments and black circles Continuous flooding treatments. The arrows link paired treatments from the same studies and the numbers close to the arrows indicate the CSI difference between them. The vertical dotted line represents the mean GHGI of studies in the dataset and horizontal dotted line, the mean WP

In the early season experiments, the CSI between AWD and CF was 0.04. Meanwhile, in the late rice season, it was 0.09. This difference between seasons resulted from a reduction of TWI during late rice and a yield increment of 13%.

The CSI also changed between AWD and CF treatments when these were combined with other agronomic managements. Chu et al. (2015) reported that AWD and CF treatments with straw incorporation scored lower CSI (CF+S = −0.01, AWD+S = 0.19) than the same water management without the straw incorporation (CF-S = 0.14, AWD-S = 0.23). In both AWD+ Straw and AWD-Straw, the water saving was similar (19–20%), however, the emissions increased 2.53 times when the straw was incorporated under CF condition, resulted in a negative CSI. This rise of GHG emissions is caused by the anaerobic litter breakdown under CF, which produces methane (Das and Adhya, 2014; Zschornack et al., 2011) The same increment of CH_4 emissions was evidenced in AWD+Straw, however, the dry periods promoted along the crop cycle allowed for greater soil aeration, constraining the anaerobic respiration.

2.4 Discussion

2.4.1 How Climate-Smart Are the Water Management Alternatives in Rice? Putting CSI in Practice

The way that indicators have been combined within the CSI is done so on the understanding that the critical factors affecting climate smartness in irrigated rice systems are the relationships between water input and yield and between GHG emissions and yield. Furthermore, it recognized that these two relationships may not be optimized simultaneously and it is therefore important to consider the potential for trade-offs between them. Indeed, this is illustrated in examples of AWD trials, in which water savings and emissions reductions outweigh yield costs, when compared with continuous flooding practices (e.g., Linquist et al. (2015); Tarlera et al. (2016)).

The CSI analysis presented here suggests universal improvements in the climate smartness of water management alternatives when compared with continuous flood irrigation. However, the performance of water management systems is also influenced by the agro-ecological conditions, climate change and social dynamics where they are implemented (De Silva et al., 2007; Sikka et al., 2018). This contextualized understanding of irrigation management is emerging within a growing body of experimental trials of these techniques. For instance, Dou et al. (2016) reported that clay soils favoured water and nutrient retention more than sandy soils, resulting in higher tiller production and grain filling of cultivars. Similarly, Carrijo et al. (2017), in their meta-analysis of the impact of AWD on yield and water use, concluded that high Soil Organic Carbon (SOC) content, low bulk density and aggregate stability can result in better AWD performance.

Consequently, we cannot explain the climate smartness associated with AWD without considering suitability. Nelson et al. (2015) designed a methodology based on a water balance model to assess the suitability of AWD. The authors claimed that sites with a negative water balance will be more suitable than regions with a positive water balance, where the rainfall excess could lead to extra cost by drainage labour. This corresponds with the results of Sibayan et al. (2017), who reported a significant reduction of water inputs in AWD, compared with CF, during the dry season (> 50%) compared with a 20% of reduction during wet season. As a consequence, AWD treatments under the dry season (CSI = 0.25 to 0.31) resulted in a higher CSI score than AWD treatments during the wet season (CSI =−0.11 to −0.16).

The way that the CSI is aggregated allows an easy association between high WP-low GHGI with climate-smartness, and low WP-high GHGI, with low climate-smartness in irrigated rice systems. Consequently, a reduction of GHG emissions might not be considered climate-smart by itself if it is associated with significant yield penalties. In the same way, where improved WP is associated with increased GHG emission, this will not necessarily represent a climate-smart change. However, situations in which individual CSA pillar improve considerably with respect to others, or even at the expense of them, should be carefully considered, as CSA priorities may not be the same in all cases (Campbell et al., 2014; Lipper et al., 2014; Totin et al., 2018). Regarding the relative nature of CSA, it would be possible to alter the weighting of the components of the CSI, in order to offer a measure of climate-smartness representative of contextual priority indicators.

While the use of composite indices may result in a loss of information (Baptista, 2014; Pollesch and Dale, 2016), metrics like the CSI can help to reduce the ambiguities associated with the interpretation of CSA; responding to a concern over the consistency of claims about what is and is not climate smart (Karlsson et al., 2018; Rosenstock et al., 2016; Saj et al., 2017; Taylor, 2018). In this sense, both the methodological approach and CSI results, bring objectiveness to the communication of evidence related to climate-smartness in rice. Thus, under an agreed climate-smartness definition and a replicable quantification of this, subjective interpretations could be avoided. The "climate-smart" labeling of agricultural systems or agronomic strategies, based on biased interpretations of CSA indicators or the misconception of a mandatory "triple win" goal, are examples of that. In both cases, the CSI could offer a transparent measure of climate-smartness.

2.4.2 Considerations About the Climate-Smartness Index (CSI) Design

Since its launch by the FAO in 2009, Climate Smart Agriculture has been reshaped and consolidated by an increasing pool of scientific evidence related with the impact of agronomic practices on CSA pillars and their suitability (Lipper and Zilberman, 2018). However, the context- dependent nature of CSA and the comprehensive range of cropping systems and environments where the agriculture is developing, add to the considerable challenge of quantitatively measuring and comparing the climate smartness of practices (Torquebiau et al., 2018; Wollenberg et al., 2016).

The approach to developing a CSI presented here, offers a means to quantitatively measuring and comparing the combined mitigation, adaptation and productivity properties of agricultural practices. The specific CSI presented is a suitable metric for contexts in which the primary climate-driven constraint, relates to water availability; and where there is concern over changing climate risks, such as drought, changing rainfall patterns or increasing temperatures and evaporation rates in the field. We have normalized this CSI for application in a systematic comparative review of rice irrigation management, by using reference values from this literature.

As explained by Dobbie and Dail (2013) and Mazziotta and Pareto (2013) indicator selection should be underpinned by a clear theoretical framework, explaining in this case what represents CSA in a given context. For the CSI proposed, the theoretical framework was focused on explaining the context in which the optimization of water use and the reduction of GHG could be considered climate-smart. For this, a water-scarcity climate risk context was given. This specification is important since rice is also threatened by other climate risks like sub-emergence, soil salinity and high temperatures (Mohanty et al., 2013), and thus the climate smartness meaning may change according to it.

Some studies, like Tivet and Boulakia (2017) in Vietnam, and Lakshmi. et al. (2016) in India, have associated low GHG emissions and high water productivity with climate smartness. However, the conceptual framework present here, also recognizes the importance of the relationships between water use and yield and water use and GHG emissions, as well as the potential that these relationships may not be optimized simultaneously within a rice irrigation system (Saharawat et al., 2012; Wassmann, 2010; Xu et al., 2015; Yao et al., 2017). The CSI could offer an easy interpretation of the trade-offs between indicators instead of relying on them being analyzed separately.

Another key aspect of CSI design was the selection of indicators, which is considered an important step in the design of composite indices and should be selected according to their relevance, robustness, availability, accuracy, etc. (Mazziotta and Pareto, 2013; Pollesch and Dale, 2016; Reytar et al., 2014). The selection of WP and GHGI was based on a deductive approach (Wiréhn and Neset, 2015), over the theoretical understanding of the variables as indicators of mitigation and adaptation ((Devkota et al., 2019; FAO, 2013; SPR, 2019; World Bank, 2016), and the trade-offs that they could represent. Although the deductive approach might be subjective, WP and GHGI have been recognized by Reytar et al. (2014) as a good proxy for environmental- related with water (Water productivity) and climate change (GHGI). The authors analyzed the indicators according to availability,availability, accuracy, consistency, frequency and differentiation and concluded that WP and GHGI have high availability and are highly relevant for decision making as well as differentiating by countries or regions, however, its accuracy and consistency is medium.

The selection of the indicators also corresponds to the trade-off that they represent. Both indicators are expressed in terms of grain yield, representing the relation between the water inputs and GHG emissions involved in rice production. In this sense, an increment of WP would be given by either an increase in productivity or reduction of water inputs (Heydari, 2014; Tuong and Bouman, 2003). The water-saving is desirable, however, if this represents a significant yield penalty, are not desirable for farmers (Bouman and Tuong, 2001; Wu et al., 2017) and unsustainable in the medium and long term. Similarly, by using GHGI as an indicator of mitigation is also considering the mitigation associated with increasing yields that could avoid increases in emissions by rice area expansion (Adhya et al., 2014).

The CSI has been bounded using generic reference values of WP and GHGI, these values are used to create a finite set of possible values that the index could take, within realistic and reliable boundaries. Given the normalization method used (Min- Max), the references min and max values selected from the literature and used to normalize the indicators are not necessarily constants into the CSI. This type of transformation is not stable since new data becomes available at some point and might be out the range of the references values (OECD, 2008). Such reference values can be changed at the light to discoveries, or be fitted according to a specific spatial or temporal baseline, or according to target and thresholds established in the frame of policies (Muthuprakash and Damani, 2019; Pollesch and Dale, 2016). The generic nature of the reference values used explains why we see, in some contexts, a relatively low sensitivity to irrigation strategy in the CSI. As climate-smart agriculture (CSA) is a relative concept the reference values could be set up based on clear-described targets or contextualized baseline conditions. For instance, the CSI compared between Asian countries showed a difference between China and the rest of Asian countries represent in the study. This gap is, in part, a result of the high yield traits of Chinese rice varieties and so it may be appropriate to use a different reference value when evaluating CSI within China, as opposed to within Asia as a whole, so that the CSI is more sensitive to differences in practice within this context.

2.4.3 Application and Potential of the CSI Approach

The methodological approach presented in this paper can be replicated for the design of metrics that support climate smartness assessments:

- Comparing the relative climate smartness of different practices in a given context, based on experimental site data.
- Comparing the climate smartness of a single practice across contexts (across space and time).
- Comparing the climate smartness of a contextualized practice to a hypothetical target or reference (which could be used for normalizing the index).
- Comparing response ratios between contrasting treatments (i.e., AWD vs. CF) across different agro-environmental contexts.

Consistently with the context-dependent nature of the CSA approach, the approach to developing a CSI set out here is designed to be flexible enough to be adapted to different cropping systems under several climate contexts, by the modification of the CSI indicators, reference values and aggregation options required. For instance, direct seasonal emissions may not represent the dominant source of emissions in all agricultural cropping systems, in these cases, the amount of sequestered carbon or indirect contributions (e.g., use of inorganic fertilizers, intensive tillage, post-harvesting residues management, among others), would represent more accurate proxies for mitigation. Similarly, adaptation objectives are context-specific, and associated with different primary climate risks (e.g., in rice systems there may be a primary concern with submergence, pests and diseases; heat stress, drought stress, and soil/water salinity).

The replicable and quantitative metric that a CSI represents within these applications, makes it potentially valuable in informing the targeting of agricultural support programs and development initiatives, and in helping to direct agronomic research agendas and evaluation methodologies, for which climate smartness is a central objective. However, it is important to highlight that there are some situations within which the CSI could be open to misinterpretation. It should avoid being interpreted as an absolute measure of the climate smartness of a practice (as opposed to a relative one) and nor should it be used to compare of contrasting agronomic management in different contexts (e.g., AWD in Asia vs. CF in Africa).

2.5 Conclusions

An approach to developing a climate smartness index is presented and then applied in a systematic review of irrigated rice systems. The process of developing the index follows four steps: (1) defining system specific climate smartness; (2) selecting relevant indicators; (3) normalizing against reference values; and (4) weighting and aggregating by additive methods. The CSI presented here offers a novel contribution to the growing body of literature on CSA by providing a single quantifiable metric of climate smartness. The approach is applied in comparative measures of the climate smartness of irrigation strategies in which the predominant mitigation concern relates to field level emissions, and the predominant adaptation actions aim for tackle the limitations in water availability. Future developments of this work may focus on the development of equivalent metrics for application in other agricultural systems and contexts, contributing to the building of a replicable and comparable evidence base for climate-smart agricultural practice and planning.

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Chapter 3

Using process-based models with climate-smart indicators to assess rice management options

[1]**Laura N. Arenas-Calle**;[2]Alexandre B. Heinemann; [3,4]Julian Ramirez-Villegas; [5]Stephen Whitfield and [1]Andrew J. Challinor

[1]*Institute Climate and Atmospheric Science (ICAS), University of Leeds, Leeds, United Kingdom.*

[2]*Embrapa Arroz e Feijão Rodovia, Santo Antônio de Goiás, Brazil*

[3]*International Center for Tropical Agriculture (CIAT), Colombia*

[4]*CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), c/o CIAT, Cali, Colombia*

[5]*School of Earth and Environment, Sustainability Research Institute (SRI), University of Leeds, Leeds, United Kingdom*

Abstract

Irrigation management replacedis keytechniques have been suggested in order to foster sustainable and climate-resilient agricultural systems; therefore, several irrigation strategies are promoted from Climate-Smart Agriculture (CSA) practices portfolio. The term "climate-smartness" is used to express the extent to which a system can be productive, adaptive, and mitigating of climate change fulfilling the 2030 Agenda for Sustainable Development. Whilst metrics of climate-smartness do exist, they are usually limited to trials in specific fields, which cover a limited range of environments and management options. One way to broaden the applicability of CSA metrics is to use them with crop simulation modelling, which can explore a much larger range of conditions. Accordingly, this study explores the potential for modelling tools and CSA metrics to be used jointly in developing a climate-smartness assessment of irrigation management in rice. The study focuses on a rice field experiment in tropical, where four water management options were used: Continuous Flooding (CF); Intermittent Irrigation (II); Intermittent irrigation until Flowering (IIF); and Continuous soil saturation (CSS). The DNDC model was used to simulate rice yields, GHG emissions and water inputs for these experiments. The model outputs were used to calculate a previously-developed Climate-Smartness Index (CSI), based on Water productivity and Greenhouse Gas Intensity (GHGI). A sensitivity analysis, varying rainfall and temperature systematically, was used to explore possible impacts of climate in the CSI. Results showed. CSI values calculated from simulated data are highly correlated with the observed CSI scores (R^2=0.9). The CSS treatment exhibited the highest simulation-based CSI, due to its high mitigation potential and the reduced water inputs. The CF treatment showed the lowest CSI. The irrigation treatments also showed seasonal variability in CSI as well as sensitivity to forced rainfall and temperatures changes. We conclude that combining models with climate-smart indicators has the potential to facilitate scientific input to decision-making, since it is a reproducible way to communicate CSA-related evidence generated from modelling approaches. The methodological approach used in this study can be used to fill gaps in observational evidence of climate-smartness, in regions where calibrated crop models perform well. It can also be used to explore changing climates. These efforts will in turn will support the scaling up of effective CSA options.

3.1 Introduction

To maintain sustainable rice production, farmers need to adapt to climate change and reduce Greenhouse Gases (GHGs) emissions in rice systems (FAO, 2019).In this sense, advocates of Climate-Smart Agriculture (CSA) have been promoting strategies to simultaneously achieve goals of mitigation, adaptation, and productivity in rice systems and, in this way put agricultural systems in attendance to 2030 Agenda for Sustainable Development, intending to achieve goals 2 (Zero hunger), 6 (Clean water and sanitation), 12 (Responsible consumption and production) and 13 (Climate action) (Lakshmi et al., 2016).

Irrigation practices like mild-season drainage or Alternate Wetting and Drying (AWD) can reduce GHG emissions by up to 60% and save water by up to 30% without affecting productivity (Carrijo et al., 2017; Jiang et al., 2019; Liu et al., 2019). However, a key challenge is that these objectives often cannot all be achieved to the full extent; thus, they need to be prioritized according to context, and the trade-offs associated with them weighed up. The effectiveness of irrigation practices will vary according to the context and the generated trade-offs and synergies between CSA objectives.

Several approaches have been developed to assess and monitor the performance of CSA strategies and bring a quantitative measure of such effectiveness also so-called "climate-smartness" (van Wijk et al., 2020). Among the available methodological approaches, the Climate-Smartness Index (CSI) is a metric that brings a quantitative measure of climate-smartness. The CSI is a composite index-based on agronomic indicators of CSA, normalized, and aggregated to in such a way that represents the synergy/trade-off between water productivity and the greenhouse gas intensity in cropping systems under water-oriented adaptation strategies (Arenas-Calle et al., 2019).

The CSI was applied by Arenas-Calle et al. (2019) to compare the climate-smartness of conventional irrigation management and and the Alternate Wetting and Drying (AWD) irrigation at different contexts. The CSI identified trends in AWD treatments across geographical locations and quantified the climate-smartness of AWD treatments across locations. To date, the use of climate-smart indices based on field data is limited to the spatial and temporal scales of the underlying measurements i.e., historical trials at the field scale.

The use of crop model simulations with climate-smart indices has potential to reduce this limitation. The results from simulated climate smartness could be useful as way of expanding the domain in which climate-smart indices are applied. This approach could be used to identify CSA practices, inform the robustness of future interventions, or estimate trade-offs across spatial and temporal scales that could undermine scaling up efforts (Nowak et al., 2019; Pringle, 2011).

This study presents and assesses the first logical step in using climate-smart indices with crop models: to calculate the indices based on crop model projections, and thus provide an assessment of simulated climate-smart practices that go beyond the environment and management conditions that have been trialled in the field. Thus, we present a climate-smartness assessment based on model simulations and CSI for water management strategies in rice. The assessment was developed for a 5-year experiment that evaluates four irrigation strategies in irrigated rice following two steps: 1) modelling of rice yield, GHG emissions and water inputs (Section. 3.2.2), and 2) calculation of CSI from simulated indicators for irrigation treatments during 2014-2019 cropping seasons and sensitivity analysis outcomes (Section. 3.2.6).

3.2 Material and Methods

A climate-smartness assessment based on simulations of CSA indicators was carried out for several water management strategies using irrigated rice in Brazilian tropical region as a case study. First, the DNDC v.9.5 model was parametrized and evaluated using field data from two cropping seasons (2016-2018). Using the model calibration, it was simulated yield, water inputs and GHG emissions for all irrigation treatments during 2014-2019, for which the Climate-Smartness Index (CSI) was calculated. Additionally, the treatments were simulated for the 2014-2019 period under different rainfall and temperature changes scenarios calculated from the baseline climate data. The application of modelling tools to simulate CSA indicators and the analysis of such results were analysed and discussed.

3.2.1 Field experiment

This study used data from a 5-year experiment carried out in the Brazilian Agricultural Research Corporation (EMBRAPA Arroz e Feijão) experimental station "Palmital" in the municipality Goiânira at the central-west region of Brazil (16°26'8.45"S - 49°23'38.31"O, altitude 729 m). The location has a tropical climate with a well-defined dry and wet season. The annual mean temperature is 23°C, with the minimum mean temperature reported in June (12.8°C) and the maximum temperatures in September (32.3°C), and annual precipitation of 1485 mm distributed across wet periods in October to April (220 to 270 mm/month) and dry periods in May-September (6.6. to 11 mm/month) (INMET, http://www.inmet.gov.br).

The experiment assessed four irrigation managements as follows: Continuous Flooding (otherwise described as conventional irrigation) (CF); Intermittent Irrigation (II); Continuous Soil Saturation , where the soil kept saturated or above field capacity (CSS); and Intermittent Irrigation until Flowering where the continuous flooding conditions were maintained until harvesting (IIF). The N fertilization consisted of basal dressing application at sowing and two split doses: the first at the beginning of the tillering (25-28 days after sowing) and the second at effective tillering (40-45) days after sowing. In addtion, fertilizer was applied inside the base of the chambers installed in the soil to sample the GHGs. The N fertilizer applied was adjusted proportionally to the chamber area. The rice varietal used in the experiment was BRS-Catiana. This genotype presents high yielding potential and medium cycle length (116 days in tropical conditions and 132 in subtropical conditions), suitable for cultivation in 17 of 26 states of Brazil. Detailed description of the field experiment has been published by Barbosa (2018).

Weather data (min. temperature, max. temperature, precipitation, humidity, solar radiation, and wind speed) were available for the whole period assessed (2014 to 2019). Yield data were available for all treatments during the assessed period except for season 2015/2016. Methane (CH_4) and (N_2O) nitrous oxide emissions were measured during 2015/2016 and 2016/2017 seasons in the plots under CF, II and CSS treatments. Water inputs were available for the 2016/2017 and 2017/2018 cropping seasons and all irrigation treatments.

3.2.2 Modelling of rice yields, direct GHG emissions and water inputs using DNDC model

The DNDC model (https://www.dndc.sr.unh.edu/) is a carbon and nitrogen biogeochemistry process-based model in agro-ecosystems with 2 main components. In the first component, the soil climate, crop growth, and decomposition sub-models simulate physical and chemical soil proprieties, and the second component, composed of nitrification, denitrification, and fermentation sub-models simulate plant-soil gas exchange (Li, 2000). Although DNDC is commonly use to modelling carbon and nitrogen dynamics in soil, the model also can simulate crop growth using a GDD-based sub-model (Zhang et al., 2016). We used the DNDC v.9.5 to simulate rice yield, water inputs and GHG emissions (CH_4 and N_2O) for the irrigation strategies assessed in the experiment described in section 3.2.1

3.2.2.1 Input data and calibration of cultivar parameters in DNDC model

The input requirements in DNDC model consist of 1) climate data, 2) soil data, 3) Crop parameters and 4) agronomic management such as fertilization, tillage, irrigation or flooding as well as dates of planting and harvesting. Daily weather data (maximum and minimum temperature (°C), precipitation (cm), wind speed (m/s) solar radiation (MJ/m^2) and humidity (%)) were obtained from the local meteorological station located at experimental station for the period of the experiment (2014-2019). Average climate parameters for the 5 cropping seasons are summarised in table 3.1.

Table 3.1: Summary of mean min and max temperature and cumulative rainfall in each cropping season

	Seasons				
	2014/2015	**2015/2016**	**2016/2017**	**2017/2018**	**2018/2019**
Min. Temp (°C)	18.5	19.3	18.6	18.5	18.5
Max. Temp (°C)	30.8	31.2	30.4	30.1	31.3
Cumulative Precip. (mm)	817	834	739.3	978	476

Soil parameters such as texture, Clay portion (%), Bulk density (gr/cm^3), Organic Matter (gr/kg, OM) and Total carbon (%), pH were obtained from soil analysis of the experimental site, while some parameters were calculated. Porosity was calculated based on the bulk density and the soil particle density (2.65 gr/cm^3) as is showed in Equation 3.1. Water Filled Pore Space (WFPS%) at field capacity and wilting point were calculated based on gravimetric soil water content at 33kPa and 1500kPa and bulk density according to equations 3.2. and 3.3. All soil parameters setting as initial conditions are summarised in table 3.2

Table 3.2: Soil parameters used in DNDC parametrization

Soil parameters	**Value**
Soil texture	Sandy clay loam
Clay content (%)	21.6
pH	4.9
Bulk density (BD, gr/cm3)	1.4
Porosity (%)	51
WFPS at field capacity (%)	60
WFPS at wilting point (%)	42
Soil Organic Carbon (kg C/kg)	0.02
Hydro-conductivity (m/hr)*	0.023
NH4+ N (mg/ kg)*	0.05
NO3-N (mg/kg)*	0.5

*Parameters calculated by DNDC model based on BD, Texture, SOC content and Porosity (%)

$$Porosity(\%) = 1 - \frac{BD(gr/cm^3)}{PD(gr/cm^3)} \tag{3.1}$$

$$\%WFPS_{Field\ capacity} = \left(\frac{\Theta_{at33kPa} * BD}{1 - \frac{BD}{PD}}\right) * 100 \tag{3.2}$$

$$\%WFPS_{Wilting\ point} = \left(\frac{\Theta_{at1500kPa} * BD}{1 - \frac{BD}{PD}}\right) * 100 \tag{3.3}$$

BD, bulk density (gr/cm^3); PD, Particle Density (2.65 gr/cm^3); Θ at 33kPa, gravimetric soil water content at field capacity and Θ at 1500kPa, gravimetric soil water content at Wilting point.

Cultivar BRS-Catiana was calibrated based on traits reported in the literature and field data. Thermal degree days for maturity (TDD) was calibrated based on the range of TDD values from the five cropping seasons. The TDD selected obtained the yield and Leaf Area Index (LAI) with the lowest RMSE, which was the TDD average from the five seasons. Maximum grain biomass was manually calibrated based on independent experiments reported by dos Santos et al. (2017) and Rangel et al. (2019). Likewise, the biomass fractions and optimum temperature were taken from de Castro (2020) who used an independent experiment of BRS-Catiana located in the experimental station "Palmital" to optimize the calibration of BR-Catiana in Oryza2000 model.

Thus, default rice crop parameters in DNDC were optimized as follows: The Thermal Degree Days at maturity (TDD) was modified from 3800 to 1943, the maximum grain biomass was changed from 5200 to 4531 kg C/ha/yr; biomass fraction at maturity of grain/leaf/stem/root was modified from 0.4/0.22/0.22/0.16 to 0.48/0.07/0.25/0.2, and the optimum temperature from 25°C to 34°C.

Agronomic management were obtained from information collected during the experiment described in section 3.2.1. The irrigation treatments were parametrized based on the description of the treatments provided by Barbosa (2018), and the data records of water inflows collected from the hydrometers installed in the field. The irrigation started at the same date in all treatments between 17 to 18 days after emergence. Treatments started to differentiate after the first irrigation was completely drained (approx. one week). After the first irrigation, CF treatment kept flooded until 1 or 2 days before harvesting.The II treatment maintained an intermittent irrigation with re-flooding approximately each 5 to 7 days). The IIF treatment has a similar irrigation schedule to II but was switched to continuous flooding from flowering stage to harvesting. As SCC was in theory saturated soil, the hydrometers showed a few floods events during the crop season. For its part, the urea-based fertilization consisted of one base application during planting a top dressing fertilizer (80 kg N/ha) split in two doses as was described in section 3.2.1.

3.2.3 Validation and evaluation of DNDC model

To validate and evaluate the DNDC model were used the GHG emissions, yield and water inputs measured in the experiment described in section 3.2.1 during the the seasons 2016/2017 and 2017/2018 cropping seasons; agronomic managmenent of the seasons are described in table 3.3. Yield and water input simulations were validated for the CF, II, IFF and CSS treatments, while nitrous oxide and methane were validated for the irrigation treatments except for IIF treatment in both seasons). Total Water input were estimated based on cumulative rainfall and irrigation which was calculated using the daily water balance (Tian et al., 2021). Cumulative N_2O, CH_4 fluxes and net Global Warming Potential (Expressed as CO_2-equivalent) were calculated. The CH_4 and N_2O emissions were converted to CO_2-eq multiplying by their 100-year time horizon global warming potentials (GWP), which is 28 for CH_4 and 265 for N_2O (Myhre et al., 2013).Finally, the use of simulated data to calculate the Climate-Smartness Index (CSI), described in section 3.2.4 was also evaluated.

The coefficient of determination (R^2, equation.3.4), the root means square error (RMSE; equation 3.5), the normalized RMSE (equation 3.6) and the relative deviation (RD(%); equation 3.7) were calculated for the yield, cumulative GHGs and water inputs, and CSI to quantify the goodness fit between simulated and observed values.

Table 3.3: Agronomic management in 2016/2017 and 2017/2018 cropping seasons (numbers in brackets next to dates indicated days after planting (DAP))

	cropping season			
management (DAP)	2016/2017	Urea applied (kg N/ha)	2017/2018	Urea applied (kg N/ha)
Planting	10 Oct		27 Oct	
fertilization	10 Oct (0)	13	27 Oct (0)	20
fertilization	7 Nov (28)	30	21 Nov (22)	30
Irrigation started	8 Nov (29)		23 Nov (24)	
Fertilization	30 Nov (51)	50	18 Dec (52)	50
Harvesting	20 Feb (133)		7 March (131)	

$$R^2 = \left(\frac{\sum (Obs_i - Obs_{avg}) - (SM_i - SM_{avg})}{\sqrt{\sum (Obs_i - Obs_{avg})^2 - \sum (SM_i - SM_{avg})^2}} \right)^2 \tag{3.4}$$

$$RMSE = \sqrt{\frac{\sum (S_i - Obs_i)^2}{n}} \tag{3.5}$$

$$nRMSE(\%) = \frac{RMSE}{\overline{Obs}} * 100 \tag{3.6}$$

$$RD(\%) = ((Obs_i - SM) / Obs_i) * 100 \tag{3.7}$$

SM_i is the simulated value, Obs_i is the measured value, n is the number of measured values, $\overline{Obs}$ are the average of observed values.

3.2.4 Calculation of the Climate-Smartness Index (CSI)

The water-oriented Climate-Smartness Index (CSI) proposed by Arenas-Calle et al. (2019) was used to assess the use of modelling outcomes to quantify the climate-smartness of irrigation treatments. The CSI is calculated using Water productivity (WP), based on irrigation and rainfall, and Greenhouse Gas Intensity (GHGI). The WP was calculated dividing the rice yield by total water input (Kg/ m^3) and the GHGI, dividing the cumulative fluxes expressed in CO_2-eq by rice yield (kg CO_2-eq / kg grain). The Climate-Smartness Index (CSI) was calculated based on values of WP and GHGI that were normalized on a scale of 0 to 1, as is shown in equation 3.8 and 3.9.

$$GHGI_{(N)} = \frac{GHGI_{obs} - GHGI_{min}}{GHGI_{max} - GHGI_{min}} \tag{3.8}$$

$$WP_{(N)} = \frac{WP_{obs} - WP_{min}}{WP_{max} - WP_{min}} \tag{3.9}$$

$GHGI_{min}$ (= 0.01-kg CO_2-eq/kg grain) and WP_{min} (= 0.1 kg grain/m^3 and, $GHGI_{max}$ (= 7.8 kg CO_2-eq/kg grain) and WP_{max} (= 3.7 kg grain/m^3). The normalized indicators were used to calculate the CSI as shown the Equation 3.10.

$$CSI = WP_{(N)} - GHGI_N \tag{3.10}$$

3.2.5 Simulation of yield, Water use and Greenhouse Gas emissions for 2014-2019 period

To assess the climate-smartness of different irrigation strategies in irrigated rice under tropical conditions, DNDC simulations were set up for the four irrigation treatments evaluated under the experimental conditions described in the section 3.2.1. The simulated yields, water inputs and GHGs emissions were used to analyse the trade-offs and synergies between these agronomic indicators among irrigation treatments and calculate the CSI.

3.2.6 Sensitivity analysis

Additional simulations were done as sensitivity analysis was conducted to evaluate the response of the CSI to the variation in climate.Temperature was changed between -2 to 2 °C by 1 °C rate and the rainfall were changed -25 to 25% by a 5% rate. CSI was calculated for all irrigation treatments and seasons. The CSI was compared against the temperature and precipitation scenarios set in the sensitivity analysis. Results of CSI were compared, analysed, and discussed, as well as the use of modelling approach to its calculation.

3.3 Results

3.3.1 Model evaluation

Yield and Leaf Area Index (LAI) were used to evaluate the calibration of varietal parameters in DNDC. Both variables are independent since LAI is estimated as a model output that is not involved in the simulation of crop growth. We compared the observed and simulated LAI in the irrigation treatments during 2015-2016 and 2016-2017 cropping seasons (Figure. 3.1). The results showed that plant emergence dates coincided in both, observed and simulated LAI values. The end of the growing stages in simulated data coincided with the reduction of LAI in observed data. Given that the DNDC model does not simulate the plant senescence, LAI data after the start of senescence were omitted from the correlation coefficient calculation that showed a strong correlation of observed and simulated values (Figure. 3.2).

For its part, DNDC model generated a good estimation of rice yields (Figure 3.3). Simulated and observed yields showed a good correlation (R^2=0.68) and RMSE = 533 kg/ha, which represents a nRMSE (%) <10%. The Relative Difference RD(%) between simulated and observed yield was 1.3% for CF, II, and IIF and 5% for CSS in 2016-2017. The RD(%) in the 2017-2018 season was higher; yields in II and IIF treatments were underestimated by -6% and -8.4%, respectively. Yield under CSS was overestimated by 19%, being the poorest estimation among the four treatments in both seasons. The simulation of Total Water Inputs (TWI) showed different responses.In Overall, the model presented a poor simulation, especially for CF treatment during 2016/2017 where TWI were overestimated by 74% and IIF treatment overestimated by 117%. The 2017/2018 season showed better performance with RD (%) between 0.3 to 28% of variation. In both seasons the differences among treatments was similar with the highest TWI in CF treatments following for IIF, II and CSS.

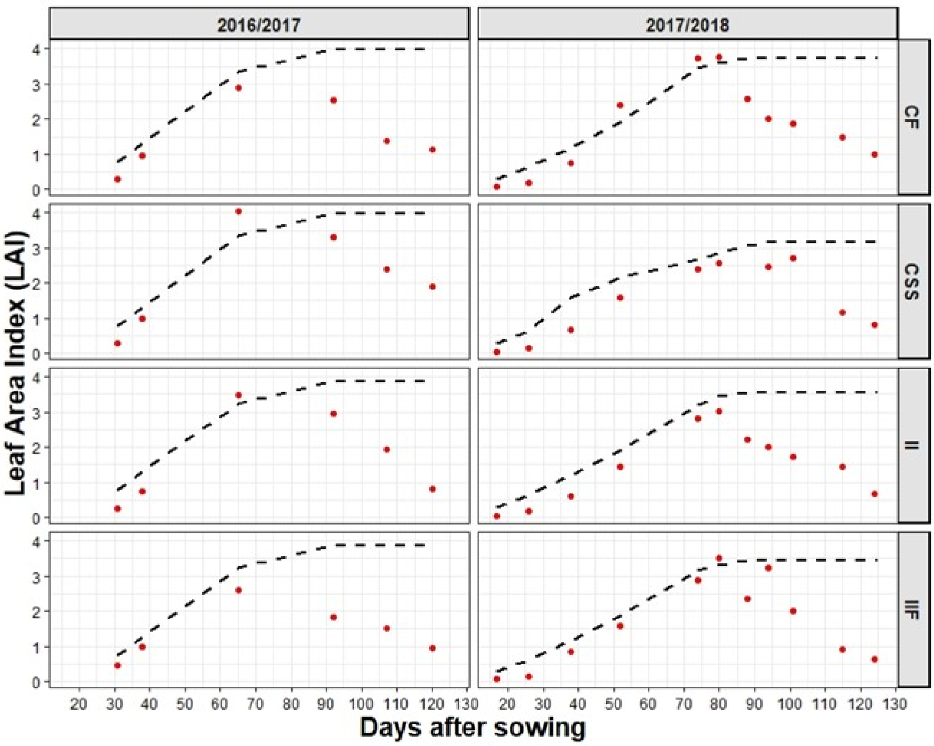

Figure 3.1: Observed (dashed line) and simulated (red dots) Leaf Area Index (LAI) for the Continuous flooding (CF), Intermittent Irrigation (II), Intermittent irrigation until flowering (IIF) and Continuous soil saturation (CSS) irrigation treatments (horizontal panels) during 2016-2017 and 2017-2018 cropping seasons (vertical panels)

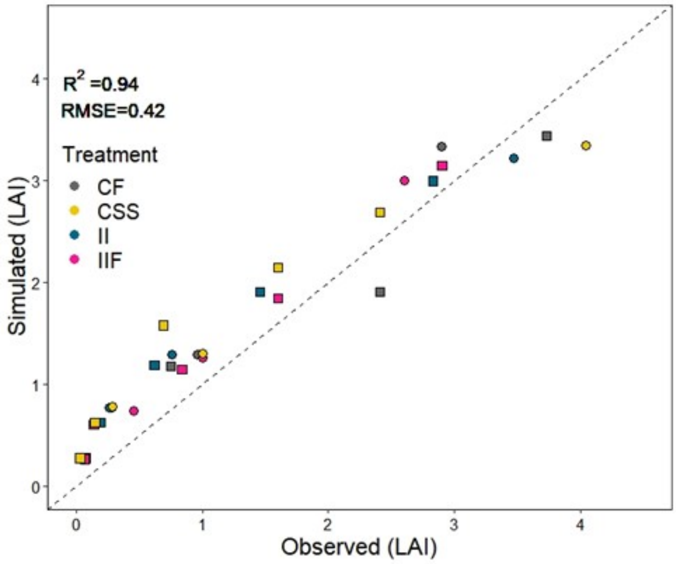

Figure 3.2: Regression of observed and simulated LAI values between plant emergence until the start of senescence in Continuous flooding (CF), Intermittent Irrigation (II), Intermittent irrigation until flowering (IIF) and Continuous soil saturation (CSS) irrigation treatments. Circles represent data from 2016-2017 season and square from 2017-2018. Dashed line represents 1:1 relation of observed vs simulated data.

The comparison of GHG emissions between simulated and observed data showed a good simulation for CH_4 emissions but underestimated N_2O emissions in all treatments (Figure 3.3).The daily fluxes of methane were moderately correlated with observed data (R^2=0.70 to -0.3); however, the cumulative fluxes showed a high correlation R^2=0.9. DNDC could performance a better simulation of cumulative fluxes of CH_4 for CF (RD%= -3 to 1%) than II (RD%= -40 to 23%) and CSS (RD%= -50 to -18%) treatments in both seasons.

Overall, the model produced a poor simulation of N_2O fluxes, which showed a low correlation with observed data ($R^2 < 0.1$). The DNDC model could capture the peaks of N_2O generated during fertilizations, but DNDC assumes zero N_2O emissions during flooding periods. In treatments with prolonged flooding conditions like CF, the model underestimated N_2O cumulative fluxes up to 90%.

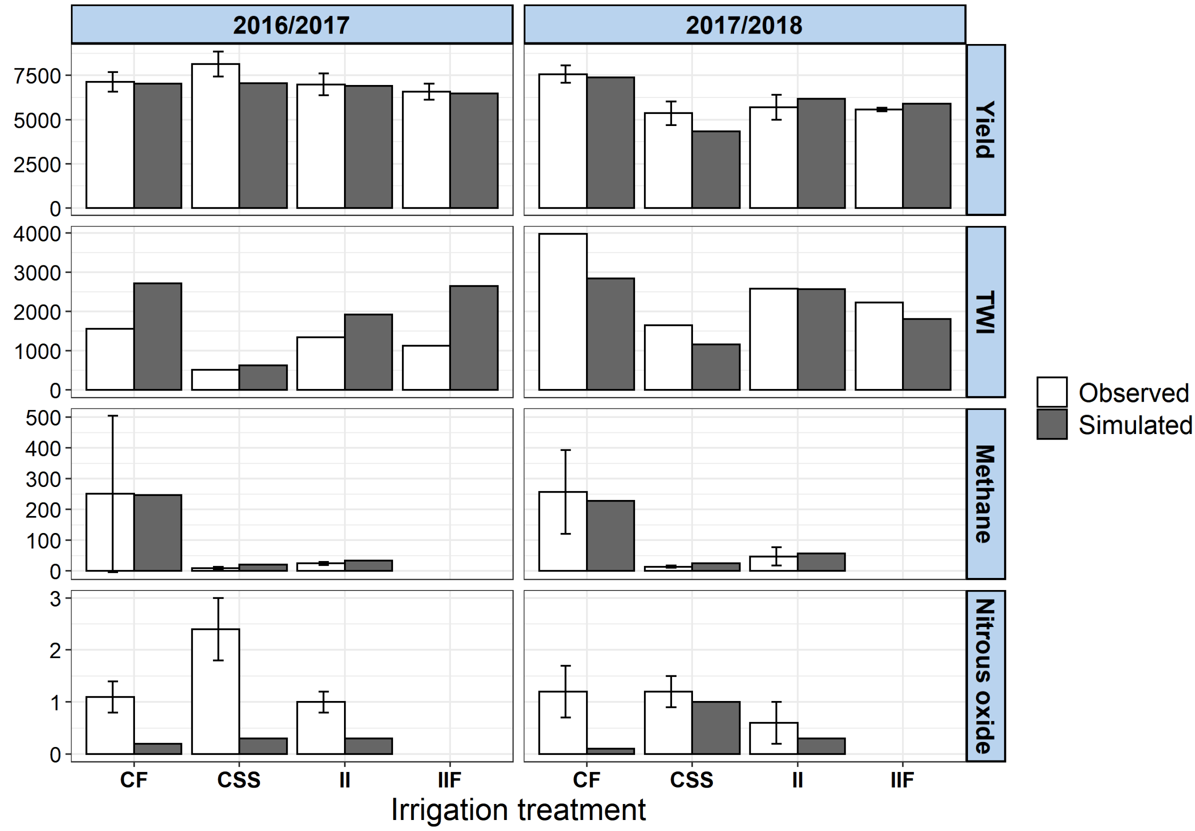

Figure 3.3: Observed (white bars) and simulated (grey bars) of yield, methane (CH_4), nitrous oxide (N_2O) and Total Water Inputs (TWI) for the 2016/20127 and 2017/2018 cropping seasons

Despite of N_2O was underestimated, the net Global Warming Potential (expressed in CO_2-eq) presented a high correlation with the observed data (R^2=0.9). The RD (%) of the net GWP was below 25% in all treatments except for CSS-2016/2017 (RD% -40%). These results evidence the main contribution of methane in the overall GHG emissions in rice cultivation, in contrast with treatments with predominantly dry conditions as CSS, where the N_2O represents the principal contributor to overall GHG emissions 3.3.par

Water productivity (WP) and Greenhouse Gas Intensity (GHGI) indicators were calculated using simulated data and compared with the observed values (Figure. 3.4A and 3.4B). Both indicators showed a good correlation with observed data (R^2=0.8 and R^2=0.9, respectively) ; however, the poor simulation of TWI for the 2016/2017 season resulted in an underestimation of WP of 52% for CF treatment. The Relative Difference (RD%) of WP between observed and simulated data varied between -36 to -5% in the 2017/2018 season. Greenhouse Gas Intensity (GHGI) simulations showed a better fit than WP, with RD% ranging between -3 to 12%, Except for the GHGI in CSS-2017/2018 overestimated by 60%. The simulated CSI resulted underestimated as a consequence of the underestimation TWI and N_2O

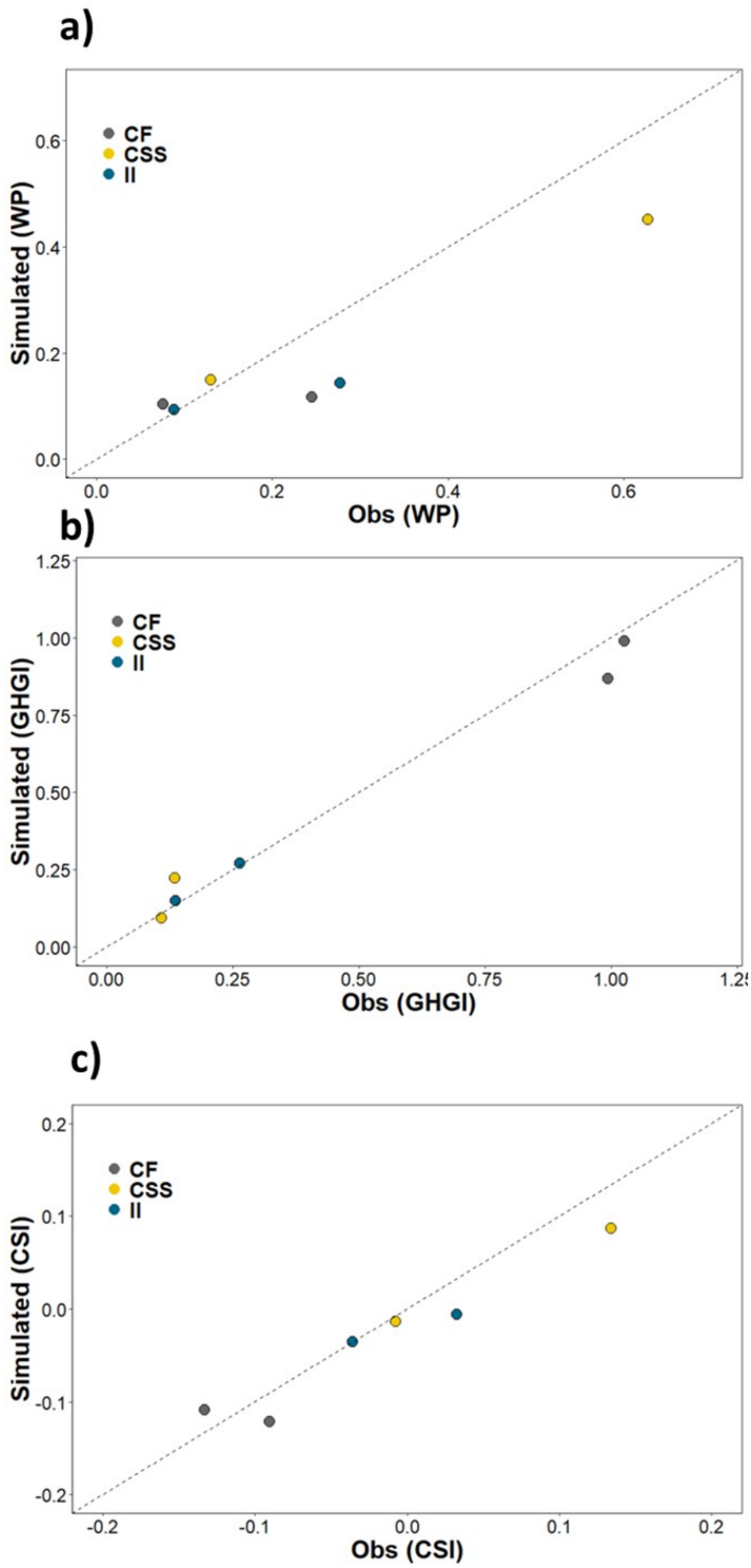

Figure 3.4: Regressions of observed and simulated A) Water productivity (WP; kg grain/m^3), B)Greenhouse Gas Intensity (GHGI; kg $CO2_2$-eq/kg grain); C) Climate-Smartness Index (CSI) for the Continuous flooding (CF), Intermittent Irrigation (II) and Continuous Soil Saturation (CSS) for the seasons 2016/2017 and 2017/2018

3.3.2 DNDC outputs during the period 2014-2019 in Goianira site

The simulations showed differences in CSA outputs under different irrigation management across the five seasons (Figure. 3.5). The season with the highest accumulated rainfall (2017/2018) presented the highest TWI for CF and IIF treatment. The lowest TWI occurred in the driest season (2018/2019). The differences in the TWI among the treatments showed that IIF, uses 4% less water than CF treatments, while II can save 20% more water compared with CF. Finally, CSS treatment presented the highest water-saving potential with 60% less water than CF.

Rice yield was 3.8% higher in CF compared with IIF, while the difference was larger compared with II and CSS, where CF was 6% and 26% higher, respectively. Rice yield also showed temporal differences; the Sustainable Yield Index (SYI) indicated that CF, II, and IIF presented similar stability (ranged between 0.76 to 0.77), while CSS showed less yield stability (SYI=0.59) compared to other irrigation treatments. The lowest yields occurred during the 2018/2019 season, which is the cropping cycle with the lowest cumulative rainfall during the crop cycle. The highest yield occurred in the 2017/2018 season under CF treatment; however, the II and IIF treatments presented the highest yield during 2015/2016 which is has the second-highest cumulative rainfall.

The GHG emissions showed marked differences among treatments and seasons. The CH_4 emissions were from high to low in the following order: CF<IIF<II<CSS. Continuous Flooding (CF) treatment ranged between 209 to 393 kg CH_4/ha/season while IIF treatments present on average 56% fewer emissions (87 to 174 kg CH_4/ha/season). The CF treatment was 74%, higher than II and 95% than CSS where the methane emissions ranged between (-0.5 to 30 CH_4/ha/season).The lowest methane emissions for CF, IIF, and CSS treatments occurred during 2018/2019, and the highest were in the 2014/2015 season.

Seasonal N_2O emissions were 16.5% lower in CF than IIF and 18% in II treatment.The irrigation treatment with the highest N_2O emissions was CSS which being 87% higher than CF. Although the differences in N_2O emissions among treatments, the emissions were generally low, ranging between 0.46 to 0.87 kg N_2O/ha/season. The N_2O emissions also showed some temporal differences: the lowest N_2O emissions occurred during the 2018/2019 season and the highest during 2014/2015. Despite CSS treatment presented the highest N_2O emissions, the during the drier seasons ocurred the lowest emissions.

The net Global Warming Potential (GWP) in CF treatments was, on average, 53% higher than IIF and 66% more than in II treatments. The lowest GWP occurred in CSS treatments (92% lower than CF treatments) across all seasons. The differences among the treatments also varied among the seasons; IIF treatment emits between 42 to 63% less GHG emissions than CF, and II between 51 to 84% less than IIF.

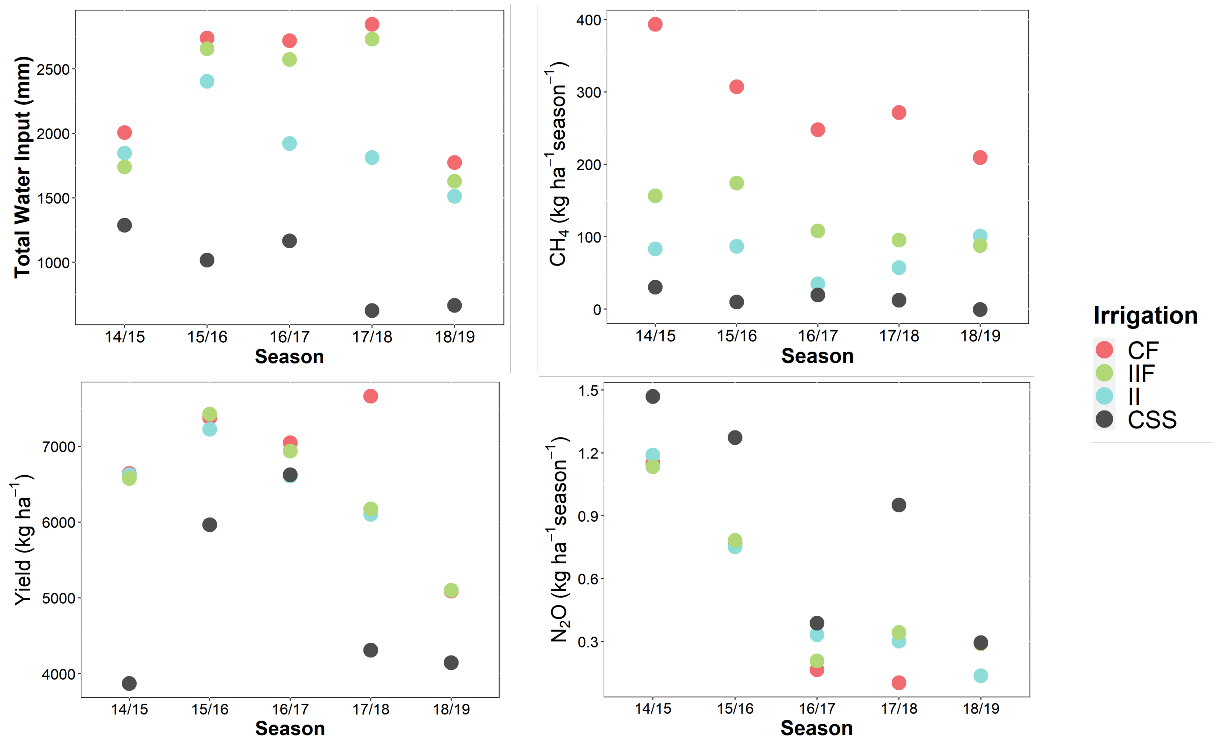

Figure 3.5: Simulations of Total Water Input (TWI), rice yield, methane (CH_4), and nitrous Oxide N_2O) under Continuous Flooding (CF), Intermittent Irrigation (II), Intermittent irrigation until Flowering (IIF) and Continuous Soil Saturation (CSS) for the period 2014-2019.

The differences in the GHGs cumulative fluxes among the treatments evidenced characteristics patterns in the proportion of each non-GHGs in the net GWP (Figure 3.6). Methane is the main contributor of net GWP in CF (95.6%), IIF (85.3%), and II (76.9%) treatments. For its part, methane represents 37.9% of net GWP in CSS treatment, where nitrous oxide represents the main contribution (62%).

The relationship between water input and yields was consistent across CF, IIF, and II treatments, reflected in water productivity ranging between 0.13 to 0.11 kg/m^3 among treatments. In contrast, CSS presented the highest WP (0.33 kg/m^3, during 2018/2019) despite having the lowest yields across the seasons. The results suggest that II and IIF treatments are effective strategies to save water and maintain rice yields; however,it could be insufficient to increase the efficiency of the rice crop. The water productivity showed seasonal variability, with the highest WP in CF, IIF and II during 2014/2015, while the highest WP achieved under CSS occurred during 2018/2019.

In all seasons, the mitigation potential of II, IIF and CSS treatments reduce the Greenhouse Gas intensity (GHGI) compared with CF, despite these treatments also reported reductions in yield. While CF treatment showed an average GHGI of 1.2 kg CO_2-eq per kilograms of grain, IIF showed the half (0.55 kg CO_2-eq/kg grain) and II treatment a GHGI 66% lower (0.4 kg CO_2-eq/kg grain) than CF. The CSS treatment with the highest impact on CH_4 showed the lowest mean GHGI (0.13 kg CO_2-eq/kg grain). The GHGI also showed seasonal differences within the treatments. The highest GHGI occurred during 2014/2015 for CF, IIF and CSS treatments, while the lowest GHGI for CF, IIF and II treatments occurred during 2016/2017. The GHGI in CSS showed the lowest value during 2018/2019, but also coincided with a relative low GHGI during 2016/2017.

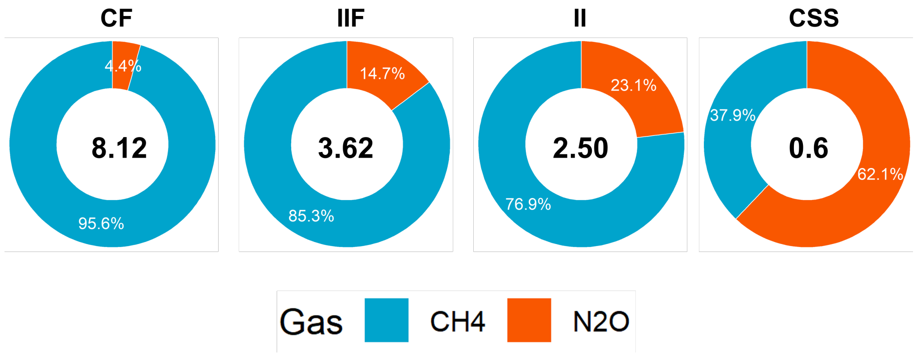

Figure 3.6: Mean percentage contribution of CH_4 and N_2O in the overall emissions of rice fields under Continuous Flooding (CF), Intermittent Irrigation (II), Intermittent irrigation until Flowering (IIF) and Continuous Soil Saturation (CSS) for the period 2014-2019. Numbers in the centre of each plot indicate the mean seasonal emissions expressed in ton CO_2-eq/ha/season.

3.3.3 CSI values and intercomparison of water management options based on DNDC outputs

The most effective synergy among the irrigation strategies occurred in CSS, where the water-saving and the CH_4 mitigation showed the highest potential compared with the other irrigation treatments (Figure. 3.7). Conversely, CSS presented the lowest emissions and N_2O mitigation potential among the irrigation treatments. In contrast, the high yields (compared with the other irrigation treatments) and the mitigation of N_2O were, on average, the most representative impact of CF treatment. The II and IIF irrigation treatments presented an intermediate methane mitigation potential, but with a similar yield to CF.

Based on the WP and GHGI results it is possible to elucidate the climate-smartness of the different irrigation treatments. Treatments with low GHGI like CSS express higher climate-smartness than treatments with high GHGI (e.g., CF treatment); similarly, relatively high WP increases the climate-smartness over other treatments with lower WP.

To provide a quantitative measure of climate-smartness based on WP and GHGI, the Climate-Smartness Index CSI was calculated (Figure ??). Based on CSI results, the climate-smartness of irrigation treatments from high to low are in the following order: CSS>II>IIF>CF. The CF treatment presents the lowest climate-smartness (-

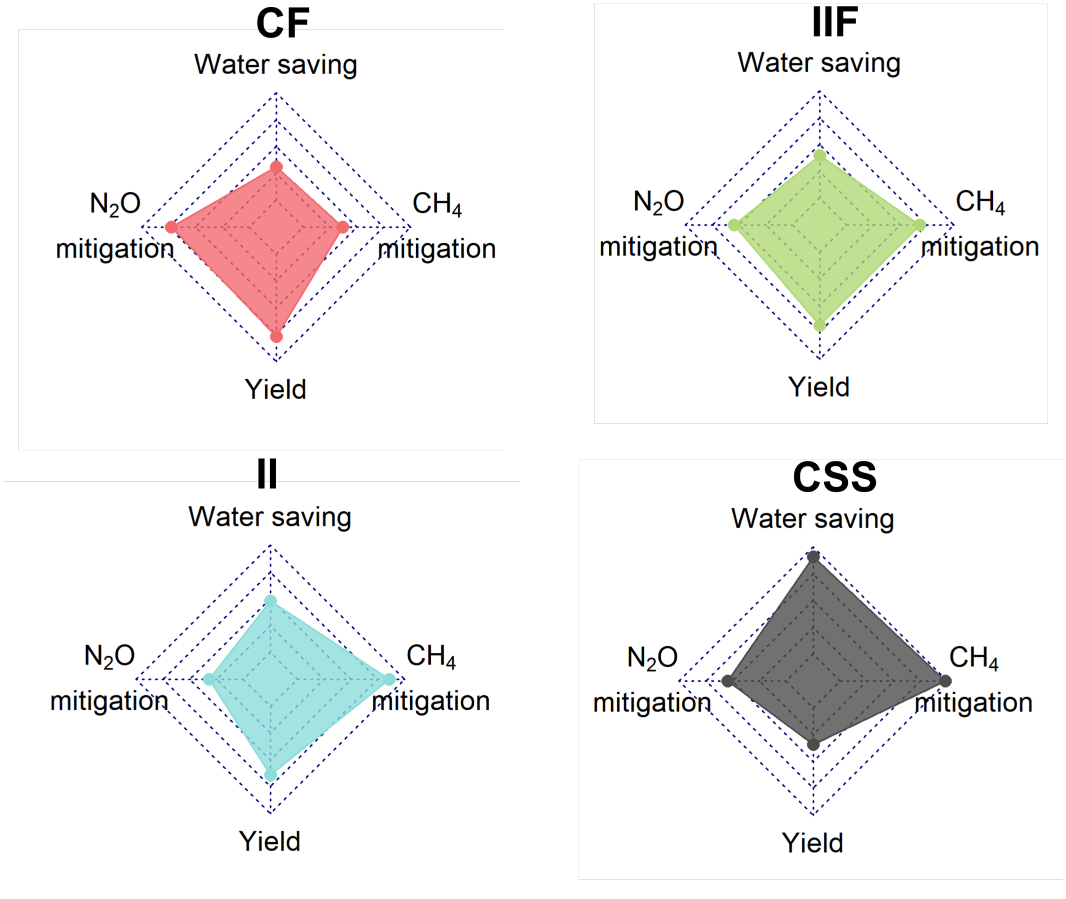

Figure 3.7: Radar plots of the performance of Continuous Flooding (CF), Intermittent Irrigation (II), Intermittent irrigation until Flowering (IIF) and Continuous Soil Saturation (CSS) based on normalized (0-1) averages of CH_4 seasonal emissions, N_2O seasonal emission, Total Water input and yield.

0.14, with the lowest CSI scores reported in 2014/2015 season (CSI=-0.2). The IIF and II also score negative CSI values, ranging between -0.083 to -0.054 for IIF and -0.061 to -0.02 for II. On the contrary, CSS presented the highest CSI scores ranging between -0.027 to 0.1 and was the only treatment to score positives CSI.

The Climate-Smartness Index (CSI) varied among cropping seasons. The CSS treatment showed higher climate-smartness in the 206/2017 and 2018/2019 seasons, while the highest CSI scores for II and IIF were obtained during the 2016/2017 season. The Continuous Flooding (CF) treatment expressed the lowest climate-smartness in 2014/2015 season, that improved during 2016/2017.

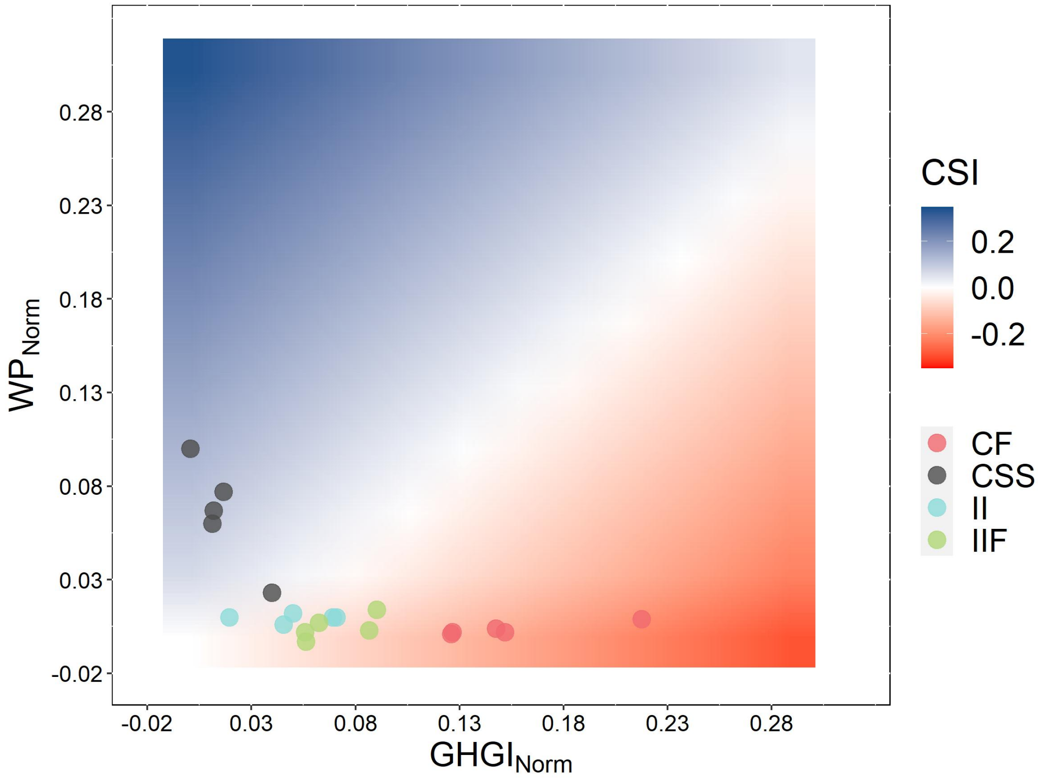

Figure 3.8: Heatmap of Climate-smartness Index (CSI) scores of the Continuous flooding (CF), Intermittent irrigation until flowering (IIF), intermittent irrigation (II) and Continuous soil saturation (CSS) treatments.

3.3.4 Sensitivity analysis of Climate-Smartness Index (CSI)

To assess the sensitivity of CSI to changes in climate, the CSI was calculated for the four treatments and five seasons under different temperature and rainfall scenarios. According to the results, CSI is sensitive to changes in temperature: warmer conditions reduce the climate-smartness in all treatments, while a reduction of temperature improved the CSI scores (Figure 3.9).

The Climate-Smartness Index (CSI) in CSS treatment presents the lowest sensitivity to temperature, followed by II treatment. Continuous Flooding (CF) and IIF treatment showed higher sensitivity to changes in temperature, where +1 °C reduced the CSI up to 26% and +2 °C up to 42%. Climate-smartness increased between 1 to 25% in CF and IIF treatments when the temperature decreased -1°C and 11 to 34% when decrease -2°C. The CSI in CSS treatment increased between 0.6 to 11% with temperature -1°C to ambient and 4-17% in -2°C.

The sensitivity of CSI to rainfall was lower than observed to the temperature (Figure. 3.10).The CSI decreased when the precipitation increased for all treatments during 2014/2015, 2017/2018, that are the seasons with the highest cumulative rainfall. During 2015/2016 and 2016/2017, CSI slightly increased (0 to 1%) in all treatments except for CSS where CSI decreased in scenarios with more rainfall. The treatment with the highest sensitivity to rainfall changes was the CSS; CSI decreased between 7-15% for each 5% increase in rainfall. Irrigation demand decreased proportionally with the increase in rainfall. In DNDC model, the the increment of rainfall reduce the irrigation demand; thus, Water productivity (WP) presented negligible changes in treatments like CF, IIF, and II. On the contrary, the WP in CSS treatments decreased in the scenarios with increased rainfall because the TWI increases were higher than yield gains.

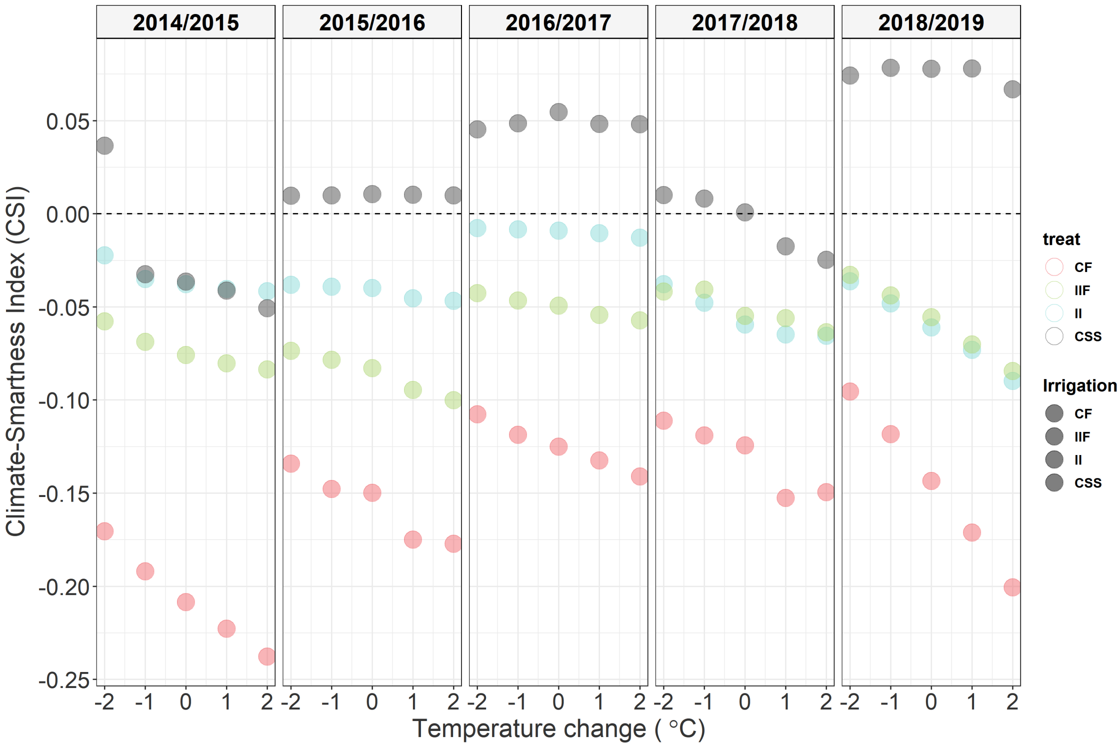

Figure 3.9: Sensitivity analysis of Climate-Smartness Index (CSI) to changes on temperature of rice crop under Continuous flooding (CF), Intermittent irrigation until flowering (IIF), intermittent irrigation (II) and Continuous soil saturation (CSS) treatments.

Greenhouse Gas emissions showed negligible sensitivity to rainfall in CF, II, and IIF treatments. However, the yields increased between 0-3% per each 5% increases in rainfall, generating a reduction of GHGI that increase the climate-smartness of CF, IIF, and II treatments during 2015/2016 and 2016/2017. Contrary to the other three treatments, GHG emissions were more sensitive in CSS treatment. Although CH_4 emissions increased by less than 1% for each +5% increase in rainfall, N_2O increased up to 18%, while drier conditions reduced N_2O and CH_4 emissions. As the increasing of GHG emissions and yields were proportional across the increased rainfall scenarios, the GHGI was stable, thus, the climate-smartness was mainly affected by the reduction in WP in CSS treatments.

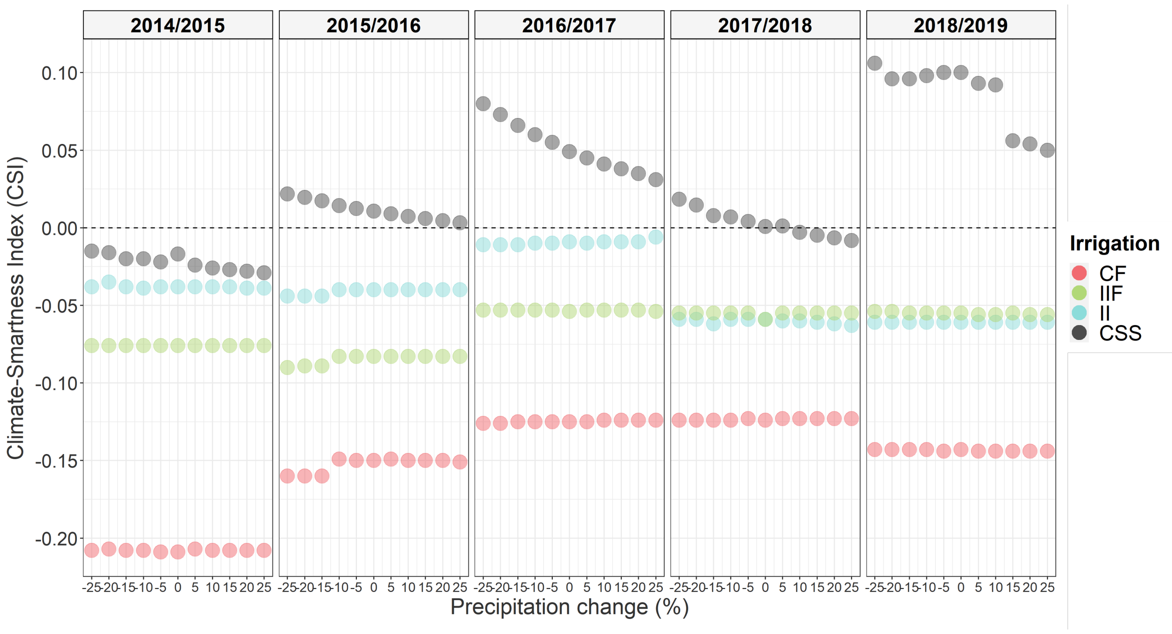

Figure 3.10: Sensitivity of Climate-Smartness Index (CSI) to changes on rainfall of rice crop under Continuous flooding (CF), Intermittent irrigation until flowering (IIF), intermittent irrigation (II) and Continuous soil saturation (CSS) treatments.

3.4 Discussion

This study used the DNDC model with the Climate-Smartness Index (CSI) to assess the climate-smartness of irrigation management strategies in irrigated rice systems. Driven by field data, the DNDC model simulated various irrigation strategies and the outputs were used to develop a climate-smartness assessment and evaluate the sensitivity of CSI to temperature and rainfall.

3.4.1 Use of the DNDC model to simulate climate-smart water management options

Process-based models are widely used to evaluate the performance of different agronomic strategies, bringing the option of assessing practices for a wide range of agricultural contexts and climate scenarios (Xiong et al., 2014). For climate-smartness assessments, modelling tools represent a cost-efficient methods to reevaluate climate-smart strategies and interpret the trade-offs and synergies between mitigation, adaptation, and productivity across different time and spatial scales.

The DNDC model has been used to simulate GHG emissions and soil carbon dynamics in rice systems under different combinations of agronomic management at the site and regional scales.The list of published studies that use DNDC can be consulted in the Global DNDC network webpage. Most of the studies that have applied DNDC to rice fields have focused on the modelling of GHG emissions; in studies such as Tian et al. (2018),Pandey et al. (2021) and Shi et al. (2021) simulated the trade-offs (using DNDC outcomes or coupled with other process-based models) between GHG emissions and yields. Tian et al. (2021) simulated the relationship between yields, GHG emissions and TWI; however, this study is the first attempt to apply model results to a simulation of a climate smartness index. The first step towards the use of modelling tools in climate-smartness assessments was the evaluation of the DNDC model to perform of GHG emissions, yield and water input simulations. Overall, the validation results indicate that the model performed well in simulating rice yields and seasonal CH_4 emissions; however, underestimate N_2O emissions and showed discrepancies between observed and simulated Total Water Inputs (TWI).

Although DNDC is not a crop model, the results showed it could effectively simulate crop yields, achieving reasonable results. Similar conclusions were drawn by Zhang et al. (2016) from their review, where summarized the application of the DNDC model to crop modelling. The authors remarked that rice along with maize, barley, rapeseed, soybean, and sugar beets have been the main crops simulated in DNDC that account with validations in several geographical locations.

For instance, other studies obtained imilar validation results reported in this study .Ku et al. (2015) obtained a nRMSE(%) of 15-19% under different fertilization schemes using DNDC. Similarly, Pandey et al. (2021) which validated the DNDC model for organically fertilized flooded rice systems. To improve yield estimations in DNDC it is necessary to adjust the default crop parameters (optimum crop yield, biomass fraction, and biomass C/N ratio); this is also important for improving the fit of GHG emissions simulations (Nie et al., 2019).

Despite the reasonable good results that have been obtained by DNDC simulating rice yields, the model presents limitations simulating more detailed physiological and phenological processes Tian et al. (2018). Moreover, the modelling of yields at regional scales using DNDC may be limited by the calibration approach used for the model where only one rice cultivar can be calibrated regardless of the area covered (Zhang et al., 2016). An alternative to overcome such limitations could be the coupling with crop models such as ORYZA200O, DSSAT or CERES-Rice

The agreement between observed and simulated CH_4 emissions resulted in a good fit of Net-GWP with observed data despite the underestimation of N_2O emissions; except in the case of the CSS treatment during the 2016/2017 season, in which the majority of GWP was due to N_2O. Similar results were reported by Zhang et al. (2019) which argue that, despite discrepancies in the N_2O simulation, owing to the strong agreement with methane fluxes and the low contribution of N_2O the model can be used to estimate GWPs from tropical paddy fields.

The poor performance of the model in simulating N_2O may occur because the model assumes homogeneous microbial distribution and overestimate/underestimate the soil moisture under different drainage soil conditions (Tonitto et al., 2010). Moreover, DNDC model simulates suppressed rates of nitrification in anoxic soil conditions (i.e., during continuous flooding periods) leading to zero N_2O emissions (Babu et al., 2006; Hao et al., 2016). In addition, nitrification and denitrification occurred simultaneously in the soil during a redox condition window between well-drained and saturated soil conditions, thus inaccuracies in the parametrization of water affect the estimation of Eh and the concentrations of NO_3^- and NH_4^+ in the soil (Simmonds et al., 2015). Our results confirm that in treatments with a negligible N_2O emissions the poor simulation of this gas may not affect the net GWP; however, the accuracy of N_2O gains relevance when assessing the mitigation potential of water management strategies that are prone to increase N_2O emissions like AWD (Lagomarsino et al., 2016) or mid-season drainage (Liu et al., 2019)

In this study the flooding events were parametrized based on the irrigation schedule and the duration of flooding events set based on the description of irrigation treatments and the hydrometers records, this parametrization approach may lead discrepancies in the amount of water used and the water column.The parametrization of irrigation treatments can be complex when is consider the approach to modelling soil hydrology in DNDC. The model uses a tipping bucket water flow model that drains the soil profile to field capacity, which could generate an underestimation of soil moisture in treatments like CSS where soil keep saturated or above field capacity. Moreover, the fact that DNDC can underestimate rainfall drainage could lead to the systematic overestimation of TWI during the 2017/2018 season that showed the highest cumulative rainfall (Kiese et al., 2005; Kröbel et al., 2010; Uzoma et al., 2015). Although discrepancies in the estimations of TWI were consistent among treatments and comparable with TWI observed for the same treatments in other studies (Li et al., 2005; Tian et al., 2021).

3.4.2 Climate-smartness water management options and its sensitivity to climate

The simulated CH_4 and N_2O emissions in this study were consistent with the observed in other studies. The net-GWP observed in the CF treatments are consistent with the range observed by Jiang et al. (2019) in their meta-analysis, that also found similar percentage reduction between CF and controlled CF (53%) that in this study are similar to the II treatment. The CSS treatment showed the highest climate-smartness during the assessed period; however, the reduction in yield could discourage farmers to adopt it.

The sensitivity analysis evidenced that performance of irrigation management can varied with temperature and rainfall; thus, Changes in seasonal temperature and rainfall can impact the climate-smartness. The extent of this impact is influenced by the interaction of soil parameters and climate. For instance, in areas with sandy soils and high percolation rates AWD tends to perform less well than soils with lower percolation rates. Carrijo et al. (2017) also reported in their meta-analysis differences in water savings among wet and dry seasons under AWD. These results demonstrate the importance of irrigation suitability assessments, such as those developed by Nelson et al. (2015), who used a water balance model to determine the areas climatically suitable for AWD.

Reductions of climate smartness in warmer temperatures are associated with the increase of GHG emissions and, to some extent, by the reduction of WP. Conversely, cooler temperatures result in lower GHG emissions and water demand, as is reflected in the higher CSI scores compared with warmer temperatures. These results agreed with studies reported by Minh et al. (2015) and Nie et al. (2019), who used the DNDC model to simulate the sensitivity of methane emissions to climate and found that, while increased precipitation has a negligible impact on the CH_4 emissions, warmer temperatures significantly elevate them.

Deng et al. (2016) reported similar results regarding the impact of precipitation and temperature in N_2O emissions. The authors argue that precipitation could stimulate microbial activity (Giltrap et al., 2010), particularly in dry soils. This finding may explain the highest sensitivity of N_2O emissions to precipitation in CSS treatment during the driest season (2018-2019) of the period assessed, where N_2O increased up to 18% when precipitation increased by 25%.Minamikawa et al. (2016) associated the increment of CH_4 under warmer temperatures to the acceleration of SOM decomposition and N mineralization driven by a stimulation of biological activity in the soil. The authors also pointed out that the effect of temperature on GHG emissions may vary among climates zones, having a higher sensitivity in low ambient temperatures compared with warm ambient temperatures. Given that mineralization rates may increase under warmer conditions, SOM become a relevant parameter for mitigation in rice systems. In this sense modelling-based assessments would be more suitable to elucidate a wider view of soil carbon in the long term in rice fields.

Although the CSI showed a small sensitivity to rainfall, the irrigation demand was lower in all treatments with higher rainfall. This occurred because in the DNDC model the water sources for the crop comes from irrigation and precipitation. If the crop water demand is the same, the larger the proportion of rainfall, the crop will be less dependent on irrigation. A reduction of irrigation demand is desirable and could represent a contribution to climate-smart as long as it is translated into an increase in water-use efficiency, or at least if significant yields penalties are avoided. The sensitivity of climate-smartness to temperature and rainfall reinforces the idea of the strong context-dependency of climate-smart agriculture. For instance, CSS proved to be the irrigation management with the highest climate-smartness in the study site;

however, climate change could bring about changes in the climate-smartness of CSS, potentially even reducing it to negative values of CSI.

This sensitivity analysis assumed a constant concentration of atmospheric CO_2 across cropping seasons. However, it is worth mentioning that rising atmospheric CO_2 trigger an increment of photosynthetic rate in the plants, which result in higher biomass accumulation (Lv et al., 2020). In the case of rice crop, Ainsworth (2008) reported from their metanalysis, that on average, elevated CO_2 increased rice yields by 23%; as a response to increased grain mass, panicle and grain number.Moreover, the reduction of stomatal conductance under elevated CO_2 might also increase water productivity, and indirect reduction of greenhouse gas intensity.

Although elevated CO_2 might improve climate-smartness indicators, severe changes in temperature and rainfall can overshadow yield gains. For instance, Krishnan et al. (2007) simulated the impact of the interaction between elevated CO_2 and temperature on rice yields, finding a trade-off between both parameters; yield increases under elevated CO_2 (25% on average) until the temperature was increased between +3°C to +5°C, resulting in yield penalties between -10.5 to -34%.

3.5 Conclusions

In this study, DNDC model was applied to simulate cumulative CH_4 and N_2O fluxes, rice yields and water inputs from a tropical irrigated rice systems under several irrigation management strategies. The DNDC model showed a good fit with the methane and yield observations while nitrous oxide and water inputs simulations can be improved by the adequate parametrization of hydrological parameters.

The results confirm that alternative practices to conventional irrigation have the potential to address CSA objectives. They also demonstrate that seasonal variability in climate, as well as longer-term climate change, may influence the performance of these practices. In particular, increased temperature can reduce, and even reverse, the mitigation potential of practices. Thus it is important that water-oriented strategies are able to be adjusted responsively to climate if they are to be an effective adaptation measure.

Combining models and CSI might allow lending spatial and temporal continuity to the climate-smartness analysis, strengthening the discussion around the context-dependency of CSA. The simulation of agronomic/biophysical parameters brings valuable information by filling data gaps in existing experiments and by generating evidence from scenarios that otherwise will be technically impossible to measure (e.g., climate projections or hypothetical socio-economic scenarios). CSI can synthesise model output and thus facilitate interpretation of model results. This model-CSI combination might set a bridge between scientists and decision-makers, finding a comparable and reproducible way to communicate CSA-related evidence generated from modelling approaches.

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Chapter 4

Design of a Soil-based Climate-Smartness Index (SCSI) using the trend and variability of yields and soil organic carbon

[1]**Laura N. Arenas-Calle**; [2,3]Julian Ramirez-Villegas; [4]Stephen Whitfield and [1]Andrew J. Challinor

[1]*Institute Climate and Atmospheric Science (ICAS), University of Leeds, Leeds, United Kingdom.*
[2]*International Center for Tropical Agriculture (CIAT), Colombia*
[3]*CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), c/o CIAT, Cali, Colombia* [4]*School of Earth and Environment, Sustainability Research Institute (SRI), University of Leeds, Leeds, United Kingdom*

Abstract

Climate-Smart Agriculture (CSA) has had an increasing role in the agricultural policy arena, as it aims to address climate change mitigation, adaptation and food security goals in an integrated way. In regions where agriculture has been constrained because of soil degradation and climate change, CSA aims to implement soil-based strategies that restore soil function and increase carbon storage. The extent to which such strategies succeed in achieving mitigation, adaptation and productivity goals is referred to as climate-smartness. The co-evolution of yield and Soil Organic Carbon (SOC) over the years presents a proxy for the trade-off between productivity, soil fertility and carbon sequestration. Yield and SOC are widely monitored, analysed and used to inform CSA

planning. Yet their analysis is often conducted separately and for a small number of years, which neglects long-term soil fertility dynamics and their impact on crops. Given the absence of integrated climate-smartness metrics to capture the trade-offs and synergies between SOC and yield, we present a soil-based Climate-Smartness Index (SCSI). The SCSI is computed using normalized indicators of trend and variability of annual changes on yield and SOC data. The SCSI was calculated for a set of published experiments that compared Conservation Agriculture (CA) practices with conventional management. The CA treatments scored higher SCSI during the first 5 years of evaluation as compared to conventional management. Analysis of the temporal dynamics of climate-smartness indicated that minimum SCSI values typically occurred before 5 years after the start of the experiment, indicating potential trade-offs between SOC and yield. Conversely, SCSI values peaked between 5 and 10 years. After 20 years, the SCSI tended towards zero, as substantial changes in either SOC or yield are no longer evidenced. The SCSI can be calculated for annual crops under any soil management and at different time periods, providing a consistent metric for climate-smartness across both practices and time.

4.1 Introduction

Climate-Smart Agriculture (CSA) is a concept that responds to the multifaceted objectives for agriculture within the context of climate change and food insecurity (Lipper and Zilberman, 2018) The principles of CSA aim for the achievement of three general objectives: 1) sustainable increase in agricultural productivity, 2) build climate resilience, and 3) reduction the Greenhouse Gas (GHG) emissions from agricultural activities (FAO, 2013). Each CSA objective represents the general vision of productivity, adaptation, and mitigation in agriculture; however,such objectives are interpreted according to the context, and their trade-offs and synergies are a core component of the CSA approach.

In the case of cropping systems, the soils play a transversal role in the achievement of CSA objectives. Soil conditions largely determine crop productivity; loss of fertility or the accumulation of pollutants in the soil can reduce the yields even under favourable climate conditions. Besides, the degradation of soil affects the adaptive capacity of farmers due to the reduction of soil functioning relevant for climate resilience, such as like physical stability, water dynamics, or nutrient recycling (Chappell et al., 2019; Lankoski et al., 2018; Webb et al., 2017). Finally, the agricultural soils are the principal source of nitrous oxide (N_2O), while alternatively have important CO_2 sequestration potential (Paustian et al., 2016; Smith et al., 2008b).

Given the role of agricultural soils in climate change, CSA widely promotes soil-oriented strategies. Practices such as minimal soil disturbance and permanent soil organic cover, which characterise conservation agriculture (CA), increase soil water retention during droughts and heatwaves (Delgado et al., 2011; Kang et al., 2009) and reduce erosion and nutrients leaching during heavy rainfall events (Kaye and Quemada, 2017). Moreover, practices like the use of organic fertilizers or crop residue retention enhance the SOC content. A SOC increase may, in turn, increase water retention and Cation Exchange Capacity (Zingore et al., 2011) and contribute to mitigation goals in the long-term as more stable fractions of SOC are sequestered. Such changes in SOC may indicate the potential availability of C and N sources for plants and microorganisms, as well as an increased capacity for water retention, among others SOC associated soil quality parameters. (Manns et al., 2016) .

The impact of sustainable soil practices can be expected to translate into improved productivity and resilience, especially during climate related events (Kaczan et al., 2013; Thierfelder et al., 2017). SOC and yields are both affected by a broad range of agro-environmental factors, including climate, land-use history, or initial soil conditions. These factors confound the relationship between yields and soil organic carbon, even conditioning their temporal response in cropping systems under good soil management conditions (Hijbeek et al., 2017; Oldfield et al., 2019). For instance, practices focused on increasing soil organic matter may carry yield penalties in the short term (Corbeels et al., 2020). However, the expected benefits in terms of productivity and adaptation would be evidenced in the middle to long-term after a cumulative effect of continuous organic matter incorporation (Prestele and Verburg, 2019; Thornton et al., 2018). Accordingly, the synergies between the SOC increasing, the soil improvement, and the enhancement of yield, could be used as an indicator of the climate-smartness in cropping systems.

Climate-smartness, defined as the extent to which the productivity, resilience, and mitigation objectives of climate-smart agriculture (CSA) are synergistic, can be strongly context-dependent for soil-oriented strategies. Thus, climate-smartness is a joint property of both land management and the response of the cropping system to that management. Measuring climate-smartness, therefore, implies the combination of multiple measurements into CSA indicators for specific management by- environment situations in particular cropping systems. These indicators offer a useful way of understanding the trade-offs and synergies between different objectives within a given agricultural system over time (e.g. Arenas-Calle et al. (2019); Hammond et al. (2017); Manda et al. (2019); Wassmann et al. (2019)).

The last five years have seen considerable progress in the development of climate-smartness assessment methods. Many of these methods rely on the use of participatory approaches (e.g. Birnholz et al. (2017); Manda et al. (2019); Mwongera et al. (2017); Wassmann et al. (2019)), or the use of climate model results and expert opinion (De Nijs et al., 2014) , while others use household-level data (e.g. Hammond et al. (2017)) to measure climate-smartness of specific households. These approaches, however, while broadly applicable, lack the replicability and comparability required to measure climate smartness across sites and years. There is a lack of integrated measures that can provide an overall quantification of climate-smartness (Lankoski et al., 2018; Rosenstock et al., 2016; Thornton et al., 2018), particularly for comparative assessments over space and time. Indeed, questions about how the climate smartness of an agricultural system changes over time have been subject to little empirical analysis.

One area of progress is the climate-smartness index, and associated methodological framework, of Arenas-Calle et al. (2019). The index is used to represent the extent of synergy between productivity, emissions, and adaptation around water use. The index, however, is applied to single seasons at a time and takes no account of longer-term issues such as evolving soil carbon stocks. Here, the approach of Arenas-Calle et al. (2019) was extended to develop a new index of climate-smartness for cropping systems under soil-oriented climate-smart practices. The Soil-based Climate-Smartness Index (SCSI) was built using normalized indicators of trend and variability of temporal changes on yield and SOC data. The SCSI is evaluated using data from published studies of controlled trials of soil management practices, for which SCSI is calculated at different periods. The SCSI results and the considerations in the use of SCSI to measure climate-smartness are discussed.

4.2 Materials and methods

4.2.1 Design of the Soil-based Climate-Smartness Index (SCSI)

Soil-based strategies can improve the productivity within the attainable thresholds and sustain this productivity over time. A soil-based index of climate smartness therefore needs to account for the way in which SOC and yield evolve over time, both in terms of long-term trends and short-term variability. High (low) climate-smartness is associated with steadily increasing (decreasing) yields and SOC. The index also needs to describe the trade-off whereby increasing yields may be associated with decreasing SOC and vice-versa.

To provide a quantitative measure of climate-smartness in cropping systems, a Soil-based Climate-Smartness Index (SCSI) is proposed (Figure 4.1). The SCSI is based on the trend and variability of the changes in Yield and Soil Organic Carbon (SOC) data in temporal series (See table 4.1). For the SCSI design, 3 steps were followed. First, the trend and variability of annual yield and SOC changes were calculated and normalized. Second, the normalized indicators of variability and trend were aggregated to create normalized indices of SOC and Yield. Finally, yield and SOC normalized indices were aggregated to build the SCSI.

4.2.1.1 Step.1: Variability and trend of yield and SOC indicators

Yield and SOC were selected as indicators to represent the climate-smartness in crops under soil-oriented practices. The selection is grounded by literature related with CSA indicators (Bank, 2016; FAO, 2013; Mwongera et al., 2015), climate-smartness assessments of soil-related practices on cropping systems (Bai et al., 2019; Birnholz et al., 2017; Notenbaert et al., 2017) and studies of soil-based indices (Cardoso et al., 2013).

Soil Organic Carbon is considered a "keystone" of soil condition and is commonly included in soil quality indices and carbon sequestration assessments (Calero et al., 2018; Hatfield et al., 2018; Munoz-Rojas, 2018; Vasu et al., 2016). The widespread use of SOC as a soil health indicator is due to its strong correlation with Cation Exchange Capacity (CEC), water holding capacity (WHC), pH, biological activity and soil structure (Cardoso et al., 2013; Rabot et al., 2018). Such properties determine the soil aptitude for agriculture and an eventual increasing of SOC improves soil processes related to these properties. For instance, the CEC is low in sandy soils but may increase with the increment of organic negatively charged compounds present in Organic Matter (Kaiser et al., 2008; Ramos et al., 2018). Similarly, water availability can increase linearly with the increment on organic matter in soil (Lal et al., 2007; Rawls et al., 2003).

Likewise, crop yields are extensively used as an indicator of the climate impacts on agriculture (Hatfield et al., 2018) and climate-smartness assessments (Lee et al., 2014; Mwongera et al., 2017; Notenbaert et al., 2017; Shikuku et al., 2015; Shirsath et al., 2017), where the farmers and stakeholders identify the yields as a heavyweight indicator in the prioritization of CSA practices and food security. Moreover, its correlation with soil quality indices (Mukherjee and Lal, 2014; Obade and Lal, 2016; Vasu et al., 2016) shows its suitability to indicate the extent to which soil health are related with productivity benefits.

4.2.1.1.1 Sustainable Yield (SYI) and SOC (SSOCI) Indices

The variability of Yield and SOC were represented by the Sustainable Yield Index (SYI) proposed by Singh et al. (2016). SYI was originally designed to apply to yield data but in this study, it was applied to detrended data of yield and SOC. For the case of SOC, we called the index the Sustainable SOC Index (SSOCI). The data were detrended by linear regression and then re-scaled by adding the average of raw data in order to avoid negative values. The use of detrended time series allowed us to focus on the fluctuations and identify the systematic trends in the variability of the data.

The index provides a measure of how sustainable the changes observed in the data are based on the relationship between standard deviation, average and maximum values (Eqs. 4.1 and 4.2). The indices take values between 0 and 1; when values tend to 0

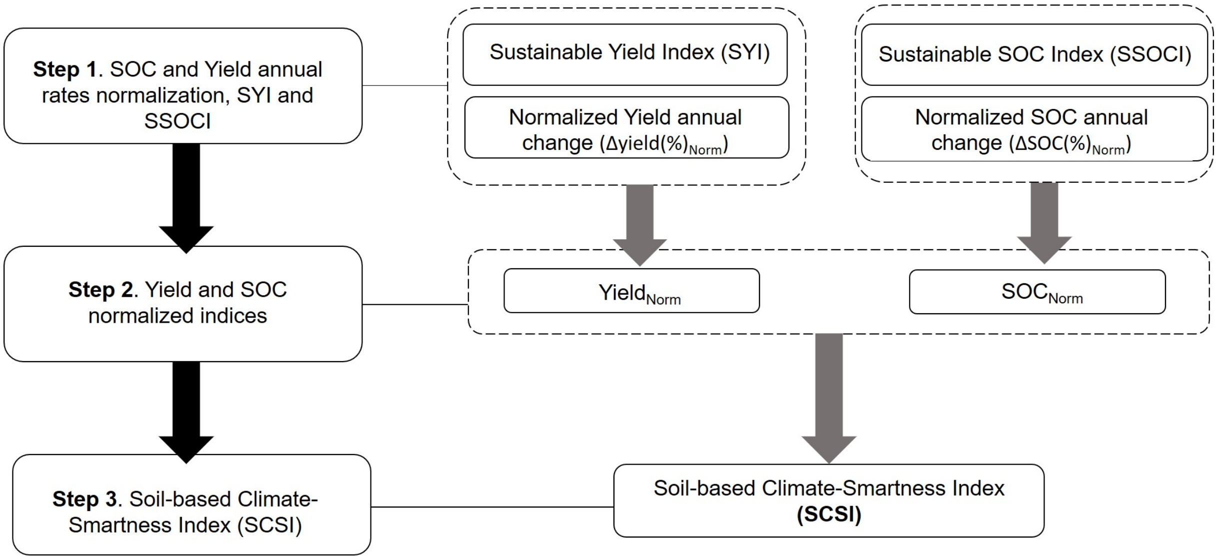

Figure 4.1: Flowchart of steps to build the Soil based Climate-Smartness Index (SCSI)

indicate high fluctuations in the data, and the indices values that tend to 1 indicate low variability in the changes observed, indicating that such changes are constant across time.

$$SYI = (\overline{yield} - \sigma_{yield})/yield_{max} \tag{4.1}$$

$$SSOC = (\overline{SOC} - \sigma_{SOC})/SOC_{max} \tag{4.2}$$

Where SYI is the Sustainable Yield index and SSOCI is the Sustainable SOC index; $\overline{yield}$ and $\overline{SOC}$ is the mean of the detrended yield and SOC data; σ_{yield} and σ_{SOC} are the standard deviations of yield and SOC detrended data, and yield$_{max}$ and SOC$_{max}$ are the maximum yields and SOC detrended values. Thus, time series with constant annual rates on for soil and yield or time series with no changes will result in high SYI and SSOCI, while time series with high dispersion in annual changes will result in low SYI and SSOCI.

4.2.1.1.2 Normalized Trend ($\triangle(\%)_{Norm}$)

The normalized trend was calculated first as the perceptual rate change of yield and SOC (Eqs. 4.3 and 4.4).

Table 4.1: Characteristics of the studies used in this study

Reference	Country	Period (years)	Sampling depth (cm)	Soil Texture	Crop	CA practices
Agbede and Adekiya (2013)	Nigeria	3	60	Sandy Loam	Yam	MSD
Campbell et al. (2007)	Canada	17	15	Loam	Wheat	MSD, CD
Chen et al. (2015)	China	10	20	Silt loam	Winter-wheat + summer maize	OG
Datta et al. (2010)	India	6	15	Loam	Wheat and Soybean	CD, OG
Dimassi et al. (2014)	France	41	80	Silty loam to silty clay loam	Wheat and Maize	MSD, PSOC
Dou et al. (2014)	The United States	4	90	Silty loam	Sorghum	PSOC
Mohammad et al. (2012)	Pakistan	6	60	loam to clay loam	Wheat	MSD, CD, PSOC
Rassmussen and Parton (1994)	The United States	56	60	Silt loam	Wheat	OG
Rothamsted Research (2017)	UK	145	23	Clay loam to silty clay loam	winter wheat	OG
Rothamsted Research (2012)	UK	145	23	Silty clay loam	Spring barley	OG
Sainju et al. (2002)	The United States	5	20	Sandy loam	Tomato	PSOC
Wang et al. (2019)	China	4	20	Clay loam	Wheat	CD, PSOC
Yadvinder-Singh et al. (2004)	India	12	15	loamy sand	Rice	PSOC, OG

CA: Conservation Agriculture; **MSD**: Minimum Soil Disturbance; **CD**: Crop diversification; **OG**: Organic Fertilization; **PSOC**: Permanent Soil Organic Cover.

$$\triangle\text{yield}(\%) = [(\text{yield}_f - \text{yield}_i)/(\text{t}_f - \text{t}_i)]/\text{yield}_i \tag{4.3}$$

$$\triangle\text{SOC}(\%) = [(\text{SOC}_f - \text{SOC}_i)/(\text{t}_f - \text{t}_i)]/\text{SOC}_i \tag{4.4}$$

Where $\triangle$yield(%) and $\triangle$SOC(%) are the annual rate of change of yield and SOC; Yield$_f$ and SOC$_f$ are the yield and SOC in the last year of the time series; Yield$_i$ and SOC$_i$ are the yield and SOC in the initial year of the experiment; and t$_i$ and t$_f$ are the initial and final year of the time series.

The percentage change rate was normalized by the min-max normalization method (Krajnc and Glavic, 2005; Pollesch and Dale, 2016). The normalization of yield and SOC trends was required to combine the trend with the sustainability indices (step 2) and then into one single yield-SOC index (step 3). For the normalization, 60% year^{-1} was the maximum reference value for annual yield changes. In the case of SOC, the maximum reference value used was 15% year^{-1} The normalized values for yield and SOC were calculated as is shown in Eqs. 4.5 and 4.6.

$$\triangle(\%)_{norm} = (\triangle\text{yield}(\%) - 0\%)/(60\% - 0\%) \tag{4.5}$$

$$\triangle SOC(\%)_{norm} = (\triangle SOC(\%) - 0\%)/(15\%) - 0\%) \tag{4.6}$$

Finding suitable references values for annual changes in yield and SOC is a challenge due to the large range of climatic zones, agro-environmental contexts and type of disturbances present in agricultural lands. The maximum reference values for yield and SOC normalization were obtained from the review of a set of published experiments in peer-reviewed journals. The yield and SOC data collected from those studies not only were used to select the reference values but also to assess the applicability of SCSI. 0% was assumed as the minimum reference value in both yield and SOC to conserve the negative sign in the cases of normalization of annual losses of yield or SOC.

Yield reference values are consistent with those reported by Soussana et al. (2019) in their meta-analysis from 32 papers, where annual crop productivity ranged between 0 and 50% (approx.) after changes on soil management for several crops in Asia, Africa and Latin America. Regarding SOC, similar SOC annual rates were reviewed by West and Six (2007), who reported a range between 0 and 8% SOC year^{-}1 (approx.) at 0-30 cm in 67 global long-term agricultural experiments with a duration greater than 5 years located in Europe, Latin America and North America. Similarly, Soussana et al. (2019) reported a relative annual change in SOC (0–20 cm) between 0 and 14% year^{-}1in soils under changes in soil management. Finally, Poulton et al. (2018) reported an annual SOC change between -1 to 18% in 16 long-term experiments in the south-east United Kingdom.

The changes observed in SOC and yield differ in magnitude because of the spatial and temporal scale that both indicators respond to the variations in the cropping systems. By re-scaling these quantities separately, the min-max normalization method brings them onto the same scale (-1 to 1) and makes them comparable. Consequently, similar annual percentage changes on both indicators will result on different normalized values (e.g. +5% of SOC increasing will result in a normalized value 4 times bigger than the normalized value resulted from the same annual percentage change in yield).

4.2.1.2 Step 2. Yield$_{Norm}$ and SOC$_{Norm}$

With the indicators of variability and trend calculated for yield and SOC (from step 1), combined sub-indices were calculated by the aggregation of normalized variability and trend indicators (Eqs. 4.7 and 4.8). These indices contain information about the behaviour of yield and SOC in a single and non-dimensional metric.

$$Yield_{norm} = \text{SYI} * \triangle\text{yield}(\%)_{norm} \tag{4.7}$$

$$SOC_{norm} = \text{SSOC} * \triangle\text{SOC}(\%)_{norm} \tag{4.8}$$

The higher and more stable the annual changes, the higher Yield$_{Norm}$ and SOC$_{Norm}$ will be. Where those annual changes are more irregular, Yield$_{Norm}$ and SOC$_{Norm}$ will be lower. The same relationship applies for negative Yield$_{Norm}$ and SOC$_{Norm}$, where values close to -1 come from regular negative growth annual rates that become less negative if the negative rates become unsteady.

4.2.1.3 Step 3. Soil-based Climate-Smartness Index (SCSI)

The SCSI was built from the aggregation of Yield$_{Norm}$ and SOC$_{Norm}$ (Eq. 4.9). In the process, no weighting was assigned to Yield$_{Norm}$ and SOC$_{Norm}$. The decision to use this weighting method implies that the index will be an arithmetic average or counting of indicators (Greco et al., 2019) . However, in the SCSI the use of min-max normalization method implicitly weighted the SOC and yield trends because of different reference values were used for each one (Mazziotta and Pareto, 2013).

$$SCSI = (Yield_{norm} + \text{SOC}_{norm}) * 0.5 \tag{4.9}$$

A linear approach was selected to aggregate Yield$_{Norm}$ and SOC$_{Norm}$. This aggregation method is simpler than geometrical methods and is used when is seeking to represent a compensatory effect between indicators (Notenbaert et al., 2017). With this aggregation, the synergies and trade-offs between yield and SOC are clear: a good or bad performance of both indicators will lead to a clear climate-smartness or lack of climate-smartness respectively. On the other hand, the trade-off will be more or less climate-smart according to the predominant trend (e.g. slight positive trend on SOC and a loss on yield the first years might result in negative SCSI). Those situations occur since positive changes can not compensate an increasing negative trend.

The SCSI has a scale between -1 to 1. Values close to 1 indicate that yield and carbon increase at a constant rate, and values close to -1 refer to cases where both SOC and yield decrease constantly. The possible values of SCSI in function of the trend and the variability of indicators are described in Fig. 4.2. Both SOC and yield indices are calculated from annual rates, therefore SCSI will tend to zero when annual SOC and yield responses to the CSA treatment begin to plateau.

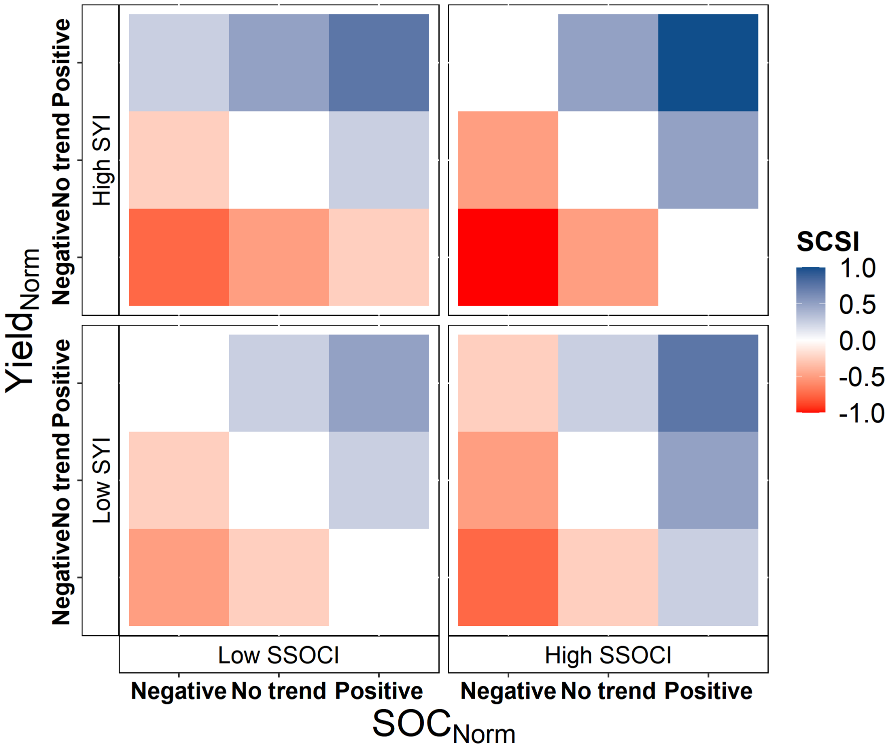

Figure 4.2: Values of Soil-based Climate-Smartness Index (SCSI) in relation with the trends (Negative, No trend, Positive) and the Sustainable indices (SYI and SSOCI) of SOC and yield Normalized indices. (High ≥ 0.5; *Low* ≤ 0.5)

4.2.2 Evaluation of Soil-based Climate-Smartness Index (SCSI)

Data from 11 experiments published in peer-reviewed journals and data from 2 long-term experiments at Rothamsted Research unit were used to assess the application of the SCSI. All the experiments assessed CA practices that are compared with conventional management or control treatments without N fertilization, often used as a “blank” treatment. The experiments assess the CA practices in different crops (wheat, maize, rice, sorghum, soybean, yam, spring barley and tomato) and different evaluation periods that ranged from 2 to 147 years. Details about the location of the study, crop, agronomic management, treatments and period of evaluation are shown in Table 4.1.

For each treatment in the studies a set of SCSI scores were obtained. The SCSI were calculated for the minimum data points required (3 data points). Data points were then added one-by-one, with SCSI recalculated each time. The resulting SCSI values were analysed by comparing the CSCI across the time and between treatments. Results from the analysis were used to draw conclusions on the climate-smartness of

CA, and on the broad applicability of SCSI to quantify trade-offs and synergies between CSA pillars across timescales.

4.3 Results

A total of 240 SCSI scores resulted from the 11 peer-reviewed publications and 2 long-term experiments from Rothamsted Research unit. From the total data, 55.4% of scores correspond to Conservation Agriculture (CA) practices like Minimum Soil Disturbance (MSD), Crop Diversification (CD), Permanent Organic Soil Cover (PSOC) and Organic Fertilization (OG). For its part, 19.6% of scores correspond to conventional practices (treatments with conventional management like mechanical tillage or synthetic fertilizer) and 25% from control treatments (treatments used as a "blank" treatment without N fertilization). From the total of SCSI scores, 33% correspond to treatments with duration <5 years. The SCSI scores calculated for treatments with a duration between 5 and 10 years were 13% of total data, whereas 12% correspond to treatments with a duration between 11 and 20 years. Most of the SCSI scores (41%) correspond to treatments with duration >20 years.

4.3.1 Yield$_{Norm}$: Sustainable Yield Index (SYI) and normalized yield trends (yield$\triangle(\%)_{Norm}$)

The Yield$_{Norm}$ resulted from multiplying the SYI by the yield normalized trends (yield$\triangle(\%)_{Norm}$). The results are summarised in Fig.4.3 (lower panels), and the heatmap scale represents the possible values that Yield$_{Norm}$ could take. The observed temporal changes in Yield$_{Norm}$ as well as the differences among the practices (CA, Conventional and Control), varied in function of temporal dynamic in SYI and the $\triangle(\%)_{Norm}$.

Based on SYI results, annual changes in yield have high variability in the first 5 years of soil strategies implementation where the SYI fluctuated between 0.41 and 0.99 during this period without marked differences among practices (CA, Control and Conventional). The variability in yield changes tends to decrease, as can be seen in the SYI values that range between 0.6 and 0.9 after 5 years and closer to 1 in treatments assessed between 11 and 20 years. Although the SYI tends to decline with time, some treatments with >20 years of assessment, presented lower SYI values towards the end of this timespan, than observed in previous years, indicating that even if the annual changes tend to decrease, long-term yield fluctuations may continue to be observed.

The greatest annual changes in yield occurred in treatments with a duration between 2 and 5 years (-25 to 60%). During this period, 78% of the annual changes were negative and 21% were positive. This proportion between negative and positive annual changes was similar in all the practices (77% : 22%). However, the proportion changed to 60% : 40% in periods between 5 and 10 years and then 32% : 68% in treatments with periods between 11 and 20 years. When the data were disaggregated by practices, we found that CA, Control and Conventional still have a very similar proportion of negative and positive changes even after 5 years. However, the positive and negative annual changes observed in CA practices were higher than Control and Conventional, with an exception of a data point from a Control practice.

The relation between negative and positive changes across the time indicated that regardless of the practice, the yield losses are higher than yield gains at the beginning of the implementation of soil-oriented strategies. Although the trends tend to be positive with time, the magnitude of such changes is lower than initial years. The yield$\triangle(\%)_{Norm}$ range was -0.41 to 1 in the first 5 years and -0.1 to 0.09 in periods between 5 and 10 years. After 20 years, annual changes were unnoticeable that was reflected in the yield$\triangle(\%)_{Norm}$ range -0.01 to 0.04. These results are reflected in the values of Yield$_{Norm}$ that conserved the same proportion between negative:positive annual changes and were higher during the first 5 years (-0.33 to 0.56) and then tended towards zero after 10 years (-0.06 to 0.06).

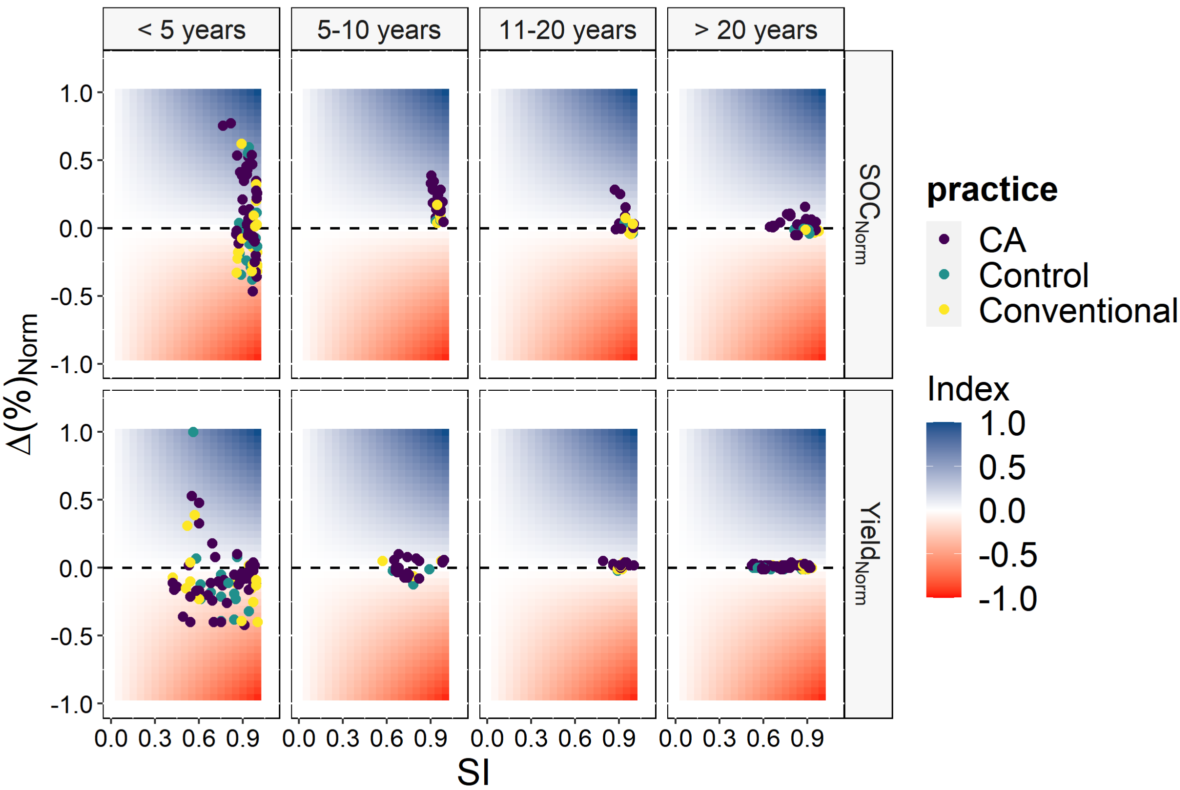

Figure 4.3: SOC$_{Norm}$ and Yield$_{Norm}$ heatmaps calculated from the multiplication between Sustainable Indices (SSOCI and SYI) and Normalized change rate (SOC$\triangle(\%)_{Norm}$ and yield$\triangle(\%)_{Norm}$). Vertical panels correspond to evaluation periods and horizontal panels correspond to SOC$_{Norm}$ and Yield$_{Norm}$ values. CA: Conservation Agriculture

4.3.2 SOC$_{Norm}$: Sustainable SOC Index (SSOC) and normalized yield trends (SOC$\triangle$(%)$_{Norm}$)

SOCNorm results from the multiplication between SSOCI and SOC$\triangle$(%)$_{Norm}$, which are summarized in the upper panels of Figure 4.3. The SSOCI range was higher than the SYI range, suggesting that SOC annual changes are more constant than yield changes. In contrast to SYI, SSOCI presented differences between practices. Conventional and Control practices presented higher SSOCI (0.8 to 0.99) than CA practices (0.64 to 0.9), evidencing that some CA treatments are prone to present higher fluctuations in annual SOC changes. It is important to point out that such variations occurred in the treatments with >20 years, which brings evidence of the long-term effect of CA practices on the soil.

The SOC$\triangle$(%)$_{Norm}$ also showed differences among practices across time. In treatments with assessed periods between 2 and 5 years, SOC$\triangle$(%)$_{Norm}$ ranged between -0.46 and 0.77 (53% of these cases displayed negatives annual change and 46% were positive). However, this proportion of negative and positive annual changes differed among practices. While 44% of annual changes in CA were negative, in Control and Conventional practices 66% of annual changes were negative. Likewise, SOC gain in Control and Conventional treatments were observed in 22% of the cases; less than half as frequent as the SOC gains cases found in CA treatments (54%).

As with yield, SOC annual changes (positive and negatives) became smaller over time. After 5 years, all SOC(%)Norm values were positive but with a higher trend in CA. After 10 years, the SOC(%)Norm was nearly zero in almost all cases with some exceptions in CA practices that showed a larger positive trend (0.04 to 0.38) compared with Control (-0.05 to 0.05) and Conventional (0.03 to 0.17) practices. Although to a lesser extent, SOC changes in periods >20 years, were still relatively larger in CA compared with Conventional and Control, supporting the evidence that under CA, the SOC gain is still likely to happen at long-term.

The SOC$_{Norm}$ resulted from the multiplication of SSOCI and SOC (%)$_{Norm}$. The SOC$_{Norm}$ in Control and Conventional practices showed similarities that contrasted with CA practices over time. In the first 5 years, the SOC$_{Norm}$ ranged between -0.45 to 0.63 in CA practices, which was higher than Control (-0.36 to 0.56) and Conventional (-0.31 to 0.55) ranges, in both, gains and losses of SOC. Although SOC$_{Norm}$ tended to decrease over time in all practices, the annual rates in CA practices did not decrease as much as in Control/-Conventional practices, generating a bigger difference between CA and Control/Conventional practices over time.

Between 5 and 20 years, the SOC$_{Norm}$ in Control and Conventional practices ranged between 0.04 and 0.1. After 20 years, the SOC$_{Norm}$ in such practices were mostly negative (96% of the cases), with values near to zero (-0.04 to -0.02), evidencing that

Control and Conventional conditions lead to SOC losses at long-term. These results contrasted with the SOC_{Norm} range found for the periods between 5 and 20 years in CA, that was relatively higher (0.04 to 0.38) than in Conventional-Control practices. This difference is higher after 20 years, where CA practices showed a range between (-0.05 to 0.16). In this case, the negative SOC_{Norm} values in CA represented 45% of the data; however, the range of these negative values was between -0.05 to -0.001, while positive SOC_{Norm} values represented 55% of the data and ranged between 0.003 and 0.16) which is even higher than the range of positive SOC_{Norm} in Control and Conventional practices in periods <20 years.

4.3.3 Soil-based Climate-Smartness Index (SCSI)

The visualization of the synergies and trade-offs between $Yield_{Norm}$ and SOC_{Norm} are summarized in Fig.4.4, where the heatmaps represent the possible scores that SCSI can take. The results show that independently of the practices implemented, it is more likely to have a negative synergy than a positive synergy between yield and SOC during the first years of implementation. In the first 5 years, 46% of the data presented negative synergies (Yield Loss-SOC Loss). During the same period, 13.6% of the experiments had positive synergies (Yield Win-SOC Win) and 32% had the 'Yield Loss- SOC Win' trade-off that was more frequent than the 'Yield Win - SOC Loss' trade-off (7.5%).

The relationship between Yield and SOC appears to become more synergistic over time. Between 5 and 20 years, the cases of positive synergies (Yield Win-SOC Win) passed from 13% to 38%, while no negative synergies (Yield Loss-SOC Loss) were present. During this period, 36% of the experiments were 'Yield Loss- SOC Win' trade-offs, which did not differ too much from past years. Although the practices were not equally represented in all periods, the disaggregated data indicated that most of the positive synergies during the period 5 to 20 years corresponded to CA practices (18 out of 24 cases).

After 20 years, 19% of data represented positive synergies, all of which correspond to CA practices; this means that after 20 years just CA maintained positives synergies between SOC and Yield. On the contrary, overall negative synergies represented 29% of the cases. From this percentage, just the equivalent to 7% of data came from CA treatments (2 out of 29 cases). The temporal dynamic of such synergies and trade-offs determined the values observed in the SCSI.

In relation to the $Yield_{Norm}$ and SOC_{Norm} results, the most negative and positive SCSI scores occurred in the 5 first years (-0.28 to 0.34). Although the positive synergies increased and the negatives were absent after 5 years, the SCSI range was lower (-0.09 to 0.15) than the calculated in the first years. After 20 years, all the SCSI scores ranged between -0.02 to 0.06 indistinctively of the practices. This suggests that after this point, the SCSI provided little information about the impact of soil management on the Yield and SOC trend and variability.

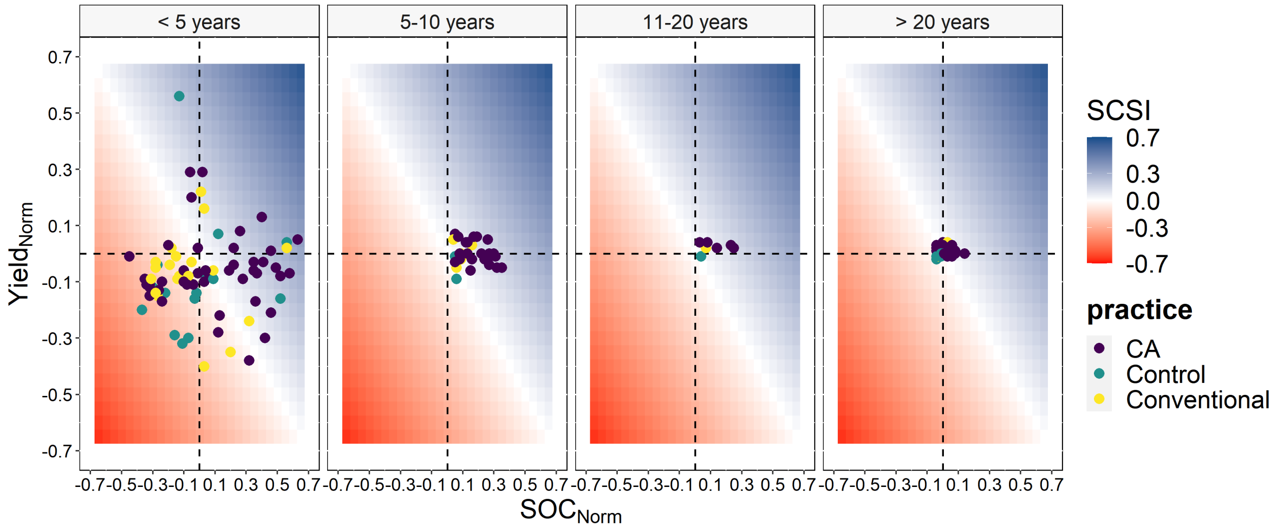

Figure 4.4: Soil-based Climate-Smartness Index (SCSI) heatmaps calculated for Conservation Agriculture (CA), Control and Conventional practices. Vertical panels correspond to evaluation periods.

The mean SCSI during this period was not only higher in CA (mean SCSI = 0.28) than Control (mean SCSI = -0.03) and Conventional (mean SCSI = -0.0185) practices, but also showed a higher number of positive SCSI scores (Fig. 4.5). The positive SCSI scores in CA represent both, positive synergies and trade-offs that favoured an increase in yield or SOC over a potential decrease of such indicators. According to the SCSI scores, the climate-smartness are also mediated by the response time of the system to soil management; however, CA always presented a higher climate-smartness than Conventional and Control independently of the period.

The SCSI scores were fitted to a local polynomial curve regression, that showed a similar pattern in the data distribution across 50-year time span. The fitted curves pointed out a "SCSI peak" in CA and Conventional practices in approximately the tenth year, which started to fall until flattening around 20 years. In the Control practices, there was no peak since there are not any soil management activities involved. The differences between CA and Conventional curves are that the peak in CA is higher than Conventional indicating that CA data tend to reach higher SCSI scores. There is a further difference in the timescale over which the line flattens. In the case of CA, the curve flattens approximately after 30 years, while in Conventional it is approximately at 20 years. This confirms that CA has an impact on the system's properties for a longer span of time as compared to Conventional practices.

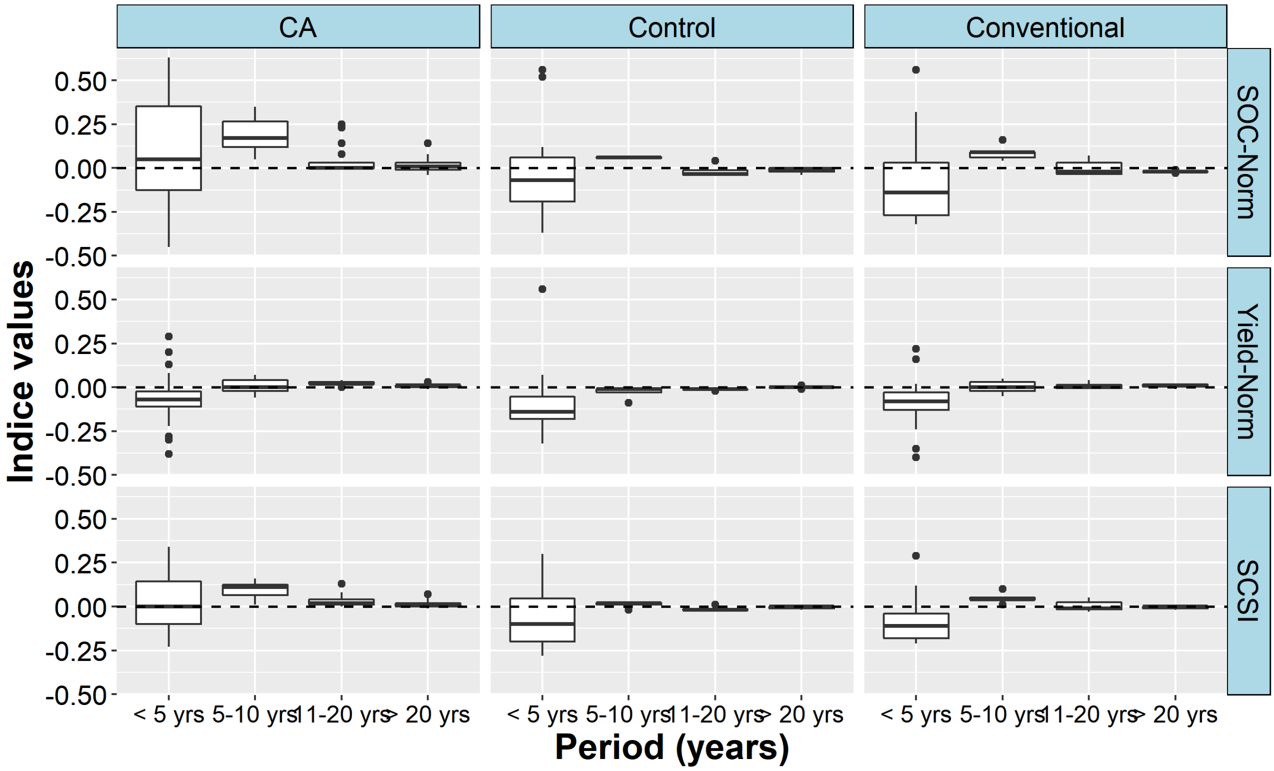

Figure 4.5: Boxplots of SOC_{Norm}, $Yield_{Norm}$ and SCSI for Conservation Agriculture (CA), Control and Conventional practices at different periods. Numbers in the bottom of SCSI panel correspond to the number of data per practices and period.

the different CA practices grouped in this category. In Fig.4.6, The CA category was disaggregated into 3 CA practices mentioned in the first section of results. The CA practices with the greater data representation were OG (Organic Fertilization) and PSOC (Permanent Soil Organic Cover). Of these practices, PSOC practices reached the highest peak. It is important to point out that some of the PSOC treatments also included chemical fertilization, while most of the OG case use just organic sources. The curves also showed that CA practices differ in their temporal response and in the implementation span in which the major impacts are achieved. For instance, even when OG achieved a similar peak to PSOC, its curve started to flat almost 10 years later than all the other practices, suggesting that positive changes under such practices might take a longer period to achieved potential thresholds.

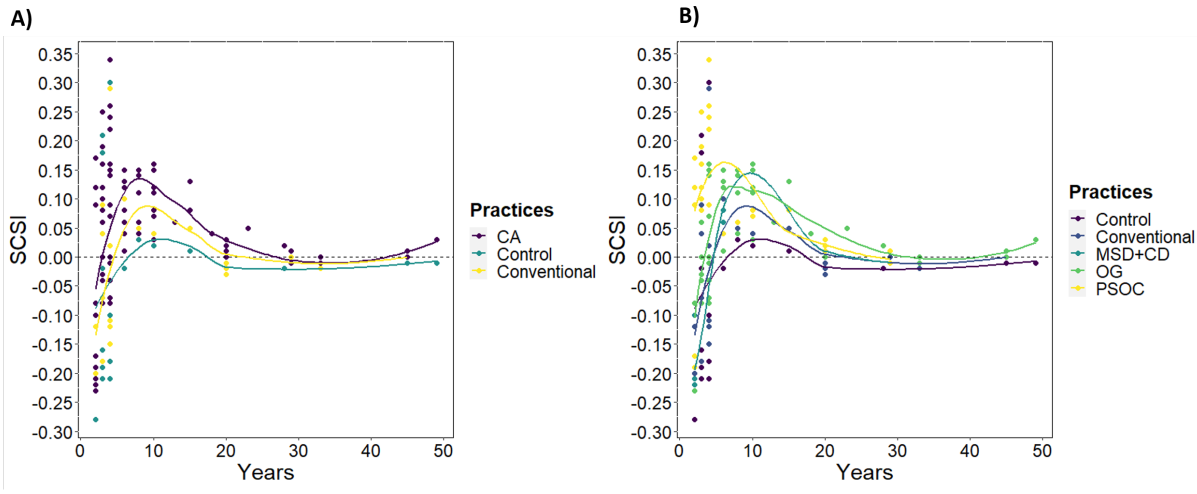

Figure 4.6: Scatterplots of Soil-based Climate-Smartness Index (SCSI) across 50 years period for A) Conservation Agriculture (CA), Control and Conventional practices, and B) Control, Conventional, Minimum Soil Disturbance + Crop diversification (MSD + CD), Organic Fertilization (OG) and Permanent Soil Organic Cover (PSOC) practices.

4.4 Discussion

The Soil-based Climate-Smartness Index (SCSI) can provide a measure of the climate-smartness and capture its temporal behaviour in cropping systems under different soil practices. The analysis of SCSI showed that scores range between highly positive to highly negative during the initial years of implementation and then, tend to stabilise towards zero in the long term. Consequently, all possible trade-offs and synergies (illustrated in Fig. 4.7) between yield and SOC occurred during the first years of implantation. Overall, the synergy (with negative trends) and the trade-off 'yield loss and SOC gain' are the most common among the practices, also evidencing a transitory lack of climate-smartness in some treatments under climate-smart practices. These results underscore the importance of considering the temporal response of the crop systems to the soil-oriented strategies within climate-smartness assessments.

The negative SCSI values in CA resulted from the synergy between SOC and Yield (most of negative SCSI) or from the trade-offs between negative trends on yield with the SOC. In both cases, the lack of climate-smartness resulted from the yield penalties in early stages of CA implementation. This yield penalty is reported by several studies as a constraint on CA adoption and scaling-up (Brouder and Gomez-Macpherson, 2014; Cooper et al., 2016; Giller et al., 2009; Van den Putte et al., 2010).Pittelkow et al. (2015), found some negative yield response in several crops during the first 1–2 years of No-till adoption. Nyamangara et al. (2013) reported similar results from 48 CA experiments conducted in semi-arid regions of Zimbabwe, where 26 to 50% of the

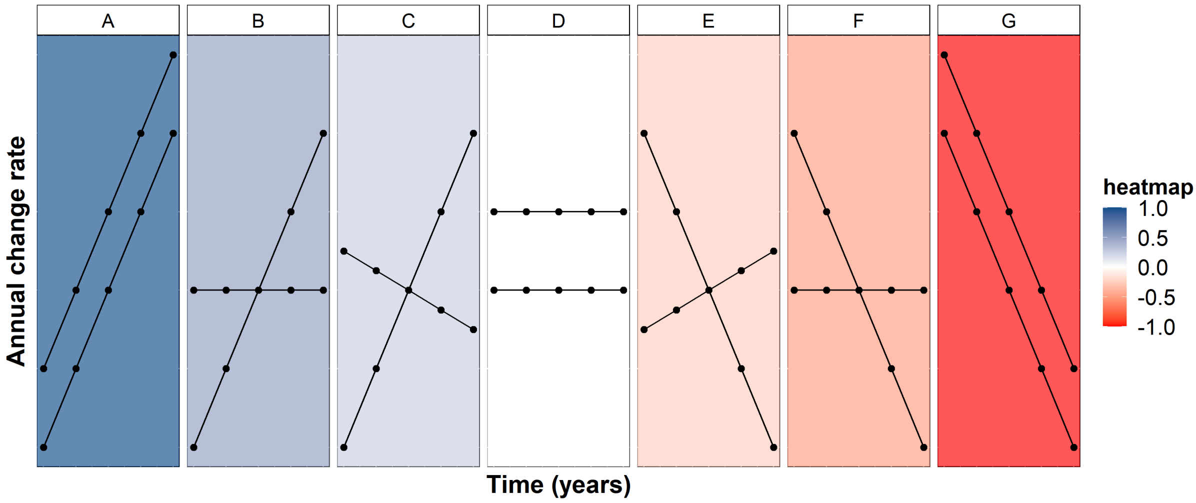

Figure 4.7: Synergies exist where both trends are of the same size, and these can be positive (panel A) or negative (panel G). Trade-offs exist when the slops are of opposite sign (Panels B,C,E and F).

experiments presented negative changes on yield. Corbeels et al. (2020) Likewise, indicate that the limited yield benefits (4% compared to conventional tillage systems) from CA constrains its adoption for small scale farmers.

Along with yield penalties, some treatments also showed negative SOC. The SOC depletion in Conventional and Control practices are expected due to the limited OM recycling in such practices (Ogle et al., 2005). However, the negative SOC changes (19% of SOC_{Norm} in 5 years) also occurred in CA practices. Negative SOC_{Norm} in CA were evidenced in negative synergies with yield and in positive trade-offs of yield, where negative SOC outcomes were compensated by large positive yield benefits. Although SOC depletion under CA is unexpected and most of the studies highlight the potential of CA to increase the soil carbon, some studies reported this effect for some CA practices (Liang et al., 2016; Mrabet, 2002). A meta-analysis carried by Luo et al. (2010) found that the benefits of no-tillage on SOC are inconclusive since significant SOC depletion was also observed along with SOC increment. For their part, Poeplau and Don (2015) reported that 9% of the experiments reviewed in their meta-analysis indicated SOC stock depletion after implementation of cover crops.

Although less common during the first years of implementation the SCSI also resulted from positive synergies between indicators, showing a positive outcome in yield as has also been reported by previous studies. For instance, some CA experiments in Southern Africa reported an increase in maize yield during the first and second cropping seasons after starting the implementation (Thierfelder et al., 2013). Similarly, in their meta-analysis, Zhao et al. (2017) reported an increase on rice yield to 2.6% during ¡5 years of implementation of No-tillage, and Huang et al. (2013) found that crop residue retention has an impact of 4.7% on rice yield in experiments with 3 years of evaluation in China.

The SCSI results come from different experimental and agro-climatic conditions, that led to a different response of SOC and yield in the CA experiments. It is important to remember that potential yields will depend on a combination of non-limiting agronomic and climate conditions, reducing the gap between actual to potential yield, which also might vary according to crop genotype.

The period needed to reach the soil carbon saturation under certain agronomic practices may depend on the interaction between geographic location, climate, and land transition scenarios.Qin et al. (2016) reported in their meta-analysis that the magnitude of SOC depletion after cropland conversion and the former land use influence the C sequestration rates, which generally results in a negative correlation between initial SOC stock and SOC accumulation rates (Georgiadis et al., 2017). Moreover, soils in the tropics might reach a SOC equilibrium faster than soil in temperate regions where it could take around 100 years after the land-use change (Smith et al., 2008a).

At a smaller scale, the soil texture partially determines SOC accumulation; clay and silt content generate an advantage to SOC storage by the stabilization of SOC in Sil + Clay particles and reducing its microbial decomposition (Chenu et al., 2019; Stewart et al., 2008). At a regional scale, the OM turnover rates may differ among climate zones; the wet, tropical and warmer areas prone to have faster decomposition rates (Chenu et al., 2019; Sommer et al., 2018; Stewart et al., 2008). For its part, yield also depends highly on climate and soil conditions (Nyagumbo et al., 2020). Pittelkow et al. (2015) reported yield response to CA practices varies among dry and humid climates. Likewise, the soil proprieties that control the water infiltration have a strong influence in the yield on CA practices, several authors reported reduction on yields when CA practices are implemented in poorly drained soils (Corbeels et al., 2014; Thierfelder and Wall, 2012).

In contrast with the high variability in the SCSI scores observed in the early periods of implementation, the positive synergies and trade-offs of SOC were the most common relationships between both indicators, resulting in positive SCSI scores during the period between 5 and 10 years. These results evidence that changes in SOC may have a greater contribution to climate smartness in the mid and long term. Although the trade-offs and synergies become more climate-smart over the time, the magnitude of such climate-smartness tends to decrease according to the attainable yield and SOC in a given the context and the CA practices performance. Thus, the SCSI can help to identify the point where the soil management (or any agricultural management that could be attributed) can generate the greater changes (negative or positive) and from what point such changes, are redirected or became inconstant.

After 10 years, the SCSI tends towards zero because of a deceleration of the SOC and yield rates. The peaks observed in the SCSI data coincided with the behaviour of SOC sequestration rates observed in several CA experiments. Tadesse et al. (2018) and Yang et al. (2015) observed the highest soil carbon stock after 10 years of CSA implementation. Similarly, Zanatta et al. (2007) identified for a subtropical location that, the higher SOC changes in the first years but the peak of SOC accumulation ocurred in the 9th year.

Although the SCSI in the first years of CA implementation seems to contain most of the information, the response period (For how long SCSI are changing) also inform about the climate-smartness and the “lifetime” of CA practices. These results reflect the importance of long-term monitoring of CA treatments, especially for the temporal dynamic of SOC sequestration. In this study, most of the data come from periods 10 years which is the period when most of the changes happened, however, the representation of all periods was unequal, and data gaps were observed, particularly in the periods comprised between 20 and 50 years.

Overall, CA practices showed higher climate-smartness than Control and Conventional, however, the SCSI scores presented high variability in CA practice, suggesting that some practices under certain context might present higher climate-smartness than others. The regression curves calculated for each practice within CA were based on some experiments located in temperate regions and correspond to specific conditions. Thus, the curves can bring new insight about the temporal dynamic of the climate-smartness but cannot be seen as definitive conclusions.

These differences in CA practices can be explained by the suitability of the practices and the context. For instance, no-till and crop diversification do not involve direct incorporation of organic matter and may have a little effect on SOC, (especially in tropical moist or dry conditions) but could improve if is complemented with crop residue retention, (Das et al., 2013; Ogle et al., 2005; Thierfelder et al., 2013). On the contrary, practices like PSOC and OG that involve the incorporation of organic matter can contribute more with the soil carbon storage.

However, OM incorporation also has important implications on crop yield and in the decision to replace partially or completely the chemical fertilization by organic amendments. In this study, the PSOC practices achieved the highest SCSI scores but were also characterized by the use of chemical fertilization, which probably helped to support the yield during the early stages of the OM turnover in the soil (Yan and Gong, 2010).

Along with the decision to replace the chemical fertilization, the quality of the crop residues contributes to the climate-smartness of the practices. The source of the residues determines its composition and its decomposition rates that might vary according to soil moisture and temperature conditions. For instance, crop residues with high lignin content have slower decomposition rates, and could result in low SOM (Stewart et al., 2015); likewise, crop residues with high C:N ratio decompose slowly and contribute poorly to N inputs (Kong et al., 2005; Palm et al., 2010; Wang et al., 2017). Thus, the replacement of chemical fertilization in CA practices is a key technical decision that needs understanding about the relationship between soil conditions, organic inputs quality and crop requirements, not only to estimate SOC sequestration potential but also to protect yield stability.

The crop nutrient management and its influence on the SCSI score also will depend on other initial experiment conditions. For instance, the timing and N fertilizer rates, or the use of Rhizobium inoculants used in the experiments reported by Datta et al. (2010) and Campbell et al. (2007), might influence the N use efficiency (Davies et al., 2020). Moreover, the use of high-yielding varieties like the high yielding wheat used by Campbell et al. (2007) and the high-yielding with low lodging potential of sorghum variety used by Dou et al. (2014) might also represent an advantage independently of CA implementation and will influence the SCSI overall score.

4.4.1 Soil-based Climate-Smartness Index (SCSI): Strengths, limitations and future work

The design of the SCSI was motivated by an evidence gap around CSA practices and the lack of available metrics that allow standardized comparisons and facilitate a simultaneous interpretation of three CSA pillars at different temporal and spatial scale (Lankoski et al., 2018; Rosenstock et al., 2018). For the metric presented in this study, we defined climate-smartness under the context to cropping systems under soil-based management practices. Under such systems we identified climate-smartness as representing a synergy between climate resilience and productivity with added benefits of mitigation via soil as a carbon sink.

The SCSI presented here can provide a measure of the temporal response of cropping systems and its impact on soil and productivity. However, the SCSI is insufficient to provide a climate-smartness measure from a social or economic view that might be partially represented by the yield indicator. In any case, the SCSI could be analysed along with social-economic indicators to find associations between the climate-smartness and the improvement of farmers livelihoods, or the yield indicator could be combined with a food availability index or an income indicator. Within the concept boundaries, metrics like SCSI can provide simple and quantitative assessments for policymakers which are needed for tracking the effectiveness of plans and projects framed within the Climate-smart Agriculture approach (Bell et al., 2018).

The interpretation of the SCSI, just as any index, should be subject to the data context. Although the positive scores are associated with climate-smartness and negative scores with unsustainable conditions, is the researcher criterion that discerns the contribution (negative or positive) of agronomic and experimental conditions to the

SCSI score. This statement takes greater relevance if we intend to compare the SCSI scores from different sites that differ in their experimental layout, climate conditions and land-use history.

Along with the different perspectives (social, economic, environmental), the meaning of climate-smartness varies in function temporal and spatial scales. However, Prestele and Verburg (2019) pointed out that climate-smartness assessments still ignore the spatially variable impacts of CSA practices, especially at large scales. The temporality of the climate-smartness needs further consideration and discussion by the those supporting, leading and funding CSA implementation. The SCSI could contribute with a measure of climate-smartness at different spatial and temporal scales. Where applied in a spatially-explicit manner, the SCSI provides a means to objectively compare the climate-smartness of specific practices between sites or landscapes. However, as the idea of climate-smartness is closely attached to the context, their interpretation in each case should be relative to technically feasible thresholds.

The importance of context implies that a specific SCSI score can be only considered "too high" or "too low" relative to other practices implemented under similar conditions. For example, a positive but low SOC-index can result from highly contrasting situations, such as a site where soils are near to SOC saturation, and a site with a high SOC deficit and low return of biomass to the soil. In both cases, the CA practices can barely help to increase the soil carbon (reflected in the SCSI score). However, only in the second case is the low SCSI the result of poor application of CA practices.

The SCSI can be calculated using yield and SOC data from experiments across spatial scales (farm to regional scale) for a minimum duration of 2 years. As the SCSI uses the annual rates and their variability, the periods for which the SCSI are calculated depends on the data availability (annual, bi-annual, every 5 years), or according to project timelines and plans. As field measuring could be expensive and time demanding, simulated SOC and yield data represent a means of projecting SCSI across space and time. The SCSI also can be calculated for studies that simulated both yield and SOC. The modelling approach allow the assessment of a wide combination of agricultural practices, adaptation scenarios and time frames like the study published by Soler et al. (2011) where simulated SOC and crop yield from different crop rotations treatments in a semi-arid region, or the study published by Zhang et al. (2017) who simulated the long-term effect of the continuous and discontinuous fertilization and straw incorporation on yield and SOC.

The additive aggregation method used in the SCSI is the most used aggregation method for the design of composite indices because of its low computation complexity and because allow a compensatory relationship between indicators (Gan et al., 2017). In the SCSI, this type of aggregation allowed the association of negative SCSI scores with the negative synergies/trade-off and the positive SCSI scores with positive relationships. However, as any composite index, the aggregation of the indicators involves loss of information that could lead to a simplistic conclusion about a complex concept (Saisana and Tarantola, 2002). This limitation becomes more evident for the SCSI values resulting from trade-offs, where it is unclear which indicator is reducing and which is increasing. Regarding to this limitation, the normalized method selected for SCSI become crucial to the reliability of the SCSI.

Given that indicators were not assigned any weights, the changes in SOC and yield have the same importance. However, the weighting of the indicators can be set by the normalization method (Mazziotta and Pareto, 2013). This internal weighting depends on the reference values, which generate equivalences between the annual changes on both indicators (e.g. 5% of annual change in SOC, would obtain a higher normalized score than the same percentage in yield). This normalization method could represent an advantage for the type of metrics needed in CSA. Since the min-max normalization method can be calculated using reference values according to the context, these can be adjusted and set based on a specific annual crop, management, climatic regions or even based on policy targets and regional stats. However, a challenge of this normalization method is that it limits the comparison between studies that use contrasting reference values.

4.5 Conclusions

A Soil-based Climate-smartness Index (SCSI) was designed using the variability and the annual changes of soil organic carbon and yield. The SCSI provides a measure of climate-smartness based on the trade-offs and synergies observed between both indicators. The SCSI results confirmed that Conservation Agriculture (CA) practices are climate-smart compared with conventional management, mainly due to its effect on increasing SOC in the long term. The SOC and yield changes that result from the implementation of climate-smart practices are temporally dynamic, thus, the climate-smartness varied across the time in all CA practices. The temporal dynamic of the climate-smartness reflects the practices performance under a given context, hence, the overall impact of CA practices can be better understood when the temporal dimension is considered.

4.6 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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Chapter 5

Discussion

5.1 Summary

The concept of climate-smart agriculture (CSA) has been mainstreamed in international policy agendas, becoming increasingly relevant to national agricultural plans worldwide. Since its launch in 2010, there have been ongoing efforts to coordinate actions among stakeholders to build evidence around practices and strategies aligned with CSA principles, assessing their adoption potential, and designing scaling-up strategies (Lipper et al., 2014). CSA has been in continual development, and the knowledge gained has continually reshaped the concept (Lipper et al., 2018).

To date, CSA-related evidence supports stakeholders in making science-based decisions; however, drawing robust conclusions from this evidence is challenging given the range of contexts assessed. As a response, initiatives that aim to extract generalized messages from the pool of CSA-evidence are becoming more relevant; a god example is the Evidence for Resilient Agriculture (ERA) platform. So far, the ERA platform compiled 1446 studies from Sub-Sahara African countries with paired comparison between conventional agronomic practices and "improved" agricultural technology, providing an interactive visualization of mitigation, adaptation, and productivity indicators and their trade-off and synergies (Nowak et al., 2019). Moreover, several studies reported meta-analyses for specific CSA-related practices like Conservation agriculture (Huang et al., 2018; Li et al., 2018), agroforestry (Kim et al., 2016) or the performance of water-oriented strategies in rice (Jian et al., 2020) like alternate Wetting and Drying (AWD; Carrijo et al. (2017)).

The analysis of CSA-related evidence allows the identification of promising agronomic strategies and the potential trade-offs and synergies among CSA pillars. Identifying if CSA interventions generate a combined effect on mitigation adaptation goals, or by the contrary, one of the goals improve at the expense of the other, determines to a large extent the success of its adoption and scaling up plans (Chandra et al., 2018; Klein et al., 2005). Thus, the starting point of this thesis was to recognise the importance of assessing trade-offs and synergies of CSA across spatial and temporal contexts and explore its use as a theoretical framework for the design of novel metrics to measure climate-smartness.

In this sense, this thesis aims to contribute -as described in section 1.9, to filling well-known research gaps. First, fill the gap between the analysis of mitigation, adaptation and productivity indicators and their interpretation as climate-smartness. Second, contribute to the design for standards to monitor and measure climate-smartness given the lack of available CSA-oriented metrics. Also, the thesis aims to explore the use of process-based models as a source of CSA-related evidence and its potential to model climate-smartness through the CSA metrics proposed in this thesis.

Although assessing the trade-offs and synergies in CSA is an underpinning aspect of climate smartness, its use as a conceptual framework for the construction of climate-smartness composite indices represents a novelty in the development of CSA-related metrics, its application in this thesis represents the first attempt to synthesise in a composite index such relations as a metric of climate-smartness. This resulted in the design of two climate-smartness indices: Climate-Smartness Index (CSI) presented in chapter 2 and the Soil-based Climate-Smartness Index (SCSI) introduced in chapter 4. Both chapters present the properties of the composite CSA indices, along with their associated advantages and limitations.

The application of CSI and SCSI showed the potential to represent a reliable and objective metric of climate-smartness from an agronomic perspective. Moreover, the indices designed allow monitoring changes in climate-smartness over time. Finally, an extension of the CSI applications was explored by the calculation of CSI from modelling outcomes, which has brought to light the unexploited potential of process-based models for modelling climate-smartness across space and time (chapter 3).

5.2 What is climate-smart, and in what context

The rapid uptake of the CSA concept and the little discussion of its definition (which in some cases it is implicitly assumed) led to variability in the use of the the concepts related with CSA, generating ambiguous interpretations of what is or not climate-smart (Collins-Sowah, 2018; Lipper et al., 2018; Taylor, 2018). In this sense, to define what means climate-smartness, it is necessary to consider that CSA is a context-specific concept outlined by multi-dimensions (agronomic, social, political, economic) in which mitigation, adaptation, and productivity interact and generate multiple responses (Chandra et al., 2018).

The definition of CSA is subject to the context and the trade-offs and synergies between CSA pillars. Try to consider all the aspects (agronomic, climate, socio-economic, political) that influence the implementation of CSA at different spatial and temporal scales is complex. For instance, the adoption of drought-tolerant varieties with high fertilization requirements can increase climate resilience and yields, but also increase production costs and the N_2O emissions (Torquebiau et al., 2018). The study reported by (Wang et al., 2016) also works as an example. The authors reported an increase in irrigation water demand in several crops due to temperature rise; in turn, adaptation measures will also need to consider that water pricing largely affects water demand. In this sense, Steenwerth et al. (2014) calls for multi-disciplinary research that allows for the framing of a more holistic definition of CSA.

Climate-smartness refers to mitigation, adaptation and productivity priorities which strongly depend on the context and temporal-spatial configurations under consideration (Collins-Sowah, 2018). Chandra et al. (2018) reported in their systematic review that differences exist in the interpretation of CSA, associated with the context and the relative importance of mitigation, adaptation, and productivity goals. The different climate-smartness metrics presented in chapters 2 and 4 are examples of that different emphases in the interpretations of climate-smartness under different adaptation and mitigation goals and contexts.

In this thesis, two metrics to quantify climate-smartness were developed, contributing to fill the the research gaps described in section 1.9, regarding to the lack of replicable CSA-oriented metrics (chapters 2 and 4). The definition of the "phenomenon" to be measured is the first step in the design of composite indices, which helps to outline the scope of the metric (Nardo et al., 2005). The definitions of climate-smartness for the Climate-Smartness Index (CSI) and the Soil-based Climate-Smartness Index (SCSI) represent some of the trade-offs and synergies of CSA pillars in cropping systems. Both definitions are based on agronomic/biophysical indicators and are not intended to cover socio-economic or political aspects of agricultural systems.

The definitions of climate-smartness in this thesis were based on the most representative trade-offs and synergies documented by the evidence (Figure 5.1). For the CSI, the definition of climate-smartness describes the relationship between the water-oriented adaptation with adaptation and mitigation, these were represented as a reduction of water irrigation demand and a reduction of direct GHG emissions (which itself includes potential trade-off between CO_2 and N_2O emissions). In the case of SCSI, climate-smartness was interpreted as the relationship between the increase of Soil Organic Carbon SOC in the first 20 cm of soil profile (expressed as the annual change percent) and the productivity.

CA intervention	Adaptation/Mitigation		Mitigation/Productivity		Adaptation/productivity	
	Synergies	Trade-offs	Synergies	Trade-off	Synergies	Trade-off
Water-oriented practices in rice i.e., AWD)	Reduction of water irrigation demand increase water-use efficiency and reduce CH_4 production in rice paddy soils	Multiple drainage in paddy fields may lead an N_2O rise	Reduction of fuel consumption reduce indirect CO_2 emissions	-	appropriate adoption save water and increase productivity	Inappropriate adoption may reduce yields
					Reduce irrigation water demand reduce irrigation costs (fuel, water charges)	Alternate flood periods save water but increase weed density involving more labour
Soil-oriented practices (CA)	CA enhance climate resilient by increase soil quality while reduce indirect CO_2 emissions by reduction of fuel consumption	-	Minimum mechanization reduces indirect CO_2 emissions and production costs	-	Increased soil quality improves soil productivity (crop yields and residue biomass)	In the short term, the implementation of CA may lead yield penalties
	Added Organic matter, increase soil quality and SOC sequestration				Reduced soil disturbance may increase the costs of weed control products and labour	Residue retention in soils leads to social and income trade-offs –in fodder deficit areas
	Minimum soil disturbance reduces SOC loss through erosion				Improving soil quality benefits yield stability in the long-term	

Figure 5.1: Trade-off and synergies between CSA pillars identified in two CSA interventions

The definitions of climate-smartness of both indices are related to the performance of agronomic (water use efficiency, yields, yield stability) and biophysical (soil organic content, GHG emissions) indicators. Both definitions refer to the same spatial scale (cropping systems at different farm sizes) but differ in their temporal scale. The definition of climate-smartness is based on seasonal variability since the nexus between climate - irrigation demand - yields- GHG emissions can vary in short time scale, as was reflected in figure 3.5. For its part, the climate-smartness definition of SCSI considers trends in the relationship between yields and SOC at different time scales.

The scope of climate-smartness definitions helps to outline the narrative around these concepts. For instance, the definition of CSI includes the reduction of direct GHG emissions as a criterion of climate-smartness but omit indirect GHG emissions (energy consumption or fertilizers use) that are also reduced along with direct emissions. For its part, the SCSI based the definition of climate-smartness on SOC and yield trends but do not include crop profitability or the potential trade-off between carbon sequestration and N_2O increase (Guenet et al., 2021). Drawn an accurate interpretation of climate-smartness can be helpful to use the CSA concepts objectively, avoiding generalizations regarding CSA potential of interventions.

Defining what is "climate-smart" and in what context, is important to making distinctions regarding the use of the concept; once it is clearly defined, it can be used to compare the climate-smartness at different scales and explore the relativeness of climate-smartness. Results from Chapters 2 and 3 illustrate how climate-smartness can be compared across studies and draw some conclusions regarding CSA practices performance. For instance, AWD treatments scored higher climate-smartness than conventional irrigation, but the score of the same type of treatment can differ across sites. Results showed continuous flooding treatments in Asian countries are less climate-smart than the same treatments in Latin America (results chapter 3 and Tarlera et al. (2016) from chapter 2).

5.3 Measuring climate-smartness

Overall, "climate-smartness" inherently represent the achievement of CSA goals under and specific context. Given the strong context-dependency of CSA, providing an accurate measure of climate-smartness for each of the possible scenarios would be challenging and time-demanding. In addition, the meaning of climate-smart agriculture vary according to how the CSA goals are prioritized. This complexity in the definition of climate-smartness is transferred to its quantification. For instance, the literature reviewed in Chapter 2 showed GHGI in rice irrigated systems ranging from 0.01 to 7.6 kg CO_2/kg grain, indicating that some sites have more mitigation potential while other sites can prioritize other pillars before mitigation.

Another example is the challenge to use as a variable of climate-smartness soil indicators such as SOC. Some soil-oriented adaptation practices enhance SOC content to improve soil resilience and increase carbon sequestration (Lal, 2011). However, soils present different carbon saturation thresholds that depend on land-use history and soil proprieties, generating context-dependent carbon storage potential (Jackson et al., 2017; Stewart et al., 2009). Moreover, the use of SOC indicator as mitigation/adaptation indicator might require monitoring the dynamic of non-CO_2 gases, in particular, N_2O emissions. In their meta-analysis, Guenet et al. (2021), conclude that mitigation potential of soil-oriented practices that involve an increase of SOC might be overestimated if N_2O emissions are overlooked. The extent to which increased SOC might enhance N_2O emissions depend on factors like the C:N ratio and the water-soluble C content; which determine the substrate availability for the growth of nitrifiers and denitrifiers bacteria populations (Wang et al., 2021). A similar response occurs in paddy fields, where the addition of organic matter might enhance CH_4 emissions by the anoxic decomposition of organic compounds (Song et al., 2019). Despite the considerations needed to interpret carbon changes in spatial and temporal scales, the SOC represents a key indicator of soil quality, and is commonly used to communicate the impact of CSA interventions.

Several authors pointed out the need for robust metrics to contribute to the monitoring and evaluation of CSA (Duffy, 2017; FAO, 2013; Torquebiau et al., 2018). Like many other research areas, in CSA it remain a gap between science and real-world solutions (Dinesh et al., 2017). Standardized and easy-to-use metrics could assist in the decision-making process by identifying and assessing the readiness, suitability, and potential effectiveness of CSA interventions at different spatial and temporal scales (Neufeldt et al., 2013). The need for consistent metrics becomes more pertinent in the context of increasing investment in CSA-related projects and the potential use of the CSA concept to ”greenwash” unsustainable agricultural practices (Taylor, 2018; Zundel, 2017).

To date, few formal metrics for climate-smartness measurement are available. van Wijk et al. (2020) reviewed existing climate-smart agriculture assessment frameworks; the authors identified the degree to which each CSA pillar are addressed. For its part, Thornton et al. (2018) listed tools and approaches available for priority-setting in climate-smart agriculture research. The authors referenced the use of participatory approaches-based rankings, which are currently the only available options to provide quantitative measures of climate-smartness. Some of the features from the available quantitative metrics of climate-smartness (included the CSI and SCSI) are compared in Figure 5.2.

The Programming and Indicator Tool designed by CCAFS uses a typology of the indicators used for CSA monitoring. The typology refers to three types of indicators are Readiness/enabling environment, Process/output, and Outcome/impacts. According to this classification, CSI, SCSI and Result index (CSA-Res) can be classified as outcomes/impacts metrics since they aim to measure the impact or effectiveness of CSA interventions. Other metrics compared in table 5.2, are the multi-criteria ranking system for climate-smart agriculture technologies or the Climate-Smart Agriculture Prioritization Framework (CSA- PF). The CSA-PF was designed to provide a measure of readiness and is more focused on scoring the adoption and scaling potential of the CSA practices. It is important to call for more metrics to support each stage of CSA prioritization, scaling-up and monitoring.

Except for CSI and SCSI (which only cover agronomic/biophysical dimensions), the CSA metrics reviewed use agronomic, biophysical, social, and economic parameters. Encompassing all the possible dimensions of climate-smartness could bring accuracy to assessments; however, it can increase data requirements. Metrics like the Results Index (CSA-Res) and the Climate-Smart Agriculture Prioritization Framework (CSA-PF) include more than 20 indicators to cover socio-economic, gender, agronomic and biophysical aspects. The aforementioned indices bring the flexibility to select the most suitable indicators for each case; however, this characteristic hinders their use to compare CSA interventions across different sites (World Bank, 2016).Try to provide an overall measure of climate-smartness that include different dimensions is highly desirable; however, data requirements can discourage their use. Finding a balance between the definition of climate-smartness and its data requirements could faciliate the widespread use of future CSA metrics.

Name /Reference	Climate-Smart Agriculture country profile (World Bank, CIAT, et CATIE 2015)	Results Index (CSA-Res) World Bank. (2016)	Climate-Smart Agriculture Prioritization Framework (CSA- PF) (Andreu et al., 2017)	Multi-criteria ranking system for climate-smart agriculture technologies Wassmann et al.(2019)	Climate-Smartness Index (CSI) Arenas-Calle et al. (2019)	Soil-Climate-Smartness Index (SCSI) Arenas-Calle et al. (2021)
Rationale	Country-level experts assign scores to CSA indicators related to productivity, adaptation, and mitigation for select technologies in key production systems and agro-ecological zones	Metric to measure performance agricultural projects in terms of agricultural productivity, adaptation, and mitigation—both individually and jointly, based on the per cent of achievement of project targets for each indicator.	Stakeholder-driven process using participatory forums to evaluate and narrow-down locally-relevant CSA practices/options	Comparative assessment of scaling potentials of CSA-technologies based on a ranking system scoring by different stakeholder groups. Farmers and extension workers/policymakers as well as research-based scoring.	Composite index based on normalized indicators and aggregated to represent the trade-off between water-oriented adaptation practices and mitigation in irrigated systems.	Composite index based on normalized indicators and aggregated to represent the synergy between the outcomes from soil-oriented adaptation practices productivity
Dimensions covered (number of indicators/variables)	Biophysical/Agronomic /Socio-economic 9 "Smartness" categories (15)	Biophysical/Agronomic /Socio-economic (22)	Biophysical/Agronomic /Socio-economic (29)	Socio-economic/Agronomic (9)	Biophysical/ Agronomic (2)	Biophysical/ Agronomic (2)
scope	Regional/ Practices/production system	Farm/projects	Regional to sub-national	Potential scaling-up of CSA practices	Farm/regional	Farm/regional
Time scale	timeless	Timeless	timeless	timeless	seasonal	Minimum 3 year
Approach	Expert based/ Participatory methods	Expert based/Likert score	Cost-benefit analysis and participatory approach	Participatory methods	Composite index	Composite index
Agricultural activity target	Cropping/livestock	Cropping/livestock	CSA portfolios	Cropping/livestock	Cropping	Cropping
Index scale	-10 to 10	0 to 5	-10 to 10	0 to 90	-1 to 1	-1 to 1

Figure 5.2: Comparison of rankings and metrics for quantify climate-smartness

All the metrics in 5.2 present some flexibility regarding spatial scale, ranging from farm size to sub-national scale. In chapters 2, 3 and 4, the indices were calculated for indicators measured at plot scale; however, the indicators used in both indices can be upscaled and modelled at the farm (as in chapter 3) or regional levels. Moreover, CSI and SCSI can use official statistics at the national or sub-national level, for instance, data from FAOSTAT and AQUACROP. However, the of use national or regional data overlook the spatial variability of the regions (Prestele and Verburg, 2019).

A difference between the CSI and SCSI to other CSA metrics is the temporal dimension. While CSI measures climate-smartness at a seasonal scale, SCSI can score climate-smartness at different temporal scales for a 3-year period. For its part, others metrics like the Climate-Smart Agriculture country profile or Climate-Smart Agriculture Prioritization Framework do not take into account the changes over time, providing an timeless climate-smartness measure. For its part, the Results Index (CSA-Res) may imply a temporal location since is calculated as a function of the achievement of agronomic project targets set within the project schedule.

Despite the exponential use of indices in environmental science and sustainability in the last 30 years Greco et al. (2019),the CSI and SCSI are the first CSA-related composite indices. This difference between methodological approaches set the CSI and SCSI as a more independent measure of climate-smartness compared with participatory approaches. In addition, CSI and SCSI calculations are reproducible in any context as long as indicators are estimated/measured, which in the case of participatory approaches, could be unlikely find the same conditions in each case.

Moreover, indices such as SCSI represent a novel tool for climate-smartness assessments since represent the relationship between the magnitude of changes in SOC and yield with data variability, weighting the systematic changes over trends with high dispersion. Between the CSA metrics discussed, the SCSI is the metric integrates most effectively the temporal relativity of climate-smartness. This property of the SCSI can be useful for monitoring soil oriented strategies and CSA strategies with a long-term response like agroforestry or land rehabilitation.

The use of composite indices to measure climate-smartness could advantages and limitations. An advantage is that it can summarise multi-dimensional issues (e.g., trade-offs and synergies) and facilitate an integral interpretation of CSA indicators compared with individual analysis. Moreover, the indices facilitate the comparison across temporal and spatial scales and supports accountability of CSA projects. However, a poor index design can send misleading messages, promoting simplistic policy conclusions and leading to wrong policies (Nardo et al., 2005).

In the design of composite indices, the aggregation method represents the relation between the indicators OECD (2008). In the case of CSI and SCSI, the indices are aggregated by additive methods, which represent a compensatory effect of the indicators.

In this sense, it is expected this compensatory effect reflects the trade-offs/synergies between Water Productivity (WP) and Greenhouse Gas Intensity (GHGI) in CSI, (Equation. 2.5); while in SCSI is expected that reflect the synergies/trade-offs that occur between SOC and yield at different temporal scales (Equation 4.9). The additive aggregation and the normalization used in CSI and SCSI, allowed the indices to represent the trade-offs as negative values. Simple additive methods employed for CSI and SCSI may be unsuitable for metrics with a large number of indicators, that in such case will require more complex mathematical development.

The normalization is a required step for the design of composite indices; this step largely determines the applicability of the indices. The indicators of CSI and SCSI were normalized using the min-max normalization method, which re-scales the indicators based on references minimum and maximum values. This method allows a similar range for all the indicators (0 to 1) that ease their aggregation; however, the selection of reference max and min values represent a challenge. If the reference values are outliers, it can bias the index. On the contrary, if the reference values exclude the outliers, there is a probability to find normalized values >1 or <0, affecting the scale of the metric.(Talukder et al., 2017)

The selection of maximum reference value for SOC exposed this limitation of the min-max normalization method. Despite maximum SOC rate change (%) value being referenced from the literature, this value corresponds to treatment with unrealistic addition of organic amendment, making it unlikely to be common practice from the agronomic perspective, and could be considered an outlier. Although the potential limitations of max-min normalization, the calculation of the SCSI allows changing the references values according to the agronomic, climate or policy contexts. Another alternative is the use of a non-linear data transformation (i.e., logarithmic) in which the asymptote can be interpreted as saturation. Given that annual rates could be sensitive just in the short term and middle term, another alternative to the use of SOC rate changes (%) is to use cumulative change. In this sense, references values might set the boundaries in which systems reached a potential saturation of SOC.

5.4 Temporal changes on climate-smartness

The results from CSI and SCSI showed the temporal variability of climate-smartness, in particular, chapters 3 and 4. The CSI calculation in Chapter 2 exhibit the spatial variability of climate-smartness and its relativity. However, in Chapter 3, it was possible to evidence the temporal variability of the CSI across the cropping seasons in the short term. For its part, chapter 4, showed how the temporal dynamics of SOC were reflected in SCSI scores in the long-term. These results help to understand climate-smartness as a dynamic concept and showed the extent to which CSI and SCSI capture this property. Capturing the temporal dynamics of Climate-smartness is relevant because it can inform us about the progress of CSA intervention across time.

Results from chapter 3 showed CSI had an intra-seasonal fluctuation in all the irrigation treatments assessed (figure 3.2). This temporal variability of climate-smartness was more evident in treatments where water inputs depend more on rainfall than irrigation. Rainfed and irrigated agriculture depends on rainfall patterns to set the planting calendar, either because they depend entirely on rainfall (rainfed systems) or because the irrigation depends on rain-fed bodies of waters for water extraction (FAO, 2016). The GHG emissions in irrigated and rainfed systems also have temporal changes associated with climate variability across seasons. The results from chapter 3 coincide with some of the studies selected in chapter 2, where dry seasons led to a higher climate-smartness due to a reduction in emissions.

Assuming that performance of CSA interventions going to perform the same across the time based on current evidence ignores the the influence of future climate. Moreover, adaptation measures need to be adjusted in response to climate variability be effective; a fixed strategy contradicts the nature of the concept (Howden et al., 2007). For instance, farmers can decide how to implement AWD; if climate conditions allow a severe versions of AWD, could help to reduce GHG emission, but if the climate conditions are drier, farmers may choose a "safe"-AWD replacedtothat protect yields (Bouman et al., 2007). Measuring the inter-seasonal climate-smartness may help to inform about the resilience gained by CSA interventions, while long term analysis can provide information about the stability and adaptation of the systems to new climate conditions.

For its part, the SCSI evidenced a temporal dynamic of climate-smartness under soil-oriented adaptation practices, where the SCSI scores presented a gaussian-like distribution in the CA treatments (Figure 4.6). The design of SCSI captured the trend of the annual changes on SOC and yield, showing a systematic trend in all treatments. Both indicators presented the most significant changes during the ten years until reaching the highest peak peak; the dynamic of SOC was the main driver of CSI distribution observed in Figure 4.6. The curves of climate-smartness observed in Chapter 4 coincided with results from Sommer and Bossio (2014) who reported a decreasing by half of carbon sequestration rates after 30 years .

For its part, negative SCSI values in the first five years of CA implementation reflect the trade-offs related to yield penalties in the early stages of CA adoption mentioned in figure 5.1. Although negative values represent a lack of climate-smartness, they could come from expected or unavoidable temporal trade-offs that do not predetermine the overall impact of CA implementation in the long term. Thus, the SCSI score needs to be analysed in function of the time for was calculated to identify how likely or unusual can be a negative SCSI score. Contrary to CSI , where the climate-smartness is associated with high CSI scores, in SCSI large scores are technically unlikely at middle and long-term. However, negative values in the middle and long term may reflect carbon losses or yield decreasing, bring information about long-term trade-offs for a given CSA intervention.

Practices that may produce "temporal trade-offs" may not be attractive, especially for small farmers or subsistence farming, which do not have access to financial mechanisms to buffer production losses (i.e. crop insurance, subsidies). This issue evidence the importance of suitability assessments of CSA interventions, which represent the first step to identify and avoid potential trade-offs. Moreover, researchers and policy-makers need to work closely to ensure that agronomic limitations in the CSA adoption do not affect farmers economies, which may be achieved by the design of strong institutional and economic support during the time required that CSA adoption delivers sustainable benefits.

Combining both indices can provide a more detailed vision of the temporal dynamic of climate-smartness. While CSI can reflect the climate-smartness at the season scale, SCSI can indicate when this climate-smartness generate the highest impact across time. In this sense, developing long term model simulations of CSA implementation and CSA metrics would bring valuable information; questions like, how likely is a trade-off in early periods under a given context?; or how much time will take to observe positive changes in agricultural systems? may be answered from the modelling of different scenarios.

5.5 Limitations, recommendations, and future work

climate-smart agriculture labels. The indices proposed in this study are based on on-farm climate-smartness; however, off-farm activities also account for climate-smartness. Thus, indices like CSI and SCSI are just one piece of the puzzle. In this sense, a recommendation is to promote in the design of CSA metrics that integrate more dimensions (e.g., socio-economic) and off-farm agricultural activities.

A probable limitation to the design of integrative CSA metrics across multi-dimensions or on-farm/off-farm is the lack of studies that assess the trade-off and synergies beyond on-farm agronomic performance of the practices (Chandra et al., 2018). Thus,more research to improve the understanding of climate-smartness would be needed and fill the knowledge gaps regarding the analysis in the trade-off and synergies among CSA pillars in mixed-farm and livestock-cropping systems and off-farm activities such as markets, financial instruments, policies, and gender may contribute to reducing this limitation (Mccarthy et al., 2011). For instance, synergies between productivity and mitigation in post-harvest interventions (i.e., food transport, wasting management), or the potential trade-offs between human nutrition and access to markets in the long-term have been poorly covered by CSA-related studies (Torquebiau et al., 2018).

Maintaining the objectivity of CSA metrics is relevant to improving the reliability of the climate-smart agriculture promotion. Composite indices like CSI and SCSI can bring objectivity to climate-smartness assessments compared to participatory approaches since the calculation of indices is independent of subjective criteria and relies on the performance of indicators. However, the combination of both methodological approaches can produce transparent and democratic metrics.

Future CSA metrics can use participatory approaches to relevant indicators for stakeholders and communities and achieve concerted climate-smartness definitions in the territories. The democratisation of climate-smartness definitions may contribute to releasing the tensions identified by Taylor (2018). The author argues that adaptation needs may be varied across social actors (landless labourers, tenant farmers, producer associations) and the assumption of generalised adaptation needs across the actors overlooks potential trade-offs that affect unrepresented groups.

Due to the lack of available reproducible CSA metrics that can use model outcomes for their calculation, the combination of modelling tools and CSA metrics to elaborate climate-smartness assessments presented in chapter 3 represents a novel application. The modelling of metrics like CSI and SCSI is a step forward to the conventional studies that simulate the individual response of biophysical and agronomic indicators of CSA. In addition to the modelling tools, the innovative approaches used in recent years to compile and re-interpret CSA-related evidence increases the opportunities for broader and faster climate-smartness analysis. Initiatives like ERA (Evidence for Resilient Agriculture) platform or the Big data analytics for climate-smart agriculture in South Asia project (Big Data 2 CSA) are examples of such tools that can provide the data for future analysis using the CSI and SCSI.

The use of CSA metrics to analyse research findings and summarise them into standardised and reproducible metrics can support the communication of CSA-related evidence and generate clear messages regarding climate-smartness. For instance, it could bring rigorous information that is comprehensible and accessible for a broad public of stakeholders and also be used to support plans and policies. Thus, CSI and SCSI metrics could create bridges between the researchers that analyse the scientific evidence and transform it into reliable and objective messages used for the stakeholders to made informed decisions.

The thesis points out the potential of modelling tools for climate-smartness assessments. Results like the sensitivity analysis of CSI (Figure 3.5 and Figure 3.5) brings an example of the information that can be obtained from the combination of models and CSA metrics. Future work can go beyond the climate sensitivity analysis and assess climate-smartness under different Representative Concentration Pathways (RCPs) climate scenarios and regional climate model projections.The simulation of CSA indicators on changing climate can outline the interaction of such practices with climate and identify their potential adaptation.

Coupling of climate, soil and crop process-based models have a proven potential to simulate climate-smartness from an agronomic perspective in a broad range of scenarios and time scales. Moreover, model tools can support the analysis of trade-offs and synergies across multiple dimensions. An example these analysis is the toolkit that links agricultural, ecological and economic inputs to national level developmental goals for CSA prioritisation developed by (Dunnett et al., 2018).Similar analysis can use CSA-related indices and indicators that summarised agronomic data to be contrasted with economic and social indicators across the broad range of future climate scenarios.

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Appendix A

Complementary material Chapter 3

A.1 Daily fluxes (CH_4 and N_2O)

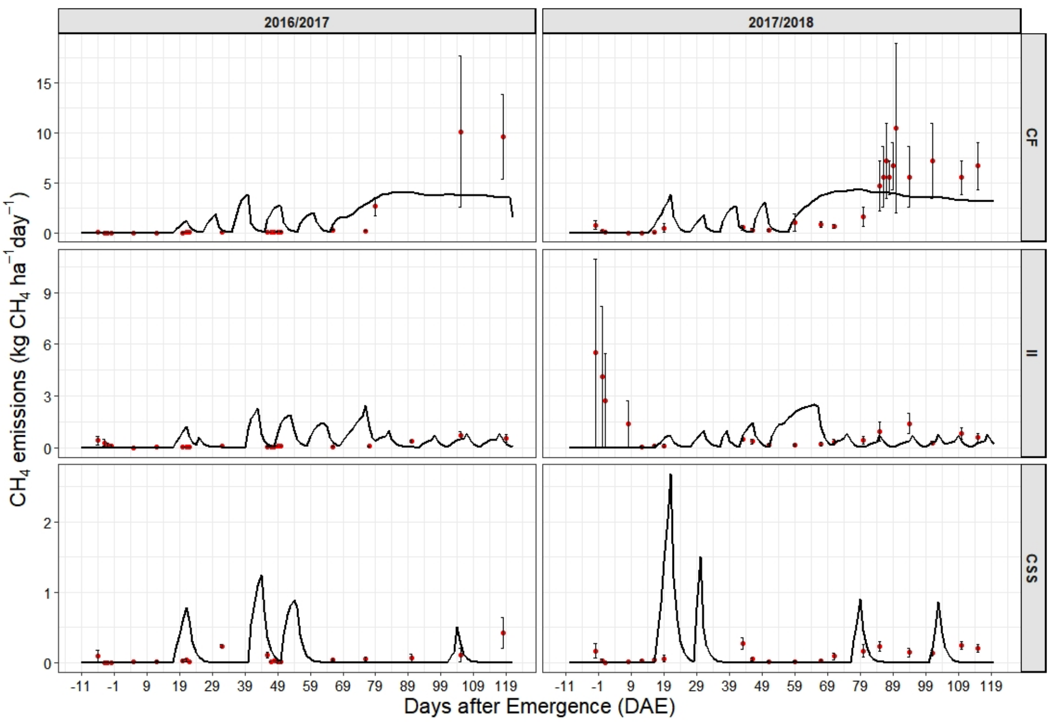

Figure A.1: . Observed (red dots) and simulated (black solid line) daily fluxes of methane (CH_4) of Continuous flooding (CF), Intermittent Irrigation (II), and Continuous soil saturation (CSS) irrigation treatments (vertical panels) during 2016/2017 and 2017/2018 cropping seasons (vertical panels)

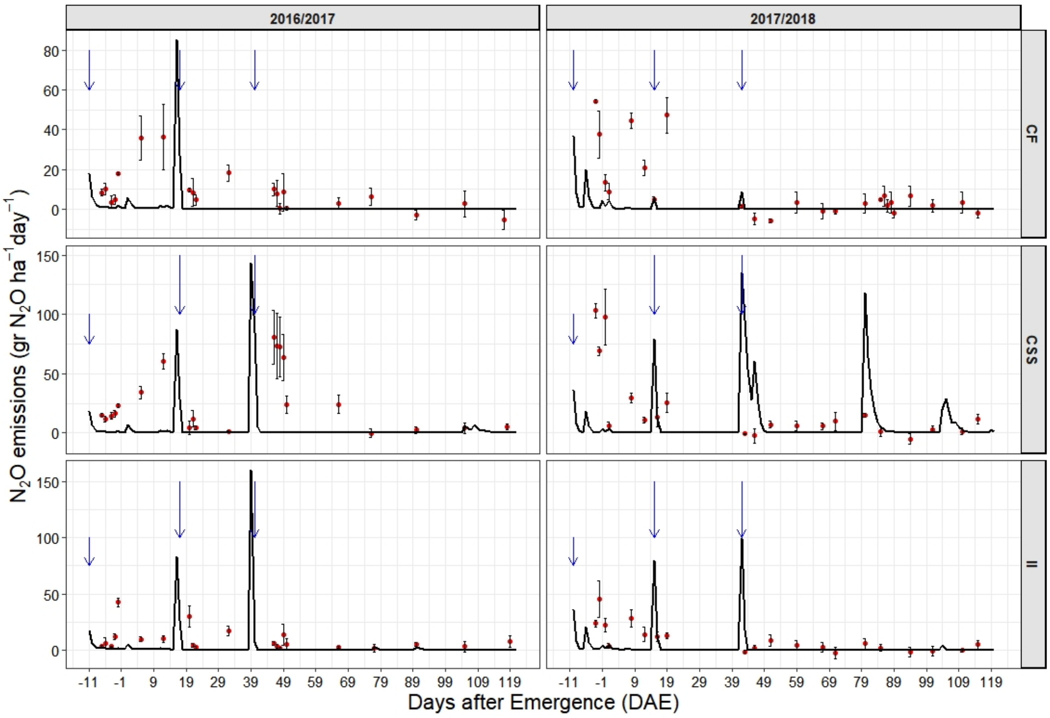

Figure A.2: Observed (red dots) and simulated (black solid line) daily fluxes of methane (N_2O) of Continuous flooding (CF), Intermittent Irrigation (II), and Continuous soil saturation (CSS) irrigation treatments (vertical panels) during 2016/2017 and 2017/2018 cropping seasons (vertical panels)

A.1.1 Cumulative GHG fluxes (kg/ha/season)

The cumulative fluxes of N_2O and CH_4 showed contrasting agreement with the observed data.

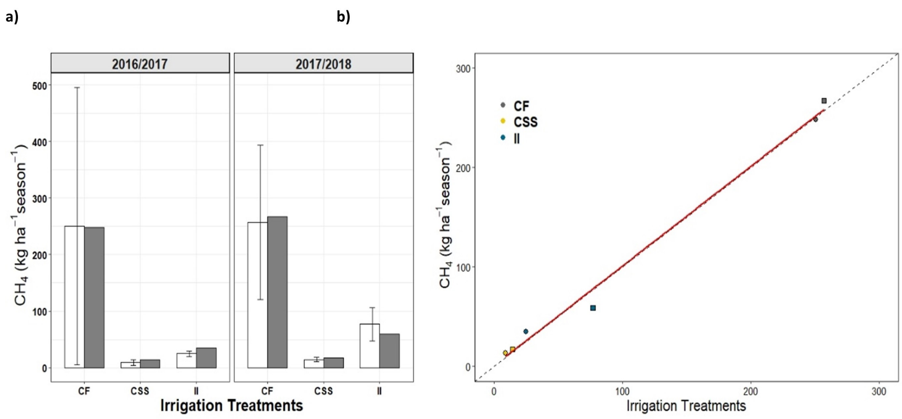

Figure A.3: Observed (with bars) and simulated (grey bars) seasonal cumulative fluxes of methane (a) and its regression (b) for Continuous flooding (CF), Intermittent Irrigation (II), and Continuous soil saturation (CSS) irrigation treatments. Circles represent data from 2016-2017 season and square from 2017-2018. Dashed line represents 1:1 relation of observed vs simulated data.

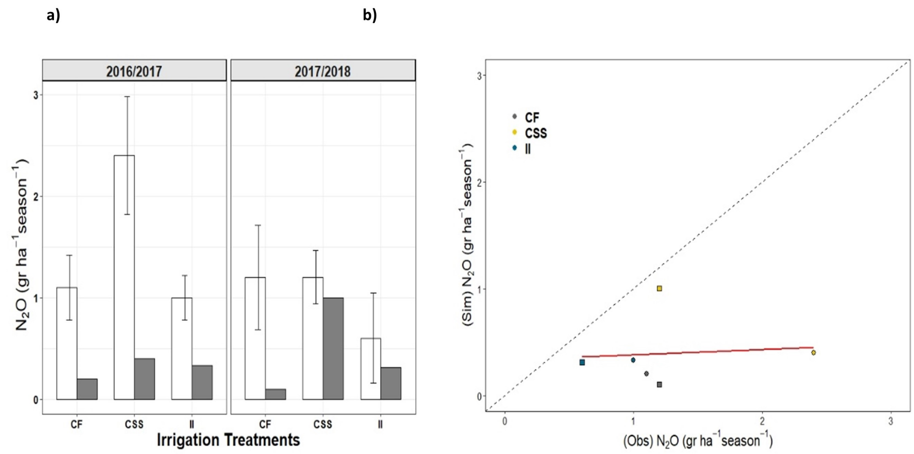

Figure A.4: Observed (with bars) and simulated (grey bars) seasonal cumulative fluxes of nitrous oxide (a) and its regression (b) for Continuous flooding (CF), Intermittent Irrigation (II), and Continuous soil saturation (CSS) irrigation treatments. Circles represent data from 2016-2017 season and square from 2017-2018. Dashed line represents 1:1 relation of observed vs simulated data.

A.1.2 water inputs (mm)

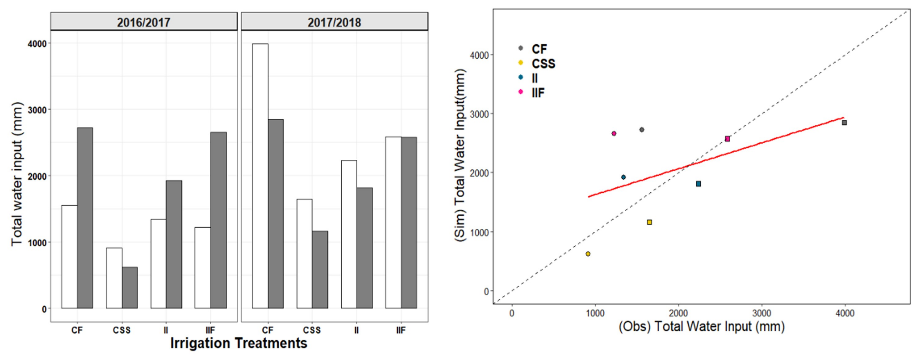

Figure A.5: Observed (with bars) and simulated (grey bars) seasonal cumulative water inputs based on irrigation and rainfall (a) and its regression (b) for Continuous flooding (CF), Intermittent Irrigation (II), and Continuous soil saturation (CSS) irrigation treatments. Circles represent data from 2016-2017 season and square from 2017-2018. Dashed line represents 1:1 relation of observed vs simulated data.