El Niño Southern Oscillation and decadal climate variability impacts on crop yields and adaptation value

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Received: 23 March 2021
Accepted: 15 June 2021

doi: 10.1079/PAVSNNR202116043

The electronic version of this article is the definitive one. It is located here: http://www.cabi.org/cabreviews

Abstract

Ocean-atmospheric phenomena (OAP) have been found to be associated with regional climate variability and, in turn, agricultural production. Previous research has shown that advance information on OAP and its climate implications could provide valuable opportunities to adjust agriculture practices. In this study, we review OAP effects on crop yields, covering both shorter-term El Niño Southern Oscillation (ENSO) and longer-term ocean-related decadal climate variability (DCV) phenomena, such as Pacific Decadal Oscillation (PDO), the Tropical Atlantic Gradient (TAG), and the West Pacific Warm Pool (WPWP). We review both statistical approaches and simulation models that have been used to assess OAP impacts on crop yields. Findings show heterogeneous impacts across crops, regions, OAP phases, and seasons. Evidence also indicates that more frequent and extreme OAP phases would damage agriculture. However, economic gains could be achieved via adaptation strategies responding to the early release of OAP phase information. Discussions on current knowledge gaps and future research issues are included.

Keywords: El Niño Southern Oscillation (ENSO), decadal climate variability (DCV), Pacific Decadal Oscillation (PDO), Tropical Atlantic Gradient (TAG), West Pacific Warm Pool (WPWP), crop yields, adaptation

Review Methodology: This paper reviews literature on the relationship between ocean-atmospheric phenomena (OAP), crop yields, and resulting agricultural sector economic welfare changes. The review focuses on the intersection of three types of inquiries, as illustrated in Fig. 1. We cover both shorter-term ENSO and longer-term decadal climate variability (DCV). To assemble our literature, we searched the following databases: Google Scholar, ResearchGate, and ScienceDirect using the following keywords: "El Niño southern oscillation" or "decadal climate variability" or "Pacific Decadal Oscillation" or "Tropical Atlantic Gradient" or "West Pacific Warm Pool," "crop yields" or "crop management," and/or "economic." Some additional criteria, including novelty, contribution, and citation count, were also used. We reviewed the retrieved literature in two steps. First, we focused on OAP effects on crop yields. Then we looked at adaptation possibilities and forecast values, hopefully providing insights into adaptive crop management and policymaking. Also, references identified by this method were checked for relevance. In turn, we selected 142 references for coverage and citation in this paper and classified those pieces in several ways, as shown in Table 1.

Introduction to ocean-induced climate variability and effects on agriculture

Agricultural productivity and its variability are highly influenced by weather conditions [1]. One set of factors affecting climate variability are those related to OAP. There are a number of classes of such OAP conditions. The most widely referenced one is El Niño Southern Oscillation (ENSO), but others have been covered by conditions identified under longer-term ocean-related decadal climate variability (DCV).

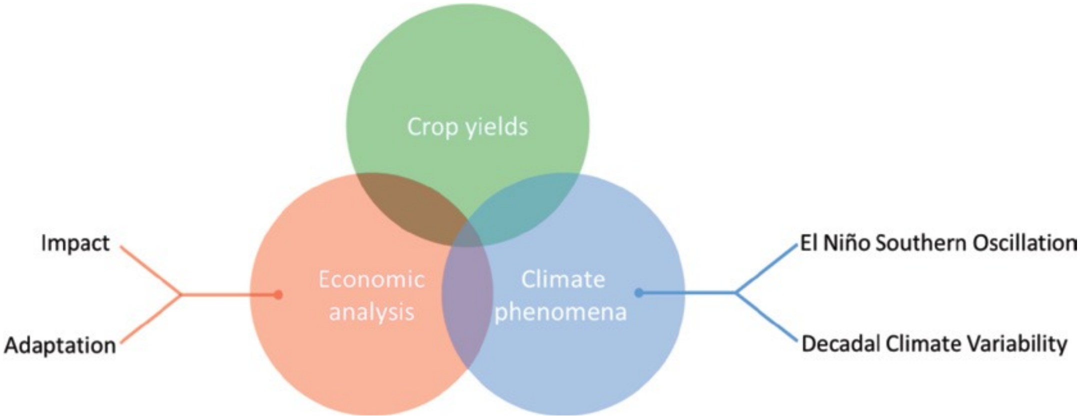

Figure 1. The scope of literature reviewed in this study.

Table 1. Reference number by category.

Category	Subcategory	Number of papers cited
By region	North America	48
	South America	6
	Asia	14
	Africa	3
	Europe	1
	Australia	10
	Multi-region/global	59
By ocean phenomena	El Niño Southern Oscillation (ENSO)	94
	Decadal climate variability (DCV)	27
	Both ENSO and DCV	10
	Other ocean phenomena	10
By topic	Impacts of ocean phenomena	65
	Both impacts and adaptation	40
	Other (prediction, experiment, etc.)	36
By year	Before 2000	34
	2000–2010	45
	2010–2020	62
Crops mentioned	Include but not limited to: Corn, Rice, Soybeans, Wheat, Hay, Cotton, Barley, Alfalfa Hay, Sugarcane	

El Niño Southern Oscillation (ENSO)

The often-discussed ENSO phenomenon refers to year-to-year fluctuations in equatorial Pacific sea surface temperatures (SST) and sea-level atmospheric pressure. ENSO has been found to have important influences on global interannual climate variability [2–5]. The Oceanic Niño Index (ONI) is commonly used to characterize ENSO phases and measures departures from normal SST in the eastern-central Pacific Ocean (Niño 3.4 region: 5°N–5°S latitude, 120°–170°W longitude) [6]. Figure 2 shows the ONI over time. Three phases exist, where an El Niño phase is designated when the ONI is at or above +0.5 for five consecutive months, a La Niña phase when the ONI is at or below −0.5 for five consecutive months, and the rest are identified as Neutral.

Many studies have linked ENSO phases with alterations in temperature and rainfall around the world. For example, in South America, El Niño brings warm and wet weather, causing flooding along the west coast when the event is strong but dry conditions in northern areas [8]. In North America, climate anomalies differ in both magnitude and geographic influence. El Niño leads to cooler and wetter winters in the southeast and southwest and warmer weather in the central and northern regions [9]. El Niño tends to be wetter in the U.S. southwest and drier in the northwest, while La Niña exerts opposite effects [10–12]. Additionally, El Niño is associated with severe drought in Central America in countries such as Mexico, Guatemala, Honduras, and El Salvador [13].

ENSO climate effects are not necessarily linear functions of ONI in that effects under strong El Niño phases are not just an amplification of effects in normal El Niño years. Also, La Niña effects are not perfect opposites of those under El Niño [14]. For instance, El Niño tends to have a much greater impact than does La Niña in some regions [15], such as (1) hotter and dryer climate plus droughts in South and Southeast Asia along with considerable spatial and seasonal

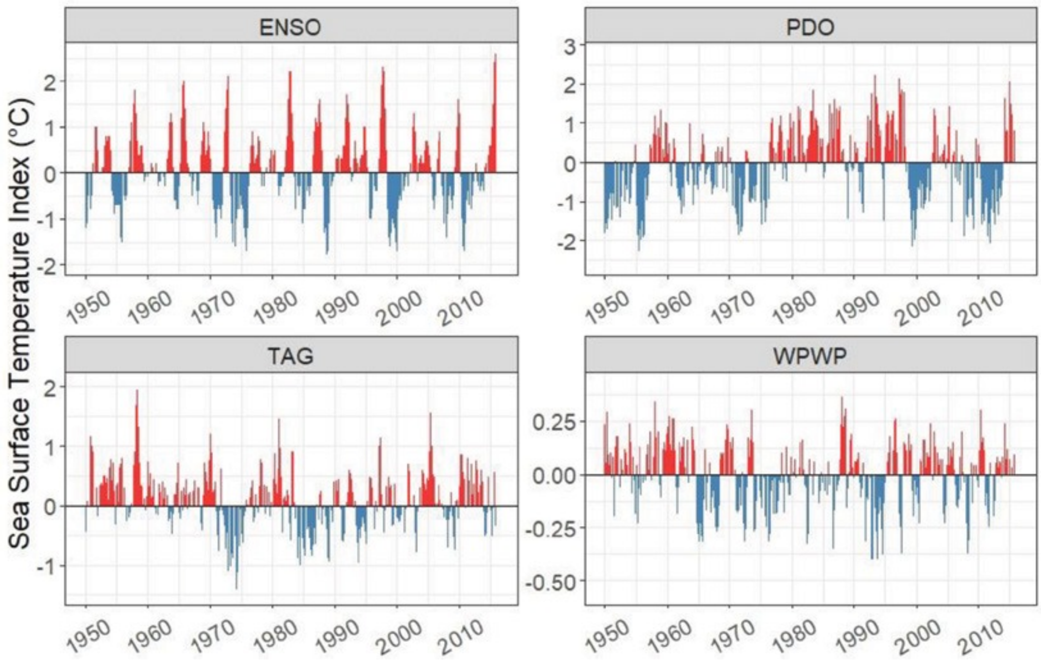

Figure 2. Comparison of ocean-induced climate variability indices. The graph is generated by the authors using data from National Oceanic and Atmospheric Administration [7].

variations [16]; (2) higher temperatures and below-average rainfall in eastern and southeastern Australia [17, 18]; and (3) droughts in southern Africa but increasing rainfall to northeastern Africa [19]. Changes associated with ENSO phases produce large climate variability from year to year and yield an increased incidence of crop failure, food insecurity, and economic loss to agriculture [8].

In addition, ENSO climate impacts are complicated and present different patterns even inside a country. For example, La Niña has been found to bring cooler temperatures and more precipitation to the northern United States and warmer, dryer weather to the south [14] during wintertime and causes droughts to the southwestern United States [20]. In China, the temperature is lower in the North and higher in the South during El Niño years [21].

However, these effects are likely to be altered by climate change [22, 23]. Namely, a number of studies have projected climate-induced changes in ENSO phenomena in the form of (1) more frequent occurrences of the El Niño and La Niña phases [22, 24, 25] and (2) more extreme occurrences of El Nino and, in cases, La Nina phases [26, 27]. In other words, more frequent and extreme non-neutral ENSO phases are expected as climate change proceeds due to effects on atmospheric convection in the eastern Pacific region [26]. This would cause larger effects on agricultural crop yields and their variability and would make agricultural economic conditions more variable. An early study done by Chen *et al.* [28] shows that welfare losses occur under such ENSO frequency or strength alterations. They also show that using ENSO forecasts in producer decision-making can partly offset the negative economic impact of the frequency and strength shifts.

Decadal climate variability (DCV)

Recently interest has grown regarding the effects of longer-term ocean conditions. Researchers have investigated the implications of longer-term ocean conditions on the terrestrial climate calling the field of inquiry decadal climate variability (DCV) [29, 30]. Studies have addressed DCV effects on crop yields [31–35]. Three major DCV phenomena have received substantial attention: the Pacific Decadal Oscillation (PDO) [36, 37], the Tropical Atlantic Gradient variability (TAG) [38, 39], and the West Pacific Warm Pool (WPWP) [40, 41].

The PDO involves Pacific SST anomalies in the region 20°N–65°N latitude, 125°E–100°W longitude [42]. The PDO is a long-lived El Niño-like pattern that involves changes in SST [36] and has two phases—positive (warm) and negative (cold) ones, and a PDO index has been developed [36]. In the twentieth century, PDO phases persisted for 20–30 years, while typical ENSO events persist for 8–15 months [43]. PDO phases have been found to have terrestrial influences. Murphy *et al.* [30] indicated that tree growth rates, the number of forest fires, and Columbia River flows in the U.S. Pacific Northwest vary with PDO phases. U.S west coast ocean salmon catch has been found to be greater during warm PDO phases than under cold phases [44].

The TAG, also known as a dipole mode of tropical Atlantic SSTs or the Atlantic Dipole, involves SST conditions in the Atlantic Ocean in the region falling between the tropical North (5°–20°N latitude, 30°–60°W longitude) and South (0°–20°S latitude, 30°W–10°E longitude) [42]. A TAG index has been developed and identifies positive (warm) and negative (cold) phases [39]. The TAG pattern changes at timescales of several seasons to a decade or multiple decades, with the primary oscillation occurring on a 12–13-year period [39]. The TAG pattern has been found to influence rainfall in Northeast Brazil and, more generally, across South America in the boreal spring [45, 46]. More broadly, it has been found to influence rainfall in West Africa, Atlantic hurricanes, water vapor influxes, and rainfall in the Southern, Central, and Midwestern United States [30, 39].

The WPWP, also known as the Indo-Pacific warm pool (IPWP), involves Pacific SST anomalies in the region falling between 20°S–20°N latitude and 90°–180°E longitude [41]. A WPWP index that identifies two WPWP phases (warm, cool) has been developed [47, 48]. Wang and Mehta [41] showed that WPWP phases can persist for several years to a decade or longer. Furthermore, WPWP SSTs have been found to be warming over the later part of the twentieth century and into the twenty-first century [40]. Specifically, Yan *et al.* [40] found that annual mean sea-surface temperature and the size of the warm pool increased from 1983 to 1987 and fluctuated after 1987, likely due to solar irradiance variabilities, ENSO events, volcanic activities, and global warming. Solomon and Jin [49] showed that the WPWP can amplify ENSO cycles. The changes in the Pacific warm pool have shown to be related to increased rainfall over Southeast Asia, Northern Australia, Southwest Africa and the Amazon, and drying over the west coast of the United States and Ecuador [50].

The values of the four OAP indices over time are presented in Fig. 2 using data from National Oceanic and Atmospheric Administration [7]. Table 2 indicates that the correlation coefficients of ENSO with PDO and TAG are significantly positive and that it is marginally negative with WPWP. The correlation coefficient between TAG and WPWP is 0.164 and is also statistically significant. Overall, the four indices show a certain degree of correlation.

ENSO phenomena effects on agriculture

A wide variety of studies have investigated the relationship between ENSO phases, climate, crop yields, adaptation, and economic impacts at varying scales.

Crop yield effects

For examining ENSO impacts on crop yields, two broad classes of methods have been used. First, studies have done econometric estimation over historical and observed data to infer relationships between ENSO events and crop yields [32, 51–53]. Second, crop growth simulation models have been operated under ENSO-related climate alterations to estimate ENSO influences on crop yields [9, 54, 55]. The major difference between these two approaches is that the statistical method also incorporates farm adaptation to the climate conditions while the simulation model isolates the climate effects of ENSO from other sources of yield alterations.

Both approaches have found that ENSO impacts differ across crops, regions, phases, and seasons [9, 52, 53]. Generally, studies indicate that about two-thirds of global cropland is impacted by ENSO-induced climate alterations, and about a third of global crop yield variability is explained by ENSO phase variation with the explanatory power reaching over 60% in some regions [55, 56]. Time of year of the growing period also matters. For instance, Nóia Júnior and Sentelhas [57] utilized a multi-simulation model approach involving the FAO-AZM, DSSAT, and APSIM crop models to determine the best sowing date for soybean and maize that minimizes the impact of ENSO. They found that the date varies with ENSO phase, location, and crop.

Global influences have been found [17, 51, 53, 55, 58, 59]. Strong yield influences have been identified in Africa, Southeast Asia, India, Australia, and parts of South and North America [17, 51, 55, 60]. Iizumi *et al.* [51] assessed ENSO impacts on gridded global-mean yields using a statistical bootstrap method and finds that El Niño increases global-mean soybean yields by 2.1–5.4% and alters yields of maize, rice, and wheat by −4.3% to +0.8%. They also found La Niña lower yields of soybean, maize, rice, and wheat by up to −4.5%. Anderson *et al.* [60] found ENSO phases alter the variance of both high- and low-production systems for maize, wheat, and soybean. Gutierrez [59] studied wheat yields and found La Niña reduces them. Chen *et al.* [58] found similar rice yield results and concluded that the effects are more intense during strong ENSO phases than those under average ENSO phases.

For the United States, ENSO influences on crop yields have been found to vary spatially. Legler *et al.* [9] simulated yields of seven field crops using the Erosion Productivity

Table 2. Correlation coefficients among studied ocean phenomena indices.

	PDO	TAG	WPWP	ENSO
PDO	–			
TAG	0.034	–		
WPWP	−0.003	0.164***	–	
ENSO	0.515***	0.093***	−0.067*	–

Note: the numbers indicate correlation coefficients between the indices presented in Figure 2. The significance levels are estimated using Pearson's p-value and are marked as follows: *P-value < 0.1, **P-value < 0.05, ***P-value < 0.01. The data were retrieved from National Oceanic and Atmospheric Administration [7].

Impact Calculator (EPIC) biophysical simulator and found La Niña enhances yields in the southeast and decreases them elsewhere with the effects likely associated with warmer and dryer conditions [61]. Legler *et al.* [9] also found El Niño cases yield different from those under neutral conditions in the southwestern United States since both dry and wet extremes are probable [62].

Many U.S. regional studies have examined local ENSO impacts [54, 63–68]. Corn Belt–based studies indicate positive impacts of El Niño and negative impacts of La Niña [47, 53, 54, 56]. Several studies have found major droughts are more likely to be associated with La Niña, while El Niño is associated with more rainfall and lower summer temperatures. Tack and Ubilava [67] found in the corn belt, La Niña and El Niño both increase downside risk and large yield ranges (−24% to 33% for El Niño and −25% to 36% for La Niña) [67]. Findings in the Marias River basin in Montana show under El Niño, yields of barley, oats, spring wheat, and winter wheat significantly increase by 5–15% relative to a neutral year, while under La Niña, the yield of alfalfa hay decreases by 6.57%, and oats yields fall by 8.79% [33]. In the southeastern United States, corn and tobacco yields have been found to be higher under La Niña but lower in years immediately following La Niña events [65]. Also, greater regional maize yields have been observed during the El Niño phase [69] with planting dates having an effect [55]. Woli *et al.* [70] found the ENSO effect significantly influences initial and terminal planting dates for peanuts in the southeastern United States.

Many studies have focused on ENSO effects on Asian climates and rice yields. El Niño has been found to create South Asian droughts [17]. Lower rice yields and production have been found under El Niño in Thailand [71], the Philippines [72, 73], Indonesia [74, 75], India [76], and Sri Lanka [77]. Slightly higher yield could be seen during La Niña, but El Niño has been found to have a much greater negative rice yield impact in Thailand than does La Niña [71]. Also, irrigated and rainfed crops have been found to be impacted differently, with yields on irrigated land being more impacted by temperature and rainfed yields being more influenced by precipitation [56, 78].

Yields in a number of other countries have been investigated. Studies have been done in Australia [79–81], South Africa [82], and South America [83]. El Niño has been found to bring heavy rains to south-eastern South America and eastern Africa, but droughts in Australia, India, and Indonesia. Cane *et al.* [82] found El Niño warm events are linked to below-average rainfall and corn yields in Zimbabwe. Low grain yields have been found to be associated with El Niño events in Australia, and higher yields were found in La Niña years [80, 81]. However, in Argentina, early season water stress along with low maize and wheat yields have generally been found to be more likely under La Niña [84]. Moreover, different regions in the same country have been found to present different patterns. For example, sugarcane yields tend to be higher under El Niño and La Niña and lower under neutral in northeastern Brazil, but contrasting trends are observed in southern Brazil [85].

Hill and Mjelde [86] argued that the impact of ENSO on crop yields is complicated and suggest incorporating other factors. A number of studies have done this. Some have incorporated other OAP phenomena, including the Indian Ocean Dipole (IOD), North Atlantic Oscillation (NAO), DCV, and the Arctic Oscillation (AO). They all found that considering additional OAP phenomena helps better explain ENSO effects on crop yields [33, 55, 63]. Hansen *et al.* [65] suggest both categorical and continuous measures of ENSO should be used so that ENSO strength information could be taken into account. Chen *et al.* [87] found including a finer phase definition improves yield estimations. Li *et al.* [88] and Rojas *et al.* [17] observed the negative impact of the El Niño and La Niña events could be partially mitigated if the event occurs in the La Niña dominant cycle, while the impact could be exacerbated if the event occurs during the El Niño dominant cycle. The possible reason may be that the crop phonological cycle also changes with the ENSO dominant cycle, and thus, crops in the La Niña dominant cycle are more low temperature tolerant.

While substantial ENSO phase effects on crop yields have been identified, there is growing interest in impacts on agricultural commodity prices. Studies indicate that prices of tropical-grown commodities such as vegetable oils [89], protein meals [90], and coffee varieties [91] are substantially affected. The price impact is found to be nonlinear and asymmetric [89]. Others have found that larger price variations are observed during El Niño and at the onset of an El Niño phase [92] than under other conditions. Price effects of ENSO on cereal grains have been found to be more complicated because cereal grains are primarily grown in temperate regions which are less affected by ENSO. Furthermore, losses in one region could be offset by gains in another region. For example, the international wheat price is found to increase at a higher rate after a La Niña shock than it decreases after an El Niño shock, with the price response to La Niña shocks being more persistent. In contrast, the ENSO effects on local wheat prices vary by region [51, 93].

As ENSO events influence crop yields and, in turn, sales revenue, welfare has also been shown to be affected [28, 58, 94]. Adams *et al.* [94] estimated that U.S. agricultural welfare is $1.5–1.7 billion lower under an El Niño phase relative to neutral and $2.2–6.5 billion less under a La Niña phase. Also, given evidence that climate change is likely to increase ENSO event frequency and strength [22], then this enhances the resulting economic damages, with Chen *et al.* [28] finding that more frequent ENSO events would lead to annual damages of $300–400 million in the United States with even larger damages when event strength increased. Economies of developing countries in Africa and Asia-Pacific within the tropical band have been found to be even more susceptible to ENSO shock with findings that up to a 2% growth reduction could result under El Niño [95].

Adaptation to ENSO information and their value

A number of studies have examined ways of adapting to ENSO-related forecast information [74, 75, 77, 82, 96–99]. Cane *et al.* [82], using a simulation model, showed ENSO information improves the accuracy of maize yield prediction in Zimbabwe, given that phase declaration is available well before crops are planted and cultivated. Such a lead time allows adaptation of crop mix and management to better accommodate the ENSO phase. Statistical methods such as nonlinear smooth transition autoregressive model [97, 100], principal component analysis [101], Neural Networks [102], random forest [103], and decision trees [98] have been used in efforts to improve the forecast ability. Guimarães Nobre *et al.* [98] showed ENSO phase information allows improved statistical forecasts of production shortages and excesses 5–6 months before the start of the European sugar beet planting. Hansen *et al.* [65] argued that using ENSO-based yield forecasts, farmers could modify practices such as cultivar selection, planting and harvesting dates, fertilizer amounts/timing, and irrigation schedules to reduce losses or take advantage of favorable conditions. Studies have found that the availability of ENSO information brings economic value to the agricultural sector since it is available soon enough to allow farmer crop mix and management adaptation [20, 104–108]. However, the ENSO forecast sometimes projects a wrong phase or weak events occur, and this complicates farmer decisions on whether to undertake adaptive actions [109, 110]. Thus a further understanding of ENSO dynamics is needed to improve the accuracy and reliability of ENSO forecast [111].

The main methods used to estimate the value of ENSO phase information have involved forms of economic simulation models. One common method has involved the use of a stochastic country-level agricultural sector model linked with a global trade model. In that case, the value of ENSO information has been calculated by comparing welfare effects with and without that information by adjusting crop yield probability distributions. Using that approach, Solow *et al.* [105] estimated that the average annual gain to the U.S. agricultural sector of a perfect forecast with full farmer adaptation would be over $300 million. Alternative forecast forms have also been considered. For example, Chen and McCarl [106] considered both the ENSO phase and associated event strength, finding that the forecasting value increases by twofold when adding the strength dimension. Similarly, Chen *et al.* [87] found that making the more refined Stone and Auliciems five-phase ENSO definition (defined as phase 1–5) would almost double the economic gain. Studies conducted for other parts of the world such as Canada [112], Mexico [113], Argentina [84], Australia [114], and sub-Saharan Africa [115] also found significant economic implications of well in advance ENSO information coupled with farmer adaptation. ENSO impacts have also been found at the regional level with Chen *et al.* [20], showing value in the joint management of water and agriculture. However, at the field or farm level, not all crops in all places have beneficial adaptations. Mjelde *et al.* [116] simulated an east-central Texas farm model finding that ENSO information has a value of $2.47–4.94/hectare for corn but little additional value for sorghum.

Decadal climate variability effects on agriculture

Studies have also been done on longer-term climate phenomena like the above discussed DCV phenomena.

DCV effect on crop yields

The effects of DCV have been studied in terms of the joint combination of phases of the PDO, TAG, and WPWP phenomena. In particular, given that each of the PDO, TAG, and WPWP phenomena has two phases, there are eight possible simultaneous combinations across them. The conventional notation uses positive (+) and negative (−) to represent warm and cool phases for the three phenomena where, for example, a declaration of (PDO−, TAG−, WPWP−) means all three phenomena are in the negative phase at that point in time.

Econometric panel data studies have shown that DCV joint phases have different influences on terrestrial climate in several U.S. regions and, in turn, on crop yields (e.g., see Jithitikulchai [117]). Jithitikulchai *et al.* [34,118] applied skew-normal regression and found that corn yields are lower in the Central, Northern Plains, and Southern Plains regions for most DCV phase combinations compared with the (PDO−, TAG−, WPWP−) case. They also found: (1) cotton yields fall in the Mountains and Southeast regions, especially during (PDO+, TAG−, WPWP−), (PDO+, TAG−, WPWP+), and (PDO+, TAG+, WPWP−) phase combinations; (2) soybean yields decrease in the Central, Northern Plains, and Southern Plains regions for almost all DCV phase combinations; (3) non-irrigated wheat yields experience decreases in the Northern Plains and Pacific regions especially for (PDO−, TAG−, WPWP+), (PDO+, TAG+, WPWP−), and (PDO+, TAG+, WPWP+); and (4) there are positive DCV impacts on yields such as for corn in the Central region under (PDO−, TAG−, WPWP+) and the Southern Plains under (PDO+, TAG−, WPWP−), (PDO+, TAG−, WPWP+), and (PDO+, TAG+, WPWP−). Similarly, Rhodes and McCarl [35] showed that when the (PDO+, TAG+, WPWP−) phase combination occurs, corn yields are lower by approximately 7% relative to the base case (PDO+, TAG+, WPWP+), while (PDO−, TAG−, WPWP−) reduces yields by about 3.5%. On the positive side, the (PDO+, TAG−, WPWP+) phase combination increases corn yields the most by about 47.5%. Sensitivity is highest for cotton and soybeans and lowest for hay and winter wheat.

In addition to nationwide DCV studies on crop yields, there are regional U.S. studies. Ding *et al.* [33] found DCV effects in the Marias River basin in Montana where: (1) barley yields under (PDO−, TAG+, WPWP+) decrease by 5–20% in southwestern and northeastern parts of the basin; (2) alfalfa hay shows significant increases in yields in most of the basin under (PDO+, TAG+, WPWP+), (PDO−, TAG+, WPWP+), and (PDO+, TAG+, WPWP−), except for yields in some counties in the southern Marias basin; (3) oats yields are mostly reduced with the range −2.5% to −35% relative to average yield under (PDO+, TAG−, WPWP−); (4) spring wheat yields increase by 2.5–25% in most of the counties under (PDO+, TAG+, WPWP−) and (PDO+, TAG+, WPWP+), while under (PDO+, TAG−, WPWP+) effects are mostly negative, ranging from −10% to −25%; (5) winter wheat yields decrease by 2.5–25% under (PDO+, TAG−, WPWP−) and (PDO+, TAG−, WPWP+) except for in the southwestern part; and (6) under (PDO+, TAG+, WPWP+), significant yield changes in winter wheat are positive ranging from 2.5% to 20% almost everywhere except Chouteau County. In the wider Missouri River basin, Mehta *et al.* [119] used the Environmental Policy Integrated Climate (EPIC) model to simulate yields of dryland corn and spring/winter wheat in the MRB in response to hydro-meteorological anomalies associated with three DCV phenomena. Their findings show that changes in corn yield in response to average values of PDO and TAG indices ranged from 5% to 30% of the average yield. Spring wheat yields also generally increased (decreased) by 5–20% in PDO+ (PDO−) and TAG− (TAG+) phases in response to average PDO and TAG indices. Huang and McCarl [31] used a hierarchical linear mixed-effects Bayesian model to study MRB county-level impacts on eight crops. They found that (1) (PDO+, TAG−, WPWP+) leads to the lowest mean yield for all crops compared to other phase combinations; (2) most crops except for corn and sorghum perform better under (PDO+, TAG+, WPWP+) than under other DCV phase combinations. In a Texas study, Ding *et al.* [32] found that the DCV impacts on Edwards Aquifer show decreases of 5–15% in wheat and non-irrigated sorghum yields under certain DCV phase combinations except for irrigated sorghum. Under (PDO+, TAG−, WPWP−), they found yields of corn, cotton, oats, sorghum, and wheat increase overall, with cotton yields increasing by as much as 67.25%.

To date, there are few studies addressing DCV effects on crop yields outside of the United States. Huang *et al.* [120] investigated DCV effects on rice yields in Africa and Asia. They found that rice yields are 7.36% higher when DCV status switches from (PDO−, TAG−, WPWP−) to (PDO−, TAG+, WPWP+). On the other hand, the rice yield is projected to be 75.68%, and 75.04% lower compared to the base scenario (PDO−, TAG−, WPWP−) under the (PDO−, TAG−, WPWP+) and (PDO+, TAG−, WPWP+), respectively. The results indicate that the rice yield tends to be lower during the WPWP+ phase when the study regions are estimated to have a higher temperature. An increase in temperatures was found to be a depressing factor in rice yields [121] as the higher temperature increases maintenance respiration rates, resulting in a reduction in the amount of assimilates available for growth and yield [122–124].

Adaptations to DCV information and their value

Advance information on DCV effects on climate and crop yields can provide information for crop mix and management adaptation. For example, farmers acting on the information can decrease the planted area of negatively affected crops and increase that of positively affected crops [31]. Some studies incorporate the DCV physical climate impacts on crop yields in the country- or regional-level agricultural sector models and then estimate the nature of adaptations and the economic value of gains from utilizing DCV information. Information on next year's DCV phase can be a perfect forecast or a conditional one giving probabilities of next year's DCV phase combinations as done in Fernandez *et al.* [125].

A nationwide U.S. study by Rhodes and McCarl [35] suggests that given a conditional probability forecast for next year's DCV phase, U.S. agricultural adaptations increase welfare by about $86 million annually. Furthermore, perfect DCV phase information increases welfare by approximately $1.1 billion annually. The resulting welfare gains are caused by crop mix and management adaptation under different DCV phases. Under conditional DCV information, the most significant net increase in hectares grown occurs when the previous year's phase combination is (PDO+, TAG−, WPWP+). Therein approximately 698,000 more hectares are planted than under the base case of no information. In contrast, a significant net decrease in hectares planted occurs when the previous year's phase combination is (PDO−, TAG+, WPWP−), with a total decrease of nearly 566,000 hectares. Alterations in crop mix are substantially larger under perfect information than under conditional information as outcomes are certain.

The values of DCV information have also been explored at the basin or aquifer scale. Net annual benefits in the Missouri River basin have been found to be $28.84 million given conditional DCV information and $82.30 million given perfect information [125]. The corresponding crop mix adaptation shows the largest crop mix adjustments when the current year is (PDO+, TAG−, WPWP−). In contrast, when the current year's DCV phase is (PDO+, TAG+, WPWP+), the crop mix adjustment is relatively small. Crops that appear more sensitive to DCV forecasts are alfalfa hay, barley, and oats. Differences in the magnitude of crop mix adaptation and the direction are also found in the Missouri River basin when switching from conditional forecasts of DCV phases to perfect DCV information. In a Texas study, Ding *et al.* [32] reported that the average economic value of using conditional DCV information in the Edwards Aquifer is around $1.52 million per year, while given perfect DCV information, it is $40.76 million per year. The crop mix for conditional forecasts shows: (1) decreases in the cornland area under (PDO−, TAG−, WPWP+), (PDO+, TAG+, WPWP−), (PDO−, TAG+, WPWP+), and (PDO+, TAG−, WPWP+); and (2) yield reductions in winter wheat and hay for all DCV scenarios except (PDO+,TAG−,WPWP−). Findings under perfect information are: (1) positive shifts in corn, cotton, carrot, and lettuce hectares under all DCV phase combinations; (2) decreases in cabbage under all DCV combinations; (3) decreases in sorghum under all cases except (PDO+,TAG+,WPWP−) and (PDO−,TAG+, WPWP+); and (4) decreases in winter wheat under all DCV phase combinations except (PDO+, TAG−, WPWP+). Ding *et al.* [32] further suggested that knowledge of phase information would enhance the overall level of production of corn, cotton, carrot, and lettuce in the Edwards Aquifer region.

Final remarks

This review summarizes studies on the effects of ENSO and DCV on crop yields and economic welfare. It also provides some agricultural adaptation insights along with estimates of the value of potential information, increasing actions for policymakers, agriculturalists, and ocean observers.

Studies on ocean effects on crop yields, crop adaptation, and economic welfare can be found at the global, national, and regional scales. The studies mainly use statistical approaches, crop simulators on yields, or mathematical optimization models to study adaptation and economic welfare. OAPs are found to have crop, location, and phase-dependent effects.

ENSO and DCV phenomena alter yields with effects varying by phases, location, crop types, and crop seasons. Decision-making studies show the early release of information on ENSO and DCV phases can provide the opportunity to adapt crop mix and crop management to increase the welfare derived from agricultural adaptations. Naturally, the extent of the benefits depends on the strength of the yield impacts and the precision of the forecasts of the phenomena. Results also show climate change may alter ENSO event frequency and strength in a way that diminishes sectoral welfare and makes forecast information more valuable.

There are several limitations of the current literature that point to possible research needs:

- The existing literature on DCV phenomena has mainly focused on U.S. crop yields, and there is a need to examine the consequences in other locations.
- To harness the value of the forecasts, there is a need to create regionalized farmer accessible information.
- Both ENSO and DCV approaches show improvements in values with more accurate climate/yield forecasts. Thus, there is a need to improve information release accuracy and lead time [59, 88].
- Adding information on phase strength may be desirable. For example, studies show more refined phase information [87, 126] or quantitative indices [127] appear valuable.
- There may be benefits from improving a wider variety of climate and socioeconomic factors in the value of information and types of adaptation modeling [56].
- Studies on crop impacts and associated adaptation economic values related to other ocean phenomena may be helpful to extend our understanding of their effects on future crop yields. This includes the Atlantic Multidecadal Oscillation [128–132], Indian Ocean Dipole [51, 133, 134], Interdecadal Pacific Oscillation [135], and the Madden-Julian Oscillation index [136].
- It would be worthwhile developing improved longer-term datasets on yields and climate so that longer-term phenomena can be more effectively studied [9, 71].
- It may be useful to work with decision-makers and farmers on their needs for and use of forecast and impact information to inform policymakers on ways to release information, so decision-makers can make better use of it [63, 73].
- It may be desirable to examine impacts, adaptation possibilities, and benefits in other climate-sensitive areas like aquaculture [137], water management [20], and livestock management [138].
- Future studies could look further into implications for market trading and insurance design [67, 68, 139].
- Since the three major DCV indices discussed in this review have some extent of correlation with ENSO [36, 45, 46, 49], further studies could assess and compare differences in DCV and ENSO impacts on crop yields and associated economic impacts.
- OAP studies could further address market implications for market incentives, input prices, and crop prices.
- Studies could be done to reveal and develop desirable adaptation strategies and marketing strategies under ENSO and DCV information [106].
- Studies could examine whether some forms of adaptations could lead to maladaptation where actions by one party reduce the welfare of others now or in the future [140].
- Researchers might explore possible effects of OAP information adaptation on co-benefits, including economic and non-economic benefits, such as creating employment, facilitating agriculture growth, improving income distribution, reducing poverty, enhancing water quality, improving biodiversity, and bolstering human health [141].

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