Received: 7 September 2022 | Accepted: 19 October 2022
DOI: 10.1002/wfp2.12052

RESEARCH ARTICLE

WFP WORLD FOOD POLICY | WILEY

Global coordination of wheat sowing: A possible policy against climate variability

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Funding information
H2020 Project MED-GOLD, Grant/Award Number: EU-776467

Abstract

Through an analysis of the sowing and harvesting times across all the regions of a tailored-for-wheat world geographic partition, we assess the temporal possibility of modifying the acreage of wheat crops in some regions in an attempt to offset the change in production caused by the El Niño Southern Oscillation (ENSO) in the others. Using a computational model able to handle the complexity of the global system of wheat markets, we found that the adoption of a policy of cooperation can smooth out the effects that ENSO would have on international markets. In particular, the optimal policy we found would bring back prices toward those observed in the neutral phase by reducing them up to about 11% with El Niño, and, on average, about 1% with La Niña. Such an optimal policy would be favorable, especially to the in-need part of the world population. Furthermore, we found that Central Asia is potentially the strategic area for policy implementation.

KEYWORDS

decentralized exchanges computational model, El Niño Southern Oscillation, international wheat markets, wheat yield variability, wheat acreage policy

1 | INTRODUCTION

Wheat is one of the four staple commodities nourishing a large part of the world population (Khoury et al., 2014). More than two thirds of global wheat is used for food, 20% for livestock feed, and another 3% to 5% for seed, industrial use, and other uses. The European Union (EU), China, and India are the major wheat-producing countries, with 40% to 50% of global wheat production. Nevertheless, the EU, China, and India are the top 3 wheat-consuming countries, with at least 40% of global consumption. On the other hand, African countries—mainly Northern Africa and Nigeria—and Southern and South-Eastern Asian countries are the major wheat-importing countries accounting for almost half of global wheat imports, while Russia, the EU, and the United States (US) account for over 40% of the export (Pittman et al., 2019).

Climate plays a significant role in the crop production process. In general, climate variation explains a third of global crop yield variability (Ray et al., 2015), and climate oscillations impact two-thirds of cropland area (Heino et al., 2018). In particular, El Niño Southern Oscillation (ENSO), as a large-scale climate phenomenon, produces a significant yield variation in half of all wheat harvested areas and several important crop-producing areas such as North America and Australia (Iizumi et al., 2014; Heino et al., 2020).

Like any other agricultural production, in official statistics (e.g., in the FAOSTAT production dataset), wheat yearly production is decomposed into two terms: Yield for each unit of land used and the size of the sowed areas. The dynamics of these two components reveal that fluctuations in wheat total production are mainly due to changes in the size of sowing areas rather than in yield.

The sharp yearly changes observed in the wheat crop areas brought us to the research question behind the present article. Can a short-run global policy concerning land planting areas, possibly supported by an international organization like FAO, help stabilize fluctuations in wheat's international markets?

Two elements contribute to the answer: Political aspects and technical feasibility. The political aspects concern the willingness of wheat-producing countries to cooperate to achieve the results. Such an achievement seems to be improbable at first. Nevertheless, as the current situation has proved, even during the Ukraine–Russia war, a sort of agreement on wheat exports has been concluded. Thus, we work under the ideal assumption that all the areas choose to cooperate.

Technical feasibility, in turn, has several other aspects. First, significant statistical relationships between ENSO and wheat yield should be found and estimated. Second, the estimates of ENSO effects, in combination with the timing of harvest, allow us to identify when the international market will be affected. Therefore, we can first evaluate the potential impact of an observed ENSO phase on the worldwide markets. Then, we can look for the not-affected areas that are about to sow and ask them to modify the quantity of land dedicated to wheat so that the change in their production balances the ENSO market effects. An illustrative example could help the understanding. Suppose country A sows in March and harvests in August, while country B sows in May and harvests in September. Suppose further that there is significant statistical evidence that if El Niño is active in April, production in A will decrease by 2% while production in B will not be affected. Now, if El Niño is detected in April, we know that in September (i.e., after A's harvesting month), wheat availability will likely decrease because of the reduction in A's production. However, if we are looking for a possible offsetting measure, we see that country B will sow in May (recall that we are presently in April), and its production will be available in October (i.e., after B's harvesting month). In this case, we could ask country B to sow more such that the reduction of A's production in September will be offset by the increase of B's production in October.

This possible solution also depends on the country's B skill to rearrange the planned land use in the desired way. In this article, we will not delve into this question but assume, as we did for the political issue, that it is possible to some extent.

Even under the two assumptions mentioned, answering our research question is still challenging. The heterogeneity of ENSO effects, in terms of magnitude and timing, and the asynchronous sowing times across the world make the international wheat system complex. We will attempt to drive the outcomes of such a complex system through coordinated policies in the remainder of this paper, which is organized as follows. We first position our work within the current literature in Section 2. Section 3 provides an overview of the international wheat markets (3.1), gives some technical details on the ENSO phenomenon (3.2), and presents the statistical analysis performed to identify ENSO effects on wheat production (3.3). Section 4 delves into ENSO and sowing timing to identify the geographic areas whose production can help offset the ENSO adverse market effects. Section 5 uses a computational model of the wheat global markets' system to measure the effects of ENSO on prices and exchanged quantities. In Section 6, the same model is used to identify the best policies to smooth out the previously identified market effects. Finally, some concluding remarks are given in Section 7.

2 | POSITIONING IN THE CURRENT LITERATURE

The present work falls within the broad literature analyzing the relationship between climate and food security. These two topics have been brought to the limelight for several decades, pushed by the climate change issue. Therefore, the literature is rich. The Food and Agriculture Organization (FAO) and the Intergovernmental Panel on Climate Change (IPCC) are the primary sources of information on the current state and evolution of these two crucial aspects of humanity (see FAO et al., 2022; ICPP, 2022, for their latest reports, and their website for updates).

At a less general level, the strands of literature relevant to the present work focus on the following:

(i) the effects of (changing) climate on food production that mostly focuses on the impact of climate variability on crop yields (Abril-Salcedo et al., 2020; Ceglar et al., 2017; Chavas et al., 2018; Creti et al., 2021; Heino et al., 2020; Iizumi et al., 2014; Najafi et al., 2020; Ubilava, 2017; 2018; Yuan & Yamagata, 2015).

(ii) the link between food production and food availability, which mostly focuses on the role of the network topology in smoothing the effects of local and global shocks (Dong et al., 2018; Fair et al., 2017; Gutirrez-Moya et al., 2021).

(iii) the problem of food prices and, therefore, food accessibility. that focuses on causes, effects, and solutions of the uneven food price dynamics (Bellemare, 2015; Janzen et al., 2014; Laborde et al., 2019; Luo & Tanaka, 2021; Martin & Glauber, 2020; Pieters & Swinnen, 2016; Tadesse et al., 2014; Thompson et al., 2012; von Braun & Tadesse, 2012)

The present paper is the result of a research project that touches on all three above items.

The first effort of the work we have been doing was to set up a geographic partitioning of the world that allows for the international investigation of wheat markets. The studies surveyed on item (i) investigate either global or local effects of ENSO on wheat yield. Our first contribution is the analysis of the same relationship by performing a statistical analysis of ENSO effects on wheat yield (and, therefore, on production) on the geographic areas making up our partition, that is, in-between local and global geographic scales. Furthermore, beyond the quantitative assessment of these effects, we analyze their timing, which, together with sowing times, provide the cornerstones of the present work.

Second, we use a computational model where the regions of our world partition interact with each other to buy and sell wheat. Therefore, using simulations, we can analyze the dynamics of the network of exchanges among our geographic entities. This step enables us to perform an analysis similar to those surveyed in item (ii). Furthermore, because our model outputs include the dynamics of wheat prices on international markets, we are also able to make considerations pertinent to item (iii). In particular, in this paper, we will measure the change in costs caused by El Niño and La Niña, especially in those areas that need to import wheat.

From a methodological point of view, we think our work is akin to Ge et al. (2021). These authors build an agent-based global trade model where agents are countries that produce and trade food items. Moreover, they use data from the FAO food and balance database concerning 165 countries and 91 food commodities. The model runs on a yearly base covering the period 2000–2013. In practice, they measure the amount of macro (calories and fat) and micro (vitamin A, iron, zinc) nutrients available in each considered country under different levels of the global trade network "carrying capacity" tuned by a parameter that they call trade saturation.

In the present work, we also use a model where geographic entities are treated as agents that produce and trade wheat through well-identified import and export hubs. We also use the FAOSTAT data to calibrate our model, though in a more extended period (1993–2016). Differently from Ge et al. (2021), our model runs monthly because the ENSO phase is established month by month. Moreover, we do not use simulations to compare the model outputs at different levels of the trade network carrying capacity. Instead, we use simulations to assess the effectiveness of a coordinated policy to balance the adverse effects of climate variability. The allocation of wheat is performed by a standard market mechanism where supply is affected by ENSO, and buyers share their demand among the various markets according to their needs and the past unit cost (i.e., price plus transport costs) observed on them.

The present paper builds on our previous work, where we identified geographic areas and ENSO effects and coded the computational model (Di Giuseppe et al., 2022; Giulioni, 2018; Giulioni et al., 2019). Its original contribution is to implement a feedback loop between the evaluation of results and the change in simulation inputs that allows the identification of the most effective policy to offset the ENSO effects on international markets. We think this is the main contribution of this work to the literature because we have not yet encountered other papers identifying and evaluating policies aiming at smoothing out the effect of a recurrent climatic phenomenon like ENSO.

3 | DATA AND METHODOLOGY

In this section, we will describe the relevant features of the two elements of this article: The international wheat markets and the El Niño Southern Oscillation phenomenon.

3.1 | Wheat production and uses

It is not easy to model a comprehensive representation of wheat production and uses. Wheat is produced in most countries worldwide, and building a dynamic model including more than a hundred countries is a rather complicated task. Furthermore, because our aim is modeling the international wheat market, a coarse partitioning of the world areas could be more suitable to achieve our goal. The FAOSTAT database provides countries' data in addition to several levels of aggregation grouped in two sections labeled “regions” and “special groups.” The “regions” section is composed of three aggregation levels: (1) The whole world, (2) the continental level, and (3) a partition in subcontinental areas, each including a few nearby countries. The “special groups” section provides aggregates for the European Union, least developed countries, and so forth.

In this study, we take as a reference the subcontinental aggregation included in the FAOSTAT “regions” section. However, we pull out from some subcontinental areas these countries that are particularly relevant in the world wheat-producing system, in particular, the United States, India, Pakistan, Russian Federation, and China. We also aggregate the Caribbean to Central America because of the small traded quantities. At the end of this review process, we end up with a world partitioning of 23 areas/countries. They are listed as the row headings in Figure 1. The colored rows of the figure give a dynamic representation of the role of the areas/countries in the international wheat markets. We compute the difference between production and uses for each year from 1992 to 2016. In the case of excess production, the area/country can provide wheat to others. On the contrary, it signals the need to gather wheat on the international markets to fulfill domestic uses.

In Figure 1, we use colors to ease a glance assessment of each area/country's excess demand time evolution. Shades of green denote excess production, whereas shades of blue denote excess demand. From the figure, we can assess, for example, that the African areas needed to import wheat during the entire period and that they never could offer their wheat production on international markets. In particular, demand was strong and persistent in Northern Africa for the period (it has a dark blue row) whereas it has an increasing trend in Eastern and Western Africa (their rows become darker as time progresses). On the other hand, the United States, Northern America, Western Europe, and Oceania rows are dominated by green. They are, therefore, major wheat suppliers, and we deduce they play a central role in international markets. Moreover, according to Figure 1, the Russian Federation and Eastern Europe have progressively gained importance as international wheat suppliers since the first quinquennium of the current century.

As hinted above, in a previous paper, we have built a computational model named CMS-wheat model that is able to simulate the dynamics of the just-described system. It is worth mentioning that the CMS-wheat model has turned out to be able to reproduce the price dynamics of monthly prices at the main US markets (Giulioni et al., 2019). In our model, each “relevant producer” organizes a market where to sell the produced wheat. Each market receives a share of domestic and foreign demands. In fact, at each time step, each area/country splits its wheat demand according to the unit purchasing cost (also including transportation costs) recorded in the past on the various markets. The “relevant producer” quote at the beginning of this paragraph needs a qualification. Let us define an irrelevant producer at the international level, an area that has never had an excess of production. In Figure 1, these areas are marked with an asterisk and can be easily identified because they never have a green portion in their row. Consequently, we assume that the production of these areas is used only domestically, and their excess demand is directed to foreign areas/countries. Note that 11 of the 23 areas/countries are in this situation, and we will refer to them as the “in-need” areas. Therefore, the remaining

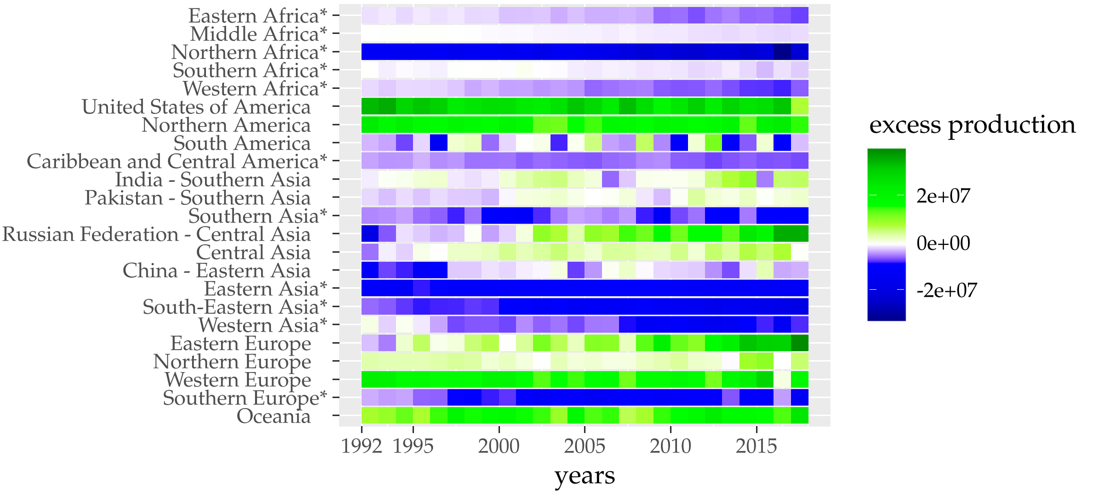

FIGURE 1 A dynamic representation of excess production. * denotes areas characterized by a persistent negative excess demand

12 areas/countries are "relevant producers," and their productions and demands are entirely supplied to the CMS-wheat model as inputs.

Net demands from the 11 in-need areas together with the (gross) ones from the other 12 areas/countries meet the relevant producers' supply in the 12 markets organized by the latter. Therefore, the model outcome is composed of 12 wheat prices (one for each international market) and the allocation of the world production among the 23 demanding areas at each time step. A time step of our model corresponds to a month. Unfortunately, despite providing monthly data, we often have to aggregate our simulation on a yearly base in order to make a comparison with the available real-world data.

3.2 | ENSO phenomenon

ENSO is a coupled oceanic-atmospheric phenomenon that develops in late boreal summer in the portion of the East-Central equatorial Pacific Ocean bounded by the following geographic coordinates: 5°S to 5°N; 170°W to 120°W. ENSO is a large-scale oscillation of seas surface temperatures that reaches an intensity peak in the winter and dissipates a few months later, during Spring. Such an oscillation directly forces weather regimes in the Pacific region and influences extratropical climate through teleconnection mechanisms (Hu et al., 2020).

ENSO can modify the distribution of precipitation and temperature patterns, then ecosystems worldwide. Often, ENSO has adverse effects on crop production, see, for example, Iizumi et al. (2014) or Rojas et al. (2014).

Using the Sea Surface Temperature Anomalies (SSTA), each month (or more precisely, each moving quarter) is classified into three phases that make up the ENSO phenomenon: El Niño (warm), La Niña (cold), and Neutral.[1] We have used such phases during the statistical analysis of the relationship between ENSO and wheat production (Di Giuseppe et al., 2022). For the

[1]See https://www.ncei.noaa.gov/access/monitoring/enso/sst for details.

readers' convenience, some details of our methodological approach are reported in the following section.

3.3 | The statistical identification of ENSO effects on wheat production

We performed a statistical analysis to detect ENSO effects on wheat production by estimating the impact of the warm (El Niño) and cold (La Niña) phases against the neutral state. The analysis considers 23 wheat producers: 18 macro-regions and 5 countries in both Hemispheres. In particular, we estimate the yield of each producer after accounting for different time lags of ENSO during the wheat-growing season. To this end, the length of the growing period is calculated from the Global Crop Planting Dates (GCPD) dataset (Sacks et al., 2010) by identifying those months most represented by planting (gathering) dates.

We adopt the one-way robust ANOVA regression model to estimate the wheat yield-ENSO correlation. In our framework, the dependent variable is the wheat detrended yield, calculated by dividing the residuals of local polynomial regression by the corresponding fitted values. On the other hand, we consider the Oceanic Ninõ Index (ONI)[2] as a predictor, that provides a classification of sea surface temperature in the *Nino-3.4* region of the Pacific Ocean. This classification corresponds to the three ENSO phases of El Niño, La Niña, and Neutral. Because of unequal sample sizes and differences in skewness among the groups, we adopt the robust version of ANOVA.

With the robust one-way ANOVA, we estimate the value of the percentage difference in yield between El Niño and Neutral, La Niña, and Neutral through the Wilcox post hoc test of multiple pairwise comparisons between the variances of each group. Finally, we select the strongest effect among those quarters of ENSO that result to be statistically significant. The reader can find major details of the approach adopted in our precedent work (Di Giuseppe et al., 2022). The estimated ENSO effects on wheat production are reported in Table 1.

4 | EMPIRICAL APPLICATION

4.1 | Timing of ENSO effects and growing seasons

To perform policy analysis, we need a concurrent examination of ENSO effects and wheat growing season timing. The latter is presented in Figure 2.

The black segments in the figure identify the wheat-growing periods such that every area begins the sowing at the left end and starts harvesting at the right segment end.[3] More formally, we identify the starting point of the segment with t_0 and the endpoint with t_T. Red and blue segments identify the El Niño and La Niña quarters that affect production, respectively. Whether the production of an area will be affected or not is known at the end of the quarter (identified with a circle in the figure). We will denote the corresponding time with $t_{\tilde{N}}$. Looking at Figure 2,

[2]ONI (version 5) definition and historical data that are released by the National Oceanic and Atmospheric Administration - Climatic Prediction Center (NOAA) and made available from https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php

[3]The harvest is typically done after the end of the growing season.

TABLE 1 Estimated effect of ENSO and wheat yield correlation

	El Niño effect (%)	La Niña effect (%)
Northern Hemisphere		
Northern Africa	−5.70	+3.95
Eastern Africa	+0.43	
Central America	−3.00	
United States		+0.23
Southern Asia	+4.63	−7.32
India	−3.37	+1.26
China	−1.78	+0.49
Eastern Europe		−6.76
Southern Hemisphere		
South America	−3.01	
Oceania	−12.54	+6.79

Note: *Effect* indicates the percentage change of yield during El Niño and La Niña with respect to the Neutral phase.

we can observe that whether the production will be affected or not is usually known during the growing period ($t_0 \leq t_{\tilde{N}} \leq t_T$). Exceptions are Eastern Africa and China in case of El Niño because they have the new in advance ($t_{\tilde{N}} < t_0$), and India, again in case of El Niño, that will observe the ENSO phase the month after the end of the growing season, that is, during the harvesting period.

4.2 | Time: a necessary condition for sowing policies

The just discussed timing is required to identify optimal policies because the more the effect gets known in advance of harvesting, the greater the possibilities to manage for weakening potential adverse effects.

The sowing time is particularly important. If $t_{\tilde{N}} < t_0$, domestic policies are possible. Otherwise, the viability of cooperation with other areas can be evaluated.

This paper focuses in particular on this possibility. In this respect, for each area that will know after sowing that its production will be affected by ENSO (i.e., having $t_{\tilde{N}} \geq t_0$), we check if other areas can help. We require the following two conditions for this to be possible: The potential helping area (i) sows after $t_{\tilde{N}}$, and (ii) it is not itself affected by ENSO. The potential effectiveness of a possible help is evaluated by looking at the harvesting time of helping areas. Such potential effectiveness fades away with the lengthening of the time gap between the helping and the affected area harvesting times. These figures for the case of El Niño are displayed in Table 2 and visually represented in Figure 3. The same information in the case of la Niña is reported in Table 3 and Figure 4.

Figures in Tables 2 and 3 expresses the number of months. In particular, in line with the notation introduced above, t_0, t_{T+} and $t_{\tilde{N}}$, identify the month in which sowing, harvesting[4] and

[4]The plus sign in the lower script highlight the harvest is collected after the end of the growing season which was previously identified with t_T.

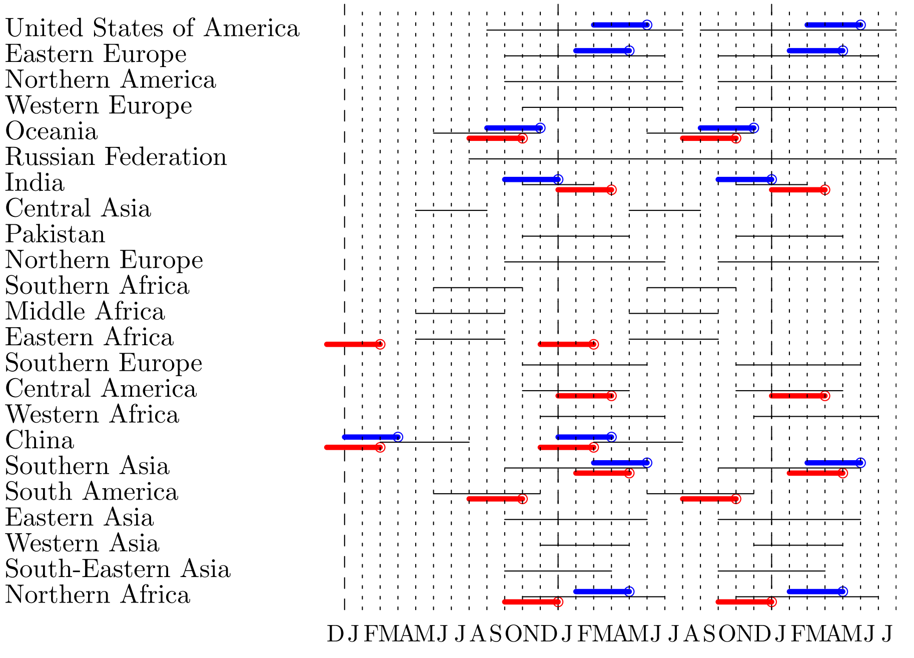

FIGURE 2 Wheat growing period and timing of ENSO effects

the ENSO phase happen respectively. Months are associated with integers in the usual manner, that is, 1 for January, 2 for February, and so on. The last two columns also express months, but the figures here mean months elapsed between two events. The second last column gives the count of months between the helping area sowing and the month the affected area discovers its production will be affected by ENSO. The larger this figure, the more time is available for the helping area to organize the sowing phase. The last column reports the monthly time lag between the helping area and the affected area harvest. It is the most important value because it denotes the time at which the policy effects arrive on the international markets with respect to the ENSO effect. The smaller the figure is, the better the possibility of offsetting the ENSO effect. Tables 2 and 3 report those helping countries whose delay is lower or equal to 6 months. A visual representation of the affected-helping areas' figure is also given in Figures 3 and 4 for El Niño and La Niña, respectively. In these figures, the links on the left-hand side show those areas that are significantly affected by ENSO and the timing of the effects. In addition, the estimated effect (i.e., the percentage change in yield) is given in brackets. On the right side the helping areas are listed together with their potential links. The thickness of the links marks of the effectiveness of the help, with thicker lines denoting shorter periods between the two harvests. Normally the helping area harvests after the affected area, except for one case in which the timing is inverted: the Eastern Africa - Central Asia link under El Niño. This case is identified with a dashed line in Figure 3. It is worth noting that this is a particularly favorable situation for the policymakers because the wheat production in the helping area has been already harvested when the needs of affected areas are shown. Furthermore, Figure 3 reveals another distinctive feature concerning China and Eastern Africa: the affected-helping link has the same area at its ends. This means that domestic policies are possible because the El Niño effect is known in advance of seeding.

TABLE 2 Possible help in case of El Niño

Affected area	t_0^A	t_{T+}^A	$t_{\tilde{N}}^A$	Helping area	t_0^H	t_{T+}^H	$t_0^H - t_{\tilde{N}}^A$	$t_{T+}^H - t_{T+}^A$
Eastern Africa	5	10	2	Central Asia	5	9	3	-1
"				Eastern Africa	5	10	3	0
Northern Africa	11	7	12	Central Asia	5	9	5	2
Central America	11	5	3	Central Asia	5	9	2	4
South America	6	12	10	Pakistan	11	5	1	5
Southern Asia	10	6	4	Central Asia	5	9	1	3
Oceania	6	12	10	Pakistan	11	5	1	5
India	11	3	3	Central Asia	5	9	2	6
China	3	8	2	China	3	8	1	0
"				Central Asia	5	9	3	1

Note: t_0 = sowing month, t_{T+} = harvesting month, $t_{\tilde{N}}$ = last month of El Niño affecting quarter. Superscript: A = affected area, H = helping area.

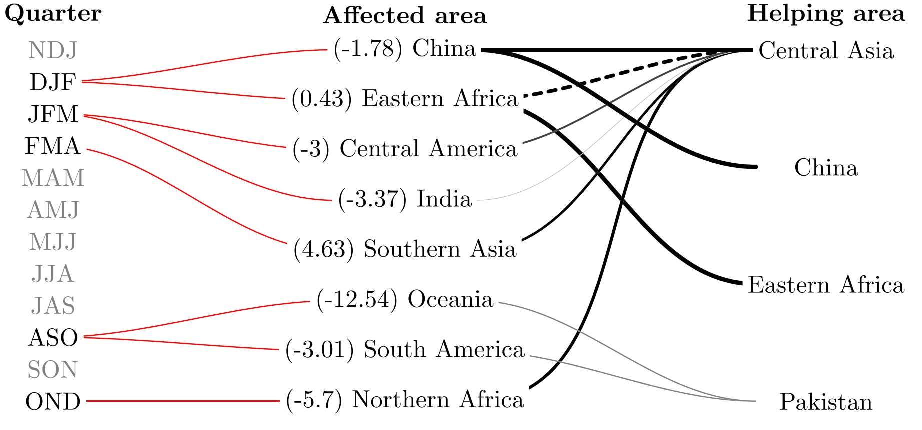

FIGURE 3 Visualization of possible helping areas in case of El Niño

At a glance, Figures 3 and 4 reveal that Central Asia is the major helping area satisfying the two-time requirements for giving help both in the case of El Niño and La Niña. In addition, Pakistan could have a role in the case of El Niño while South America in the case of La Niña. Nevertheless, these two latter wheat-producing areas have a weak potential effect because of the delay with which their productions arrive on the market. Therefore, Central Asia has a prominent role from the timing point of view, having marked links with several affected areas. Once our attention is pointed to Central Asia, we discover from Tables 2 and 3 that it sows after the news that wheat production in Eastern Africa, China, Northern Africa, Eastern Europe (and some more) will be affected by the ENSO. Moreover, most importantly, its production arrives on the markets 1 month in advance of that of Eastern Africa, 1 month after China, 2 months after Northern Africa and Eastern Europe, 3 months after Southern Asia, and so on.

TABLE 3 Possible help in case of La Niña

Affected area	t_0^A	t_{T+}^A	$t_{\tilde{N}}^A$	Helping area	t_0^H	t_{T+}^H	$t_0^H - t_{\tilde{N}}^A$	$t_{T+}^H - t_{T+}^A$
Northern Africa	11	7	4	Central Asia	5	9	1	2
"				South America	6	12	2	5
Southern Asia	10	6	5	South America	6	12	1	6
Eastern Europe	10	7	4	Central Asia	5	9	1	2
"				South America	6	12	2	5
India	11	3	12	Central Asia	5	9	5	6
United States of America	9	8	5	South America	6	12	1	4
China	3	8	3	Central Asia	5	9	2	1
"				South America	6	12	3	4

Note: t_0 = sowing month, t_{T+} = harvesting month, $t_{\tilde{N}}$ = month of Niña phase. Superscript: A = affected area, H = helping area.

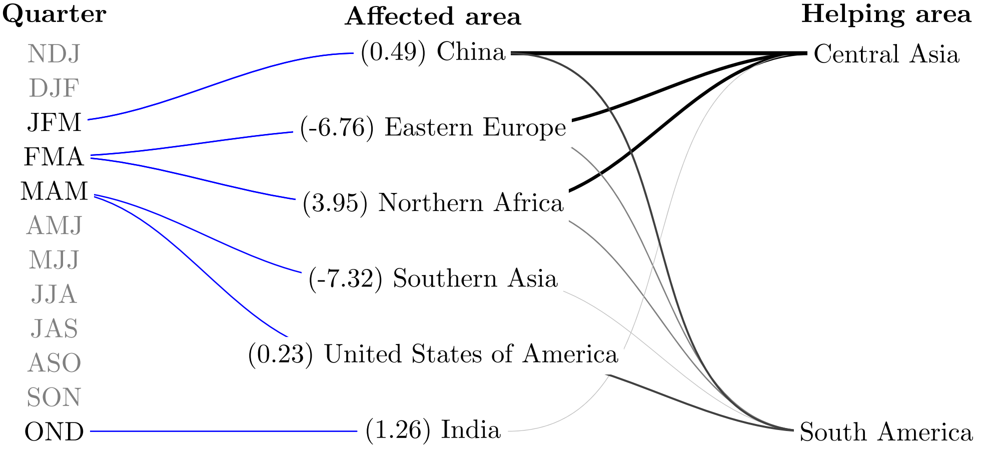

FIGURE 4 Visualization of possible helping areas in case of La Niña

5 | SIMULATIONS IMPLEMENTATION AND RESULTS

The previous section identifies the wheat-producing areas that might be activated in the case of El Niño or La Niña. However, the effects on the markets both of ENSO and policies actions to smooth them have to be assessed. We will achieve the task using computer simulations. We measure the market effects of ENSO in this section and evaluate the effectiveness of the policy in the next one.

It is worth reasserting that, in such an investigation, we do not consider bilateral agreement through which the most influential areas could have benefits disadvantaging others. This assumption moves from our declared goal of searching for a global policy that could improve the overall situation.

The task is hindered by the lengthening of ENSO phases and by the heterogeneity of their effects. We can better evaluate the complexity by looking again at Figure 4. For example, if La Niña is detected at the end of March, we expect an increase in China's production of 0.49%. At that time, we would say Central Asia should reduce its production by some convenient amount.

However, if La Niña drags on until April, we expect a reduction of Eastern Europe's production by 6.76% and an increase in Northern Africa's production by 3.95%. How Central Asia's sowing management should now be oriented?

To delve into such a complex problem, we adopt a relatively new method that is most finding application in the field of business intelligence: the what-if analysis.

5.1 | What-if analysis

"What-if analysis is a data-intensive simulation whose goal is to inspect the behavior of a complex system, such as the corporate business or a part of it, under some given hypotheses called scenarios." It enables decision-makers "to evaluate beforehand the impact of a strategic or tactical move so as to plan optimal strategies to reach their goals" (Rizzi, 2018).

The methodological framework to design a what-if application is still under development. However, Rizzi (2018) reports a process structured in seven phases: (1) Goal analysis, (2) business modeling, (3) data source analysis, (4) multidimensional modeling, (5) simulation modeling, (6) data design and implementation, and (7) validation.

We think it is not the case to detail how the work presented in previous sections relates to each of these phases. Nevertheless, it is worth discussing some relevant issues.

As also stated by Rizzi (2018), "a what-if application is centered on a *simulation model*." As mentioned above, our simulation model is the CMS-wheat model. The model has been already validated and successfully replicates yearly prices of the US wheat market for the 1992–2016 period. Because the FAOSTAT data used to calibrate the model in that work are substantially the same as those used here, we will refer to such calibrated model as the benchmark case.

Other relevant issues can be reviewed by presenting our policy investigation as a two-round what-if analysis.

In the first round, we look for a year in which all the months are characterized by a neutral phase because we want to analyze the effect of ENSO against the *steady* situation. In our case, this situation is represented by the wheat yields obtained under the neutral phase. The only year presenting this feature in the time window of study is 2013. The neutral phase which includes 2013 spans from May 2012 to September 2014. Because FAOSTAT data relates to years, having a neutral phase covering a whole year provides for full comparability of yearly aggregation of simulation data with figures from FAOSTAT databases. Unfortunately, the lack of monthly databases represents a limitation of our analysis that, otherwise, could have included more than one neutral phase occurrence.

Nevertheless, we proceed in our investigation by modifying the 2013 production of the affected areas according to the estimates of the ENSO effects and simulate to find out how the system of international wheat markets would have evolved if, in 2013, El Niño or La Niña had occurred instead of the observed neutral state. After this first step, the policymaker is informed of what happened in the two scenarios: "what-if El Niño instead of neutral" and "what-if La Niña instead of neutral."

Next, we plug a second what-if analysis that considers policy actions into the two just mentioned *ENSO phase* scenarios. In this second round, policies are accounted for by identifying and modeling *source variables*. More specifically, according to Rizzi (2018), *source variables* "enables the user to understand which are the "levers" that one can independently adjust to driving the simulation." In our settings, *source variables* are the productions of the helping areas identified in Section 4.2 (see in particular Figures 3 and 4). To allow the tuning of these "levers," we introduce a parameter for each helping area that enables the modification of the corresponding production. Such parameters, in our model, represent the change in sowing area size and will be denoted with αs.

Tables 4 and 5 show how we characterize the *Neutral* (benchmark), the *ENSO phase*, and the *ENSO phase + policy* scenarios. For the sake of clarity, the column labeled *Neutral* represents the productions obtained from FAOSTAT for the year 2013 under the neutral phase of ENSO, and they are denoted with F. This column describes the input for the benchmark scenario. The other columns show how Fs are updated in the case of a hypothetical ENSO phase (second column) and in the case of policy adoption to offset the effects of such an ENSO phase (third column). These two columns describe the input for the *ENSO phase* and *ENSO phase + policy* scenarios, respectively. We highlight in gray in the tables the areas whose production are taken as *souce variables*, and the corresponding policy "levers" that are the αs in the *El Niño/La Niña phase + policy* columns. In the αs notation, superscript o stands for El Niño, and a for La Niña; lower scripts are made up of the initials of the area's name.

Note that, in order to obtain the simulation outputs, the data concerning other years of the considered period (i.e., 1993–2012 and 2014–2016) are those obtained from FAOSTAT.

5.2 | Simulation results

Once a scenario is set up, we run the CMS-wheat model to obtain outputs. Our final step is to endow the policymaker with an evaluation of the scenario based on the simulation output. Following the standard methodology in economics, we evaluate policies in terms of distances from policy objectives. In our case, the policy objective is to offset El Niño and La Niña markets effects; therefore, we will consider the difference in simulations output between each alternative scenario and the benchmark.

The details on the computation of distances between two scenario outputs are given in the following sections, where we also define a loss function that will allow the policymaker to select an optimal policy.

5.2.1 | Distance between two scenario outputs

We brought forward at the end of the previous section that a comparison of distances between scenario outputs would enable policy evaluation. This statement needs the technical qualification that we are going to give hereafter.

Recall that the simulations have a monthly frequency. We proceed first to compute yearly aggregates. In particular, we will denote with $p_{i,y}^X$ and $IM_{i,y}^X$ the average purchasing price of imports and the quantity imported by buyer i at year y under the scenario X, respectively.

Given two scenarios, say A and B, the price and imported quantities deviations of scenario A from scenario B for buyer i at year y are computed as follows:

$$g_{p_{[i,y]}}^{AB} = \frac{p_{i,y}^A - p_{i,y}^B}{p_{i,y}^B} \quad \text{and} \quad g_{IM/D_{[i,y]}}^{AB} = \frac{IM_{i,y}^A - IM_{i,y}^B}{D_{i,y}}. \tag{1}$$

TABLE 4 Production inputs used in simulations for El Niño in the year 2013

Area	Neutral	El Niño	El Niño + policy
Northern Africa	F	$F(1-5.70)$	$F(1-5.70)$
Eastern Africa	F	$F(1+0.43)$	$F(1+0.43+\alpha^{o}_{EA})$
Central America	F	$F(1-3.00)$	$F(1-3.00)$
Southern Asia	F	$F(1+4.63)$	$F(1+4.63)$
India	F	$F(1-3.37)$	$F(1-3.37)$
China	F	$F(1-1.78)$	$F(1-1.78+\alpha^{o}_{C})$
South America	F	$F(1-3.01)$	$F(1-3.01)$
Oceania	F	$F(1-12.54)$	$F(1-12.54)$
Central Asia	F	F	$F(1+\alpha^{o}_{CA})$
Pakistan	F	F	$F(1+\alpha^{o}_{P})$
Others	F	F	F

Note: F denotes the figure from the FAOSTAT dataset. Helping areas and policy parameters are in gray background.

TABLE 5 Production inputs used in simulations for La Niña in the year 2013

Area	Neutral	La Niña	La Niña + policy
Northern Africa	F	$F(1+3.95)$	$F(1+3.95)$
United States	F	$F(1+0.23)$	$F(1+0.23)$
Southern Asia	F	$F(1-7.32)$	$F(1-7.32)$
India	F	$F(1+1.26)$	$F(1+1.26)$
China	F	$F(1+0.49)$	$F(1+0.49)$
Eastern Europe	F	$F(1-6.76)$	$F(1-6.76)$
Oceania	F	$F(1-6.79)$	$F(1-6.79)$
Central Asia	F	F	$F(1+\alpha^{a}_{CA})$
South America	F	F	$F(1+\alpha^{a}_{SA})$
Others	F	F	F

Note: F denotes the figure from the FAOSTAT dataset. Helping areas and policy parameters in gray background.

Note that we divide the change of imports by the total demand (D) because IM might have small values and significant changes compared with these amounts. The division by $IM^{B}_{i,y}$ would have resulted in (meaningless) very high values of the percentage deviations. Furthermore, we consider total demand to include the part of demand satisfied by domestic production.

Finally, the distance between two scenarios is computed by summing the deviations gs with respect to buyers i and years y. The following section reports how this is done in our case.

5.2.2 | The distance of El Niño and La Niña from the benchmark scenario

This section explains how we measure the distances for an assessment of whether El Niño or La Niña had occurred in 2013. The two simulations to be compared are composed as follows:

(i) the benchmark case, based on productions from FAOSTAT data as reported in the first column of Table 4 and 5, and (ii) *ENSO phase* scenario, based on a modification of 2013 productions due to ENSO effects as reported in the second column of Table 4 and 5.

In the framework of (ii), Equation (1) are specialized as follows:

$$g_{p_{[i,2013+j]}}^{\tilde{N}|2013} = \frac{p_{i,2013+j}^{\tilde{N}|2013} - p_{i,2013+j}}{p_{i,2013+j}}, \qquad g_{IM/D_{[i,2013+j]}}^{\tilde{N}|2013} = \frac{IM_{i,2013+j}^{\tilde{N}|2013} - IM_{i,2013+j}}{D_{i,2013}}, \tag{2}$$

where $\tilde{N}|2013$ stand for "given phase $\tilde{N}$ in 2013" with $\tilde{N} \in (Niño, Niña)$. Note that we omit the superscripts for variables obtained under the benchmark settings to lighten the notation. We, furthermore, add the index j to account for deviations in 2013 and the following years. Because the simulations are done up to 2016, $j \in (0,1,2,3)$.

Using this notation, we compute measures of aggregate distance in a given year by squaring the deviations and summing first by buyers

$$G_{p_{[2013+j]}}^{\tilde{N}|2013} = \sum_i \left(g_{p_{[i,2013+j]}}^{\tilde{N}|2013} \right)^2, \quad \text{and} \quad G_{IM/D_{[2013+j]}}^{\tilde{N}|2013} = \sum_i \left(g_{IM/D_{[i,2013+j]}}^{\tilde{N}|2013} \right)^2$$

and then by the years

$$G_p^{\tilde{N}|2013} = \sum_{j \in (0,1,2,3)} G_{p_{[2013+j]}}^{\tilde{N}|2013} \quad \text{and} \quad G_{IM/D}^{\tilde{N}|2013} = \sum_{j \in (0,1,2,3)} G_{IM/D_{[2013+j]}}^{\tilde{N}|2013}.$$

Now we put our measures of distance at work. In doing that, we highlight that our specific focus is on smoothing ENSO adverse effects in areas with negligible wheat production compared with their domestic need. Therefore, we let the sum involve only areas we labeled as "in need" in Section 3.1. They are marked with * in Figure 1. Indeed, for El Niño, we discard Eastern Africa because we found that it can implement domestic policies and increase its domestic production to contrast El Niño effects. Without eliminating Eastern Africa, such an increase would cause a decrease in Eastern Africa's import, and our computation of $G_{IM/D}$ would be biased. On the contrary, such a problem does not exist for La Niña, and we keep Eastern Africa in the sum in this case.

Computing the sums, we obtain the following distances between the El Niño and the benchmark (neutral) scenarios:

$$G_p^{Niño|2013} = 1532.21 \quad \text{and} \quad G_{IM/D}^{Niño|2013} = 16.514,$$

whereas the comparison between the neutral and the La Niña scenarios gives the following values:

$$G_p^{Niña|2013} = 552.7 \quad \text{and} \quad G_{IM/D}^{Niña|2013} = 21.743$$

Once we have obtained these values, we are able to speculate on policy actions because a sowing policy is effective if it reduces them. We will deal with this question hereafter.

6 | POLICY IMPLICATIONS

We now perform simulations with both ENSO and sowing policies. We aim to find out if policy introduction can contribute to smoothing out the distances concerning exchanged quantities and prices.

To this aim, we compare outputs obtained using the input specified in the *El Niño phase + policy* column of Table 4 with that of the benchmark in the El Niño case. Correspondingly, we have to refer to the *La Niña phase + policy* column of Table 5 and the benchmark for La Niña.

The problem now is how to choose the policy parameters αs.

Following the standard methodology in economics, we first specify an objective function for the policy maker based on αs and then look for the optimal policy using optimization techniques.

More formally, when policy parameters are introduced, the distances defined in Equation (2) become:

$$G_p^{\tilde{N}+policy|2013}(\boldsymbol{\alpha}^{\tilde{\boldsymbol{N}}}) \quad \text{and} \quad G_{IM/D}^{\tilde{N}+policy|2013}(\boldsymbol{\alpha}^{\tilde{\boldsymbol{N}}}),$$

where $\boldsymbol{\alpha}^{\tilde{\boldsymbol{N}}}$ denotes the vector of policy options to offset the effects of a specific ENSO phase. Using these distances, the objective function of the policy maker becomes a loss function because the policy maker's loss increases the far the system goes from the benchmark. We specify the loss function as follows:

$$L(\boldsymbol{\alpha}^{\tilde{\boldsymbol{N}}};\gamma_p,\gamma_q) = \left\{\gamma_p G_p^{\tilde{N}+policy|2013}(\boldsymbol{\alpha}^{\tilde{\boldsymbol{N}}}) + \gamma_q G_{IM/D}^{\tilde{N}+policy|2013}(\boldsymbol{\alpha}^{\tilde{\boldsymbol{N}}})\right\}, \tag{3}$$

where γ_p and γ_q are the weights given by the policy maker to the deviation in prices and quantities, respectively.

Therefore, the policymaker has to solve the following problem:

$$\min_{\boldsymbol{\alpha}^{\tilde{N}}} L(\boldsymbol{\alpha}^{\tilde{\boldsymbol{N}}};\gamma_p,\gamma_q). \tag{4}$$

We set γ parameters to search for short-run policies. This is because we observe that El Niño or La Niña phases usually involve one or two consecutive wheat-growing seasons, although a few cases of three consecutive years have been observed. In the short run, quantities are sluggish, whereas prices are fast-changing variables and are those to be kept under control. Therefore, we adopt the $\gamma_p = 1$ and $\gamma_q = 0$ parametrization, and the policy maker problem of Equation (4) becomes

$$\min_{\boldsymbol{\alpha}^{\tilde{N}}} G_p^{\tilde{N}+policy|2013}(\boldsymbol{\alpha}^{\tilde{\boldsymbol{N}}}).$$

Because our model is computationally demanding, a systematic exploration of the $\boldsymbol{\alpha}^{\tilde{N}}$ space is not possible. Instead, we use an evolutionary computation optimization technique, namely, the differential evolution algorithm, to find the parameters combination that solves (or is close enough to the solution of) the policy maker problem ($\boldsymbol{\alpha}^{\tilde{N}*}$).

We also likely maintain that the sowing area cannot have relevant changes in the short run, and then we bound the change of the production of helping areas to stay in the -5%, 5% interval; that is, all the α^*s satisfy $-0.05 \le \alpha^* \le 0.05$.

The results of this process and an assessment of optimal policies are given in the following sections.

6.1 | El Niño

The optimal policy identified by the differential evolution algorithm in the El Niño case is $\boldsymbol{\alpha}^{\boldsymbol{o}*} = \{\alpha^{o*}_{CA} = 0.045, \alpha^{o*}_{P} = 0.042, \alpha^{o*}_{C} = 0.049, \alpha^{o*}_{EA} = 0.042\}$. This result suggests that the concurrent increase of wheat production by 4.5% in Central Asia, 4.2% in Pakistan, 4.9% in China, and 4.2% in Eastern Africa would be the best strategy to weaken the effects that El Niño would have had on the market, especially on prices.

Furthermore, a comparison of the distances computed using the optimal policy parameters:

$$G_p^{Niño+policy|2013}(\boldsymbol{\alpha}^{\boldsymbol{o}*}) = 734.27 \quad \text{and} \quad G_{IM/D}^{Niño+policy|2013}(\boldsymbol{\alpha}^{\boldsymbol{o}*}) = 14.636$$

with those computed for the case without policy (exposed above and reported hereafter for convenience):

$$G_p^{Niño|2013} = 1532.21 \quad \text{and} \quad G_{IM/D}^{Niño|2013} = 16.514$$

reveals that the total deviation of prices decreases in a very important manner and, despite not weighting the policy maker objective function, the distance for quantities ($G_{IM/D}$) decreases, as well.

Beyond these aggregate measures, we report in Table 6 disaggregated figures for an assessment of how the policy impacts the in-need areas. In particular, the table reports the differences between the deviations computed in the *El Niño phase + optimal policy* and the *El Niño phase without policy*.

Note that a negative sign means the variable under consideration has a lower value under the policy scenario than the one without policy. The signs, therefore, have a different interpretation of prices and quantities. A negative sign for prices is in favor of the policy because the unit cost of wheat decreases, while, in the case of quantities, a negative sign adverses the policy because wheat availability decreases. The opposite can be told for the positive signs.

Looking at Table 6 with this information, it emerges that prices are almost always lower with the optimal policy than in its absence. As an example, we can observe that implementing the optimal policy in 2013 brings prices of 2014 down at least by 4% for all areas with respect to the case of no policy implementation. The Asian areas are those that most take advantage of the policy, obtaining a significant reduction in purchasing prices. According to our model,

TABLE 6 Differences in prices and quantities changes with and without a policy in case of El Niño

$y \rightarrow$ / $i \downarrow$	2013	2014	2015	2016	2013	2014	2015	2016
	$\left(g_{p_{[i,y]}}^{Niño+policy^*\|2013} - g_{p_{[i,y]}}^{Niño\|2013}\right)$				$\left(g_{IM/D_{[i,y]}}^{Niño+policy^*\|2013} - g_{IM/D_{[i,y]}}^{Niño\|2013}\right)$			
Middle Africa	−0.58	−4.16	−4.67	−0.12	0.03	0.16	−0.17	0.00
Northern Africa	−0.63	−4.41	−3.63	0.04	0.02	0.12	−0.12	−0.01
Southern Africa	−1.18	−6.01	−5.51	−2.23	0.05	0.23	−0.25	−0.02
Western Africa	−0.56	−4.02	−4.43	0.12	0.03	0.14	−0.14	−0.01
Central America	−0.45	−5.20	−6.23	−0.19	0.02	0.19	−0.18	−0.03
Eastern Asia	−1.18	−11.74	−8.30	−0.63	0.08	0.50	−0.52	−0.05
Southern Asia	−2.12	−7.63	−4.20	−1.48	0.02	0.10	−0.11	−0.01
South-Eastern Asia	−0.85	−9.85	−7.35	−3.40	0.04	0.25	−0.26	−0.02
Western Asia	−0.71	−4.35	−3.87	0.14	0.01	0.03	−0.03	0.00
Southern Europe	−0.59	−4.80	−4.11	−0.29	0.01	0.06	−0.06	−0.01

Eastern Asia is the area that most benefits from the policy in terms of unit purchasing costs being 11.74% lower in 2014 and 8.3% in 2015.

On the contrary, the deviations are smaller in terms of quantities; furthermore, the additional availability obtained in 2013 and 2014 is balanced by the reduction in 2015 and 2016. Nevertheless, both the aggregate and disaggregated distances point to the substantial effectiveness of the optimal policy in the case of El Niño, especially in terms of purchasing cost reduction.

6.2 | La Niña

After implementing the differential evolution, we found the following optimal policy for La Niña: $\boldsymbol{\alpha}^{\boldsymbol{a}*} = \{\alpha_{CA}^{a*} = 0.046, \alpha_{SA}^{a*} = 0.048\}$, consisting in a joint increase of production of 4.6% in Central Asia and 4.8% in South America. As a consequence of this policy, distances are

$$G_p^{Niña+policy|2013}(\boldsymbol{\alpha}^{\boldsymbol{a}*}) = 373.327 \quad \text{and} \quad G_{IM/D}^{Niña+policy|2013}(\boldsymbol{\alpha}^{\boldsymbol{a}*}) = 21.6.$$

Comparing them with the distances computed for the case without policy (exposed above and reported hereafter for convenience):

$$G_p^{Niña|2013} = 552.7 \quad \text{and} \quad G_{IM/D}^{Niña|2013} = 21.743,$$

we conclude that also in the case of La Niña, the distance in price decreases significantly, whereas the one in quantities is almost unchanged.

Similar to the El Niño case, we report in Table 7 the differences between the deviations computed in the *La Niña phase + optimal policy* and the *La Niña phase without policy* for each in-need area and year.

TABLE 7 Differences in prices and quantities changes with and without a policy in case of La Niña

$y\rightarrow$ / $i\downarrow$	2013	2014	2015	2016	2013	2014	2015	2016
	$\left(g_{p_{[i,y]}}^{Niña+policy\|2013} - g_{p_{[i,y]}}^{Niña\|2013}\right)$				$\left(g_{IM/D_{[i,y]}}^{Niña+policy\|2013} - g_{IM/D_{[i,y]}}^{Niña\|2013}\right)$			
Eastern Africa	−0.05	−0.98	−1.25	−0.25	0	0.02	−0.02	0
Middle Africa	−0.04	−1.03	−1.33	−0.24	0.001	0.04	−0.03	0
Northern Africa	−0.07	−1.08	−0.99	−0.18	0	0.04	−0.03	0
Southern Africa	−0.05	−1.09	−1.41	−0.17	0.001	0.06	−0.05	0
Western Africa	−0.05	−1.09	−1.30	−0.19	0	0.05	−0.04	−0.01
Central America	0.00	−1.06	−1.78	−0.19	0	0.06	−0.05	−0.01
Eastern Asia	−0.03	−0.77	−1.63	−0.35	0.002	0.12	−0.10	0
Southern Asia	−0.37	−3.35	−1.14	−0.27	0	0.03	−0.02	0
South-Eastern Asia	−0.03	−0.95	−2.07	−0.46	0.001	0.06	−0.05	0.01
Western Asia	−0.14	−1.59	−1.17	−0.20	0	0.01	−0.01	0
Southern Europe	−0.05	−0.98	−1.18	−0.15	0	0.02	−0.02	0

Here, the figures are remarkably lower with respect to the El Niño case. Nevertheless, even for La Niña the benefits of the policy are confirmed encountering all the in-need areas with a substantial reduction in prices. Differently from the El Niño case, Southern Asia shows the most relevant unit cost reduction of 3.35% in 2014, provided that the optimal policy is implemented in 2013. As expected from the observation of the quantity distance, the change in imported quantities due to the policy is negligible.

7 | CONCLUSIONS

In this paper, we put together several elements to investigate whether policies to smooth out the effects of climate variability on the international wheat markets are feasible. In particular, we refer to the ENSO—characterized by the warm phase named El Niño and the cold phase La Niña—to represent climate variability worldwide.

The first element is the statistical evaluation of ENSO effects on wheat production in each of the 23 areas of the world geographic partition we tailored for the analysis of the wheat market at the international level. We found that these effects are scattered and heterogeneous in intensity and timing.

The observation of this heterogeneity originates the core idea of this research. Indeed, heterogeneity within a system usually creates room for stabilization. We point in particular to the stability of unit purchasing cost and available quantity of in-need geographic areas. Unfortunately, these areas encounter relevant food security problems because small increases in purchasing unit costs and reductions in available quantities of a primary food staple like wheat have worrisome consequences.

The second element that lets us achieve the goal is a model that implements the dynamic process of exchanges on the international markets: the CMS-wheat model. Such a model takes as input demand and production of the geographic areas and, through a market mechanism, outputs the prices and quantities' allocation that best match wheat demand and supply on a monthly base. The model is carefully calibrated using the FAOSTAT data to accurately track the dynamic of prices observed in the US market. Both ENSO phases and sowing policies modify the production input. Consequently, they determine changes in the outputs.

The last element is the definition of a metric to evaluate the deviations of the model outputs to the FAOSTAT benchmark case.

Our reasoning lines up the previously described elements and goes on as follows. First, we measure the effect of ENSO phases on regions/countries' production. Secondly, using these results, we modify the productions of a year (i.e., 2013) that is characterized by an ENSO neutral phase as if El Niño or La Niña were active instead. Thirdly, such modified productions are given as input to the CMS-wheat model to run the *ENSO phase* simulation. Finally, using our metrics, we evaluate how far each of the two ENSO phases displaces the system from the benchmark.

The main contribution of the present work is the inclusion of policies in this framework. Once we have observed the ENSO phase in a given month and are warned by our statistical analysis that the production of a given area will be affected, we search for possible offsetting strategies. These strategies consist in modifying the production of areas not affected by the observed ENSO phase. This action is possible in areas that are going to sow, and we expect the offsetting effectiveness to depend on the closeness of these areas' harvesting time to that of the affected area. Our concurrent analysis of the ENSO, sowing, and harvesting times across all the regions reveals that such actions are possible. Once verified the feasibility, we identify the optimal policy by implementing the differential evolution algorithm. We found that adopting the optimal policy can smooth out the effects of ENSO on international markets. In particular, the optimal policy would bring back prices toward those observed in the neutral phase by reducing them up to about 11% for all areas when El Niño is in phase and, on average, about 1% when La Niña is in phase. Among others, the Asian areas would take the most advantage of policy adoption. Furthermore, Central Asia represents a potential strategic area for the implementation of the proposed policy.

We can therefore conclude that, in our model, sowing policies able to weaken the effects of ENSO on in-need areas are possible and effective.

As we hinted above, putting this kind of policy to work has significant technical and political difficulties. In the present paper, we take a shortcut to acknowledge the presence of these difficulties by bounding the change in acreage within the -5%;+5% interval. However, a deeper assessment of the relevance of these difficulties in binding the potential implementation of the proposed policy is a topic for further research. At this stage, we are satisfied to have highlighted that planting policies are possible and potentially fruitful because this can motivate an effort to overcome these difficulties. Above all, however, the results of this study join the large strand of literature showing how cooperation between countries rather than individualism can be beneficial, especially to the needy part of the world population.

ACKNOWLEDGMENTS

This research was partially supported by H2020 Project MED-GOLD 'Turning climate-related information into added value for traditional MEDiterranean Grape, OLive and Durum wheat food systems' (https://www.med-gold.eu/) grant number EU-776467.

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How to cite this article: Giulioni, G., Di Giuseppe, E., & Pasqui, M. (2022). Global coordination of wheat sowing: A possible policy against climate variability. *World Food Policy*, 1–22. https://doi.org/10.1002/wfp2.12052