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# Extreme Weather Events, Agricultural Output, and Insurance:

## Evidence from South America

Juliette Caucheteux, Jonas Nauerz, and Svetlana Vtyurina

**WP/25/52**



**2025**
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 WP/25/52

**IMF Working Paper**
Western Hemisphere Department

# Extreme Weather Events, Agricultural Output, and Insurance:

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Authorized for distribution by Mauricio Villafuerte
March 2025



**ABSTRACT:** Extreme weather has profoundly affected countries across South America (SA), given the importance of the agricultural sector for the economies. However, these effects have not yet been properly measured. In our study, we construct a unique dataset of high-frequency satellite data on temperature, precipitation, and a Normalized Difference Vegetation Index (NDVI) that proxies the agricultural yield in selected countries. In particular, we then examine the effect of droughts on agricultural yields (soy output) and find that they have a significant negative impact and that there is heterogeneity in the response across countries. While insurance could help protect farmers against severe losses, coverage in the region is low, and barriers remain high. Building on existing literature and using a calibrated structural model, we highlight the benefits of insurance for Total Factor Productivity (TFP) and offer some recommendations for its expansion.


| | |
|---|---|
| JEL Classification Numbers: | D58, G22, O11, O41, Q10, Q14, Q54 |
| Keywords: | Agriculture, Productivity, NDVI, SPEI, Weather, Drought, Insurance, South America |



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WORKING PAPERS

# Extreme Weather Events, Agricultural Output, and Insurance:

## Evidence from South America

Prepared by Juliette Caucheteux, Jonas Nauerz, and Svetlana Vtyurina[1]

[1] "The authors would like to thank Ariel Akerman, Tarek Alrefae, Sandra Baquie, Giulio Gottardo, Matt McKetty, Filippos Tagklis, Mauricio Villafuerte, Mathias Weidinger, participants at the IMF WHD seminar and colleagues from other departments for their valuable comments. We also thank Diego Gutierrez for helping with data presentation.

# Contents

# Introduction

Farming has always been an activity subject to risk and the increasing frequency of extreme weather events create special challenges, affecting growth, productivity, and wellbeing. Agricultural insurance has long been a part of farmers' risk management toolkit in both developing and industrialized economies. However, the existing data on agricultural insurance is scattered across regions, risks and instruments making a structured presentation hard to assemble. Moreover, the effects of extreme weather particularly on agricultural output in South America (SA) have not been systematically estimated. Thus, in our study, we concentrate on selected South American countries, which boast large agricultural sectors exposed to many extreme events yet employ limited risk management strategies to reduce the output loss and increase productivity. In general, these countries are prepared for the climate change to a varying degree, with Chile and Uruguay leading the efforts (Figure1).

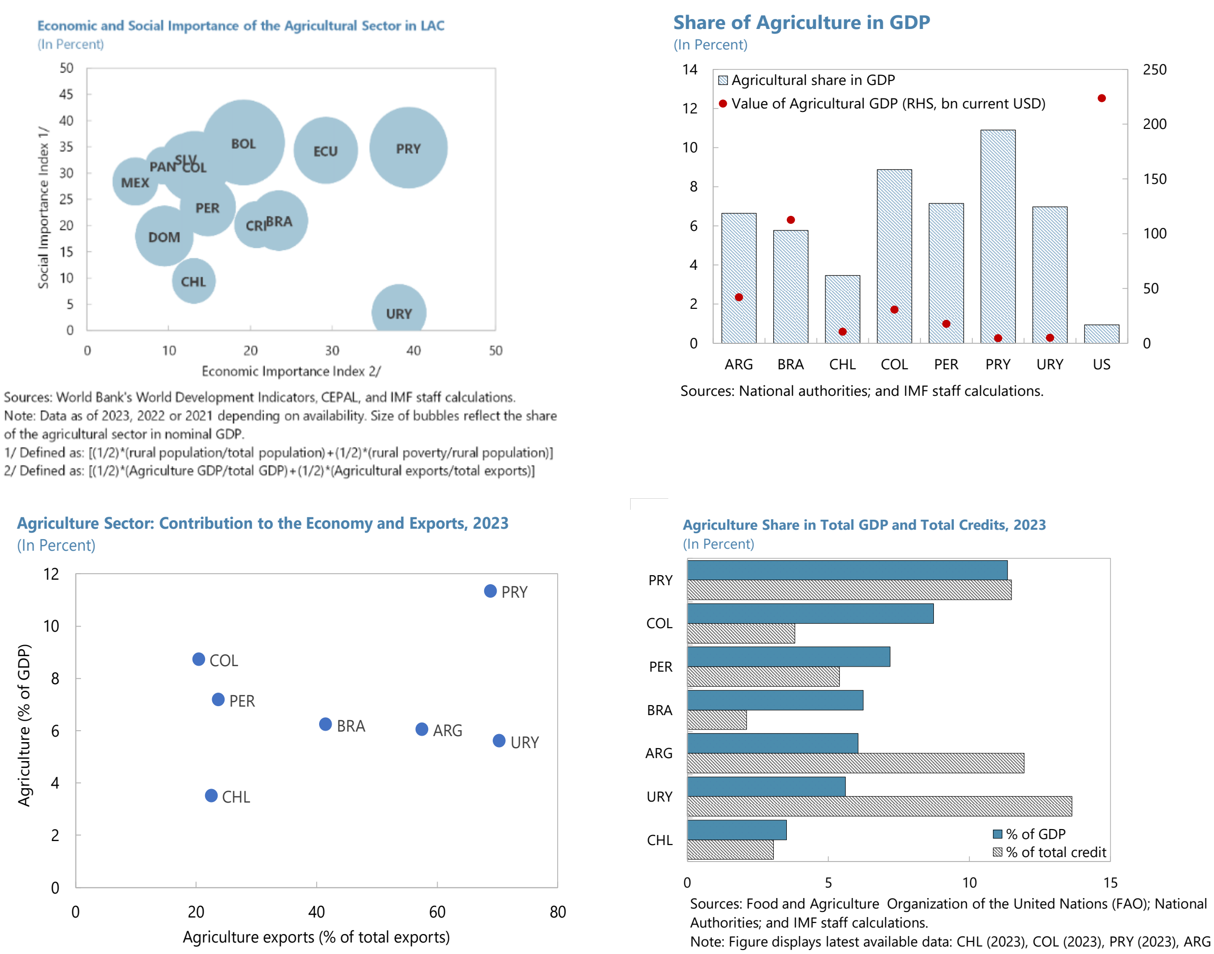
**Figure 1. Vulnerability and Preparedness for Climate Change**

On average, agriculture constitutes about 8 percent of GDP in our study sample of six SA countries (Argentina, Brazil, Colombia, Peru, Paraguay, and Uruguay) and about 40 of the total value of its exports (Figure 2).[2] Paraguay, Argentina, and Uruguay have the largest agricultural sectors as a percentage of GDP and exports, reflecting an abundance of arable land and well-established agribusiness industries. Population living in rural areas varies from about 37 percent in Paraguay to 4 percent in Uruguay, with Peru employing the highest number of people, and especially women, in agriculture. These countries are large producers of soya beans, which constitute almost 60 percent of all agricultural production in Paraguay, and above 40 percent in Argentina, Brazil, and Uruguay. Colombia and Peru have sizeable manufacturing sectors, while Chile and Brazil have relatively diversified export and industrial bases, thus depending less on one industry. However, production figures understate the importance of the agricultural sector, not least because they exclude the informal sector and ancillary industries such as food processing and distribution. The agricultural sector is also a major source of foreign exchange and fiscal revenues. Therefore, fluctuations in agricultural output can have significant bearing on related industries and the overall economy.

[2] Chile is used for illustration in Figure 2 but there is not sufficient data to include it in the analysis.

Extreme weather events are occurring with increasing frequency. Instances of floods, droughts, frosts, and heavy rainfall are intensifying, covering larger areas, and occurring in regions where they were previously uncommon. Drought is a devastating peril that affects agricultural production in almost all countries, while El Niño/a events have divergent effects on these countries. Loss from hailstorm is an important risk facing producers in Argentina, Uruguay, and southeastern Brazil. Northeastern Argentina, eastern Paraguay, Uruguay, and southern Brazil are heavily exposed to tornadoes. Assessing the economic impacts of extreme weather on output and the effect of employing risk management strategies on productivity is thus crucial for informed policy development (Becker-Reshef, et al, 2020).[3,4]

**Figure 2. Selected Agricultural Statistics**




Sources: World Bank's World Development Indicators, CEPAL, and IMF staff calculations.
Note: Data as of 2023, 2022 or 2021 depending on availability. Size of bubbles reflect the share of the agricultural sector in nominal GDP.
1/ Defined as: [(1/2)*(rural population/total population)+(1/2)*(rural poverty/rural population)]
2/ Defined as: [(1/2)*(Agriculture GDP/total GDP)+(1/2)*(Agricultural exports/total exports)]

Sources: National authorities; and IMF staff calculations.

Sources: UN Comtrade; National Authorities; and IMF staff calculations.

Sources: Food and Agriculture Organization of the United Nations (FAO); National Authorities; and IMF staff calculations.
Note: Figure displays latest available data: CHL (2023), COL (2023), PRY (2023), ARG (2022), BRA (2022), PER (2015).

In this paper, we study the effects of droughts on agricultural output. We first build a unique dataset of high-frequency satellite and weather station data. This dataset collects information on the Normalized Difference

[3] See October 2024 *Regional Economic Outlook: Western Hemisphere* Online Annex 2. On Economic Losses from Slow-Onset Climate Events in Latin America and the Caribbean.

[4] For example, see the estimates from the Assessment Tool for Measuring Climate Change Adaptation in the Context of Rural Development, which demonstrates the annual effect of crop output per country for various scenarios of a gradual temperature increase by 2100 (World Bank).

Vegetation Index (NDVI), a greenness index that is a good proxy for agricultural output in the context of soy, and the Standard Precipitation and Evapotranspiration Index (SPEI), a widely used index for droughts, as well as land use data from MapBiomas. This allows us to identify the effects of droughts on agricultural output consistently across countries. To our knowledge, this is the first paper that proposes this approach in South America.

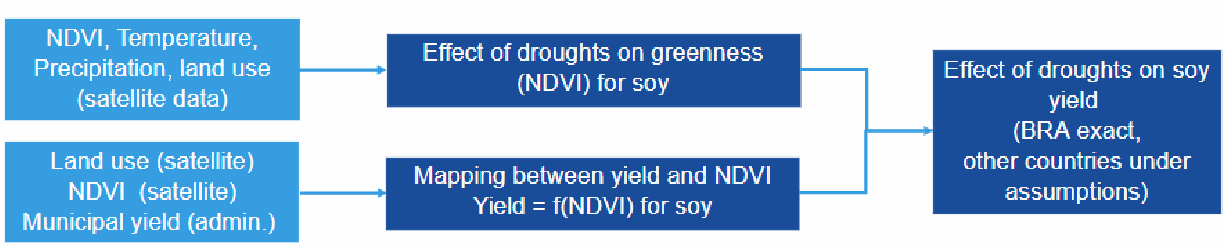
We find significant heterogeneity in the response between countries. A farmer in Brazil or Argentina loses between 0 and 1 bushels per acre, or around 1 or 2 percent of their agricultural output, while a farmer in Colombia, Paraguay or Uruguay loses between 4 and 8 bushels per acre, or between 8 and 19 percent of their agricultural output respectively. This result may be driven by the timing of droughts that varies across countries, and various adaptation abilities. We argue that insurance could help protect farmers against severe losses However, an overview of insurance in the region reveals low coverage and a market characterized by many constraints, both on the demand and supply sides. Using a dynamic general equilibrium model, calibrated to our sample countries, we then turn to quantifying the gains of insurance and find substantial benefits of broadening its coverage. Specifically, agricultural productivity could see an enhancement of 7.5 percent in Paraguay, 2.7 percent in Brazil, and 3.6 percent in Uruguay. We conclude by providing policy recommendations.

# Extreme Weather Events and Agricultural Output

## Data and Approach

The extent to which agricultural output is affected by weather variability has yet to be systemically measured in our country sample. Given the lack of full and consistent series of crop yield data by country, which is necessary to understand the effects, we use the NDVI, which is based on satellite data, as a proxy for agricultural output.[5] Exploiting this granular measure accounts for cell-level heterogeneity when estimating the response to droughts, deepening analyses that use only country level or administrative data. To obtain the actual effect on agricultural output, we use granular municipal yield data in Brazil and map NDVI to actual yield data. We then extrapolate this mapping to each country in our sample. We chose soy for this exercise, given the importance of the crop for our sample (Figure 3).

**Figure 3. Approach and Mapping**




[5] The NDVI has been recognized since the early 1980s for its value in monitoring crop conditions and forecasting crop yields (Boken and Shaykewich, 2002; Doraiswamy and Cook, 1995; Quarmby et al., 1993b; Tucker et al., 1980).

## Data sources

***Standard Precipitation and Evapotranspiration Index (SPEI)****:* To define our measure of droughts, we use the SPEI, which takes both temperature and precipitation into account. Developed by Vicente-Serrano et al. (2010), the SPEI is a standardized, widely used measure of droughts in the literature (see Slette et al. 2019; Albert et al. 2023). Positive values of the index indicate above-average moisture while negative values indicate dryness conditions, and higher values reveal more extreme conditions. The SPEI index classification common in the literature uses -1.5 as a threshold for very dry conditions (see Wang et al. 2021, Polong et al. 2019). Accordingly, we retrieve daily data on temperature and precipitation at a 0.5° resolution from the National Oceanic and Atmospheric Administration and define a drought as a month in which the SPEI falls below -1.5.

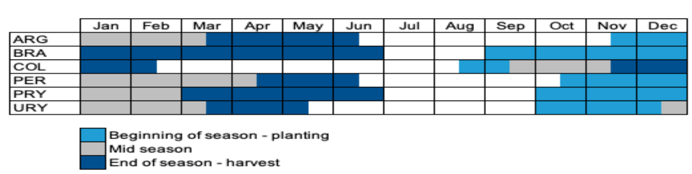
***Normalized Difference Vegetation Index (NDVI)****:* The NDVI exploits red and near-infrared lights to develop an index to quantify vegetation greenness. This data is available daily, at a 0.05° resolution (approximately a 5km x 5km grid). Several studies demonstrate that the NDVI can be a good proxy for future agricultural output, typically measured in yields per acre (bushels per acre or tons per acre). They show this by examining the correlation between the NDVI and yield data, either observed on the ground or from official statistical agencies (see Annex I for a literature review). This said, Donaldson & Storeygard (2016) have pointed out that, while the NDVI was a practical measure of agricultural output at a location, there was still the potential issue of capturing nonagricultural vegetation in the process. Therefore, in a more recent strand of literature models have been developed to improve the reliability of the index, either by overlaying satellite data with cropland information in each cell (called “masks”) that classify land (see Roznik et al. (2022) for the US); or by narrowing the period in the growing season where the index is used.

***Land Use from MapBiomas****:* We utilize land use data from the MapBiomas project to identify the cells that produce soy.[6] This data is available for all the countries in our sample, although the level of detail varies among them. In Brazil, the categories are more specific. In addition to broader land use classifications, such as agriculture or forest (available for all countries), the Brazilian data also indicates the cultivated crop.

***Yield Data****:* We use data from the Brazil Institute of Geography and Statistics (IBGE) to obtain the time series of soy yields at the municipal level between 2010 and 2020.

***Crop calendar:*** To account for the fact that soy has different growing seasons in the region, we use the crop calendar published by the United States Department of Agriculture (USDA) and locate the times for planting and harvesting for each country in our sample. This is necessary since our mapping of NDVI to yield uses the peak greenness attained during the harvesting period, which varies across countries, see Figure 2.

**Figure 4. Crop Calendar for Soy**




Source: USDA; authors' calculations

[6] MapBiomas was created by the SEEG/OC (Sistema de Estimavas de Emissões de Gases de Efeito Estufa do Observatorio do Clima, the platform monitoring greenhouse emissions in Latin America) and their annual maps of land use in Latin America are produced by a collaborative network of NGOs, universities, technological companies. Land use information, in turn, is obtained from Landsat satellite data scanning the earth at a resolution of 30m x 30m.

### Data treatment

Since the data do not all share the same resolution, we harmonize them by adjusting to a uniform 0.05° resolution. Specifically, we disaggregate the SPEI data, which is at a lower resolution, using bilinear interpolation. Conversely, we aggregate the variables using the nearest neighbor function for the higher-resolution land use data.

As noted earlier, land use data related to soy production is only available for Brazil. We employ a fuzzy matching strategy to infer potential soy-producing cells in other countries to address this gap. We calculate the median temperature, monthly precipitation levels, and median NDVI for all cells in Brazil where soy is produced. We then identify agricultural cells in other countries which exhibit characteristics like those in Brazil.

Johnson et al. (2016) suggest that the maximum greenness observed in a cell during harvest is the best proxy for yield. Therefore, we align the crop calendar with the greenness index and select the peak NDVI during harvest. Additionally, we record the droughts experienced in each cell during the agricultural season before reaching the peak NDVI.

### Descriptive statistics

We present descriptive statistics for our sample (2010–2020) by country in Table 1. Our dataset is at the cell-by-year level. On average, cells in our sample experience 1.37 droughts per year. The maximum number of droughts observed in a cell across our sample is 9 in one year, while some cells witnessed no drought. While there is some variation in the maximum number of droughts across countries, the average per cell is similar across countries. The distribution of droughts is skewed to the right, and most cells do not experience more than two droughts per year (see also Figure 7). The median of the maximum NDVI observed across cells ranges from 0.66 to 0.77, and the distribution of greenness across countries is relatively similar.

**Table 1. Descriptive Statistics**

| | Number of Droughts per Year | | | | | Maximum NDVI | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Min | Median | Mean | Max | St Dev | Min | Median | Mean | Max | St Dev |
| Whole Sample | 0 | 1 | 1.37 | 9 | 1.37 | 0.39 | 0.70 | 0.68 | 1.00 | 0.13 |
| ARG | 0 | 1 | 1.00 | 6 | 0.93 | 0.39 | 0.66 | 0.65 | 1.00 | 0.13 |
| BRA | 0 | 2 | 1.96 | 9 | 1.61 | 0.40 | 0.77 | 0.75 | 1.00 | 0.12 |
| COL | 0 | 1 | 1.23 | 9 | 1.43 | 0.40 | 0.67 | 0.65 | 1.00 | 0.15 |
| PER | 0 | 1 | 1.05 | 7 | 1.35 | 0.40 | 0.66 | 0.59 | 1.00 | 0.23 |
| PRY | 0 | 1 | 1.27 | 5 | 0.99 | 0.38 | 0.74 | 0.72 | 1.00 | 0.12 |
| URY | 0 | 1 | 0.93 | 5 | 0.87 | 0.44 | 0.70 | 0.69 | 0.99 | 0.08 |

**Notes:** The maximum NDVI is taken to be the maximum NDVI before the harvest period. The number of droughts is the sum of distinct occurrences where the SPEI is less than -1.5 in a given cell.

## Identification Strategy

### The effect of droughts on greenness

To study the effect of droughts on greenness, we run the following regression:

$$\max NDVI_{i,t} = \beta\, Droughts_{i,t} + \eta_i + \delta_t + \varepsilon_{i,t} \tag{1}$$

where *i* indicates a cell and *t* the agricultural year, which is defined as the period between beginning of planting and end of harvesting (see Figure 4). The left-hand side variable is the peak NDVI over the harvest season in that agricultural year. *Droughts* is equal to the number of droughts in a cell and agricultural year before the maximum is reached, and $\eta_i$ and $\delta_t$ are the cell and time fixed effects, respectively. We estimate equation (1) with OLS and cluster the standard errors at the cell level, to account for potential correlation structures within and across cells over time. We run this regression on the pooled sample and then separately for each country. The coefficient of interest, $\beta$ , gives us the effect of an additional month with a drought during an agricultural year on maximum NDVI.[7] Our approach leverages the local variation in weather which regressions focusing on macroeconomic data at the country level might miss.

Table 2 presents the results of regression (1) for our pooled estimate in column (1) and for each country in our sample in columns (2) to (7). Our coefficient of interest, $\beta$, is reported in the first row. For instance, the results from column (2) indicate that an additional month with a drought in Argentina causes a reduction in the peak level of NDVI of roughly 0.007. Overall, the coefficients are negative and statistically significant, meaning that droughts have a negative effect on greenness. Note that we find substantial heterogeneity across countries, with effect sizes ranging from around -0.002 in Brazil to around -0.05 in Paraguay.

**Table 2. Regression Results: Effect of Droughts on Greenness**

| | (1) | (2) | (3) |
|---|---|---|---|
| max (NDVI) | Pooled Regression | ARG | BRA |
| Droughts | -0.008658*** | -0.006534*** | -0.002829*** |
| | (0.000183) | (0.000352) | (0.000251) |
| Observations | 151,648 | 52,262 | 48,265 |
| R-Squared | 0.655184 | 0.679439 | 0.396163 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

| | (4) | (5) | (6) | (7) |
|---|---|---|---|---|
| max (NDVI) | COL | PER | PRY | URY |
| Droughts | -0.025557*** | -0.005598* | -0.05332** | -0.021627*** |
| | (0.000556) | (0.002567) | (0.01897) | (0.00099) |
| Observations | 37,669 | 1,708 | 4,881 | 6,863 |
| R-Squared | 0.566801 | 0.879735 | 0.58856 | 0.532454 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

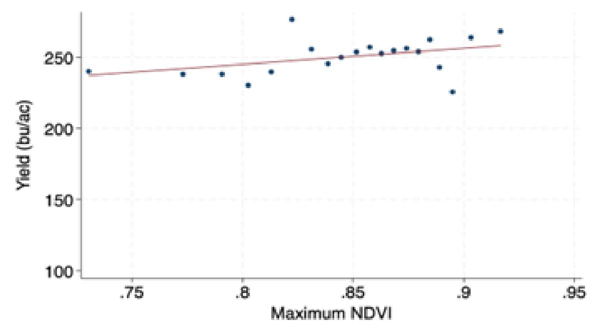
**Notes:** This table presents the results of the regression in equation (1) where our coefficient of interest $\beta$ and its standard error are reported in the first row. Column (1) shows the results for the pooled regression, while columns (2) to (7) present the results at the country level. We cluster standard errors at the cell-level and control for cell and time fixed effects.

[7] Throughout the rest of the paper, we will interchangeably refer to “a drought" and "an additional month with a drought."

### Mapping greenness into yield

To translate the estimates of the effect of droughts on greenness into actual output losses, we derive a mapping between greenness and actual output, following the methodology from Johnson et al. (2016). Our strategy relies on the assumption that Yield and NDVI are linearly related. To support this assumption, Figure 4 plots the bin-scatter between max NDVI and yield in bushels per acre across all Brazilian municipalities for 2010-2020.

**Figure 5. Yield and Maximum NDVI in Brazil**




We run the following regression:

$$Yield_{j,t} = \kappa + \lambda \max NDVI_{j,t} + X_{j,t} + \zeta_t + \mu_j + \nu_{j,t} \quad (2)$$

where $j$ is a Brazilian municipality, and $t$ the year. $Yield_{j,t}$ is the measure of yield at municipality $j$ and year $t$, in bushels per acre, and $X_{j,t}$ is a vector of controls, including the average temperature, precipitation, latitude, or longitude of the municipality. We present the results without and with year and municipal fixed effects, $\zeta_t$ and $\mu_j$.

Table 3 presents the results of the analysis. The coefficient of interest, $\lambda$, is statistically significant and positive and its magnitude is in line with the literature. Thus, we use the following mapping between yield and greenness:

$$\Delta Yield = \lambda \Delta \max(NDVI) = 130 \Delta \max(NDVI) \quad (3)$$

**Table 3. Mapping Between Yield and Greenness: Results**

| VARIABLE | Yield (1) | Yield (2) |
|---|---|---|
| max (NDVI) | 145.2** | 130.5*** |
| | (62.66) | (46.45) |
| Temperature | -12.09*** | -9.7*** |
| | (0.931) | (0.713) |
| Precipitation | 23.87*** | 15.87*** |
| | (2.492) | (4.591) |
| Constant | 107.2** | 108.5*** |
| | (48.39) | (48.39) |
| Observations | 994 | 994 |
| R-squared | 0.147 | 0.258 |
| Year FE | NO | YES |
| Municipality FE | NO | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Notes:** This table presents the results of regression (2) of yield in Brazilian municipalities on the maximum greenness index controlling for precipitation and temperature, without and with fixed effects. The coefficient of interest, λ, is in the first row.

**The effect of droughts on agricultural output and heterogeneity analysis**

We first compute the average absolute change in yield due to droughts in each country. This is given by equation (4):

$$\Delta Yield = \lambda \beta_i Droughts_i \quad (4)$$

where $\lambda$, $\beta_i$ are the estimates from regressions (1) and (2) for country $i$ respectively and $Droughts_i$ is the average number of droughts in country $i$.

We also compute the percentage change by dividing the absolute change by the average soy yield, in bushels per acre, using USDA data for each country in our sample. Table 3 presents the values used for the analysis.

**Table 4. Parameters for Loss Estimation**

| | ARG | BRA | COL | PER | PRY | URY |
|---|---|---|---|---|---|---|
| Yield (bushels/acre) | 43.09 | 52.01 | 41.61 | 22.29 | 47.55 | 32.70 |
| Average Number of Droughts per year | 1.00 | 1.96 | 1.23 | 1.05 | 1.27 | 0.93 |

Source: Authors' calculations and 2019 USDA soy yield data.

**Figure 6: Agricultural Output Loss from Droughts**

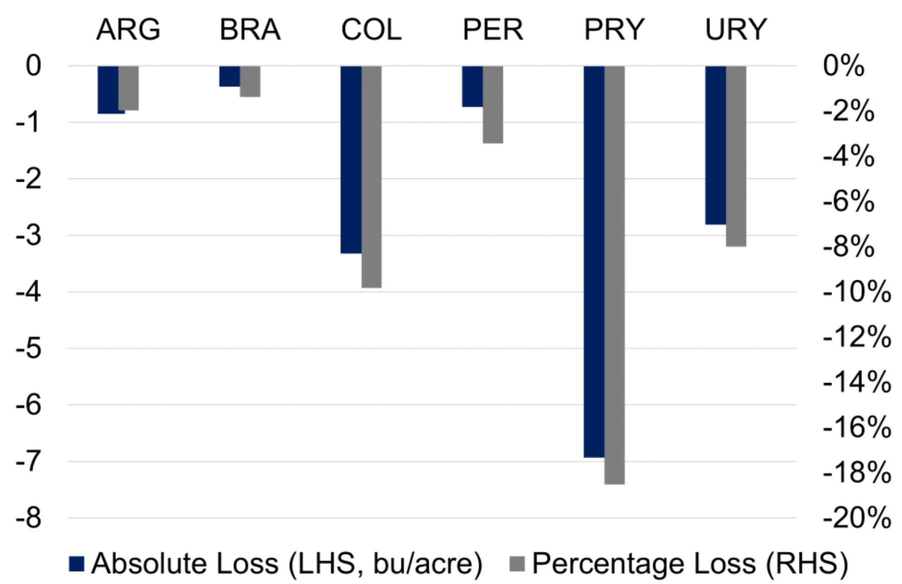



Figure 5 plots the absolute yield loss, in bushels per acre, as well as the percentage loss across countries in our sample. The results highlight substantial heterogeneity in the response of soy yield to droughts. A farmer in Brazil or Argentina loses between 0 and 1 bushels per acre on average, or around 1 to 2 percent of agricultural output, while a farmer in Colombia, Paraguay or Uruguay loses between 4 and 8 bushels per acre, or between 8 and 19 percent of production respectively.[8] In Paraguay,

[8] The estimates from the Assessment Tool for Measuring Climate Change Adaptation in the Context of Rural Development (IFAD) show heterogeneity as well.

this would mean roughly 2 percent of total GDP, in line with the few studies that evaluated the recent damages from droughts in the region.[9]

To better understand what might drive this heterogeneity, we look at the pattern of droughts between countries. We investigate whether droughts occur with the same intensity, timing, and duration between countries. Figure 6 presents the results. Panel A shows a box plot of the SPEI distribution among cells that experienced droughts in each country. Panel B presents the distribution of droughts per season in each country's specific crop cycle. Panel C finally displays the distribution of the duration of droughts, in months, across countries.

Taken together, these results indicate that droughts seem to have the same intensity and duration across countries. In fact, Peru, which exhibits one of the smallest coefficients faced more severe droughts during the sample period. However, the timing of these droughts differs, which may drive the observed heterogeneity. Panel B indicates that in Paraguay and Uruguay, droughts occur mostly during the planting season, while in Brazil or Argentina, they happen mostly during harvest or outside the cultivation cycle. Since soybeans are most vulnerable to drought stress during the early stage of growth (Poudel et al., 2023), the occurrence of droughts during this critical period in Paraguay and Uruguay could be driving the larger observed effects.

Furthermore, our regression controls for time fixed effects, and thus accounts for the common time of the shocks in the region. For instance, a potentially warmer year would affect all farmers in the same manner. It also controls for spatial factors that are constant over time, such as the fact that some farmers in some regions have more favorable growing conditions or access to different technology. The results do not control, however, for time-varying factors that are cell-specific. For instance, farmers can adapt to various shocks within a year or over time by adopting new technologies (e.g. investing in irrigation, direct seeding, precision agriculture to increase productivity, employ soybean varieties[10], which adapt to different soil and temperatures).[11] Thus, a potential explanation for our results might be that farmers in Paraguay and Uruguay have less adaptation capacity to weather-related shocks, making them less resilient.

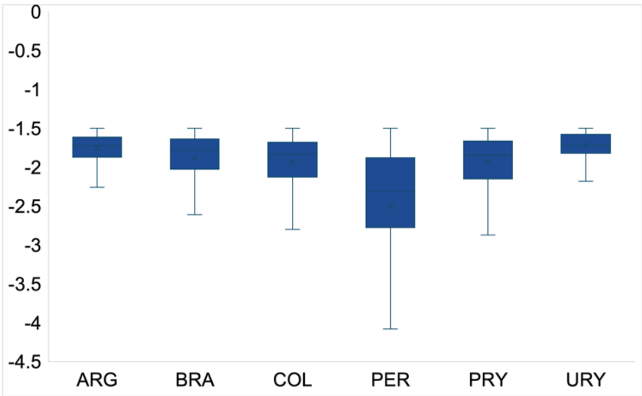
[9] For example, In Paraguay, according to World Bank (2024) analysis, the variations in past yields of the main crops grown in the country (soy, corn, wheat, beans, and cassava) indicate expected annual losses of USD 504 million, equivalent to 7.6 percent of the total risk exposure, or 1.2 percent of 2022 GDP on average. Indeed, droughts caused recessions in 2009, 2012, and 2022. Projections indicate that more severe and rare shocks, such as a once-in-a-century drought, could lead to USD 3 billion in losses, equivalent to 45.6 percent of agricultural GVA or about 7 percent of GDP as was in 2022.

[10] In Paraguay, the Chamber of Exporters and Marketers of Cereals and Oilseeds is working on a program of research and development of more resistant soybean varieties that are better adapted not only to the lack of rain but also to high temperatures. The Institute of Agricultural Biotechnology (Inbio) is evaluating HB4 soybeans, an option that could provide greater resistance to extreme weather conditions (Paraguay faces the challenge of drought: "It is the fourth consecutive harvest with setbacks due to the weather" - MarketData).

[11] Spatial measurements of yield using technological advances like on-the-go yield monitoring systems have clearly shown large within field variability in crop yields suggesting the field yields could be increased or cost decreased by varying management over space.

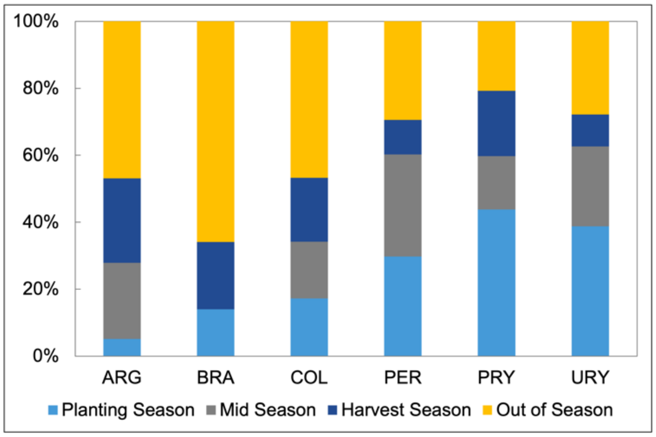
## Figure 7. Comparing Droughts Across Countries

### Panel A: Distribution of SPEI in Selected Countries



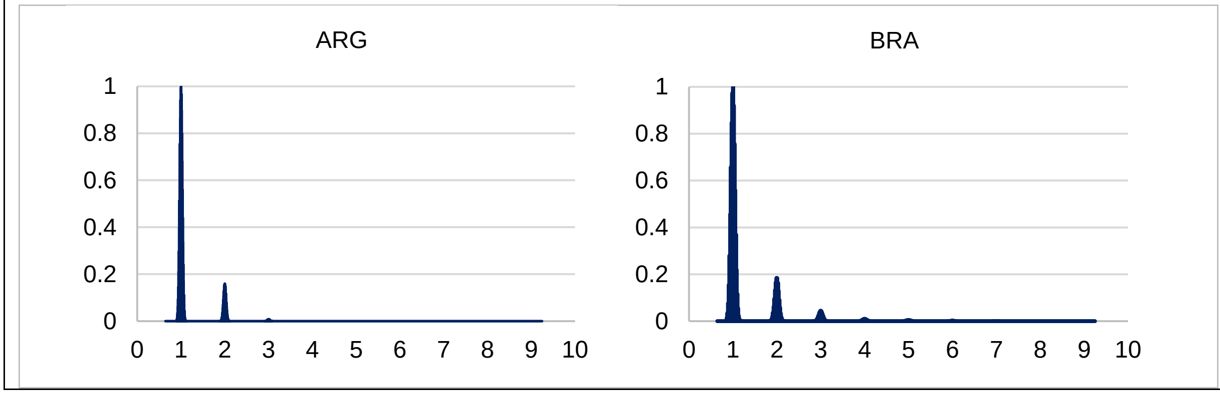

Notes: This figure presents the box plot of the SPEI in the countries in our sample, reporting the minimum, 25th, median and 75th quartile, interquartile range and maximum. We consider all years in our sample for this analysis (2010 – 2020).

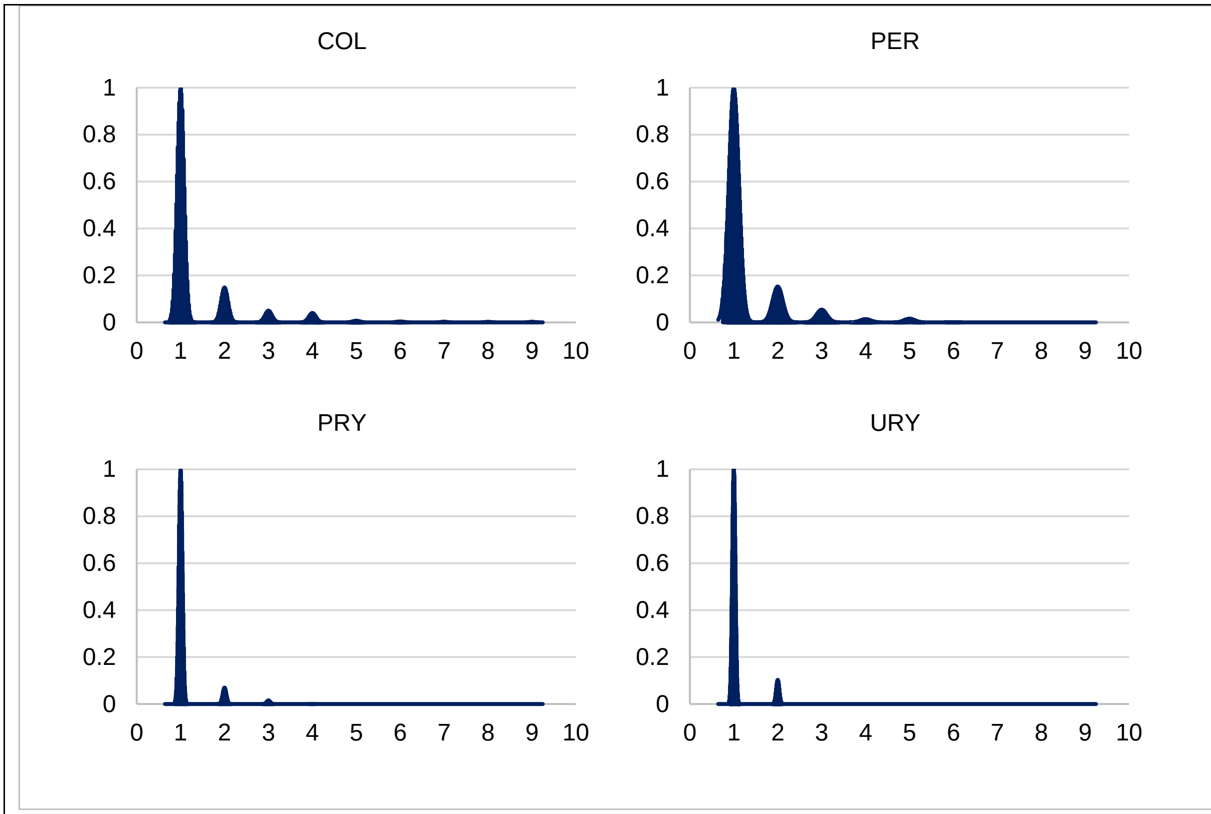
### Panel B: Timing of Droughts Per Month in Selected Countries




Notes: This panel presents, for each country in our sample, the share of droughts that took place during each country's respective season cycle. For instance, in Uruguay, roughly 40 percent of droughts happened during the planting season.

### Panel C: Distribution of the Duration of Droughts Per Country






Notes: This figure presents, for each country in our sample, the normalized distribution of the duration of droughts, defined as the number of consecutive months during which the SPEI index was below -1.5.

**Limitations and possible extensions**

The relationship between yield and reflectance may be localized and not easily extendable to other areas (Doraiswamy et al., 2003, Moriondo et al., 2007), however, this is often the preferred approach owing to their limited data requirements and simplicity to implement.[12] Although the mapping between yield and NDVI is based on Brazilian data and is extended to other countries (and thus relies on the assumption that the greenness of a cell translates to the same yield value in all countries), our approach allows us to uniquely quantify drought-related output loss and make cross-country comparison. Making yield data available at a more granular level in all countries would allow to estimate country specific yield function to address this issue.

Building on our analysis, several extensions are possible. For example, our analysis focuses on historical data and thus reveals the past effects of droughts on yield. Incorporating projections of droughts, using IPCC RCP scenarios for each country, could shed light on the future effects of droughts on agricultural yield.

12 See Lobell (2013) for the review of techniques and limitations.

# Risk Management: Agricultural Insurance

Over the years, advancements in a variety of risk management methods have aided farmers in coping with risks and output loses which can be quite large as described above. Techniques such as diversifying crops, practicing intercropping, and employing flexible use of inputs have been instrumental in sustaining crop yields (Table 5). Meanwhile, the implementation of vaccines and the enforcement of quarantines have played a crucial role in minimizing losses due to pest outbreaks and diseases affecting livestock. Furthermore, the availability of commodity futures contracts has offered farmers a mechanism to protect against price volatility. For minor and frequent losses, farmers employ self-insurance measures (like savings and contingent credit). Some producers rely on financing from microfinance institutions (MFIs) or family remittances. For the more serious but less common non-systemic losses, pooling resources into cooperative or mutual insurance schemes is a viable option.[13] Such schemes have been notably utilized in Argentina, Uruguay, and Brazil to cover fire and hail risks.

Commercial credit is an important source of rural finance in the region. Input suppliers and traders have an active role in financing commercial soybean farmers in Brazil, Argentina and Paraguay. This said, the penetration of overall agricultural lending in our country sample is very low. On average, only about 7 percent of the total credit lent by the financial system in 2023 was to the agricultural sector, although with significant variation by country. Paraguay, for example, exhibits a ratio of agricultural credit to total credit proportional to the contribution of the agricultural sector to the economy. Agricultural producers who secure loans from formal financial entities are also more motivated to acquire agricultural insurance. This is either due to the financial institutions mandating that their loans be safeguarded against weather-related risks, or because having such insurance enables them to obtain credit on more favorable conditions.

**Table 5. Risk Management Strategies and Mechanisms**

| Strategy | Informal Mechanisms | Formal Mechanisms | |
|---|---|---|---|
| | | Market based | Publicly provided |
| Ex ante strategies | | | |
| On farm | Efforts to support exposure to risk, crop diversification, income diversification, buffering of crop stocks, adoption of advanced cropping techniques | | Agricultural extension, pest management, infrastructure |
| Risk sharing | Crop sharing, informal risk pool | Contract farming, insurance, price hedging | |
| Ex post strategies: risk coping | Sales of assets, relocation of labor, mututal aid | Credit | Social insurance, social funds, cash tranfer |

Sources: Anderson 2001, and Townsend 2005.

13 In 2015, cooperatives and mutual insurer schemes accounted for 61 percent of total premiums in Paraguay, 45 percent in Argentina, and 37 percent in Uruguay.

While on-farm risk management and adaptation strategies or self-insurance measures can help farmers to cope with minor losses, significant and frequent systemic losses from extreme weather events are often transferred to commercial insurance and reinsurance companies. Besides risk management, agricultural insurance can play a crucial role in safeguarding farmers and the broader economy (Figure 7). By compensating for crop losses, agricultural insurance helps farmers bounce back after setbacks. This resilience is essential for food security and economic stability, especially in regions where agriculture remains a vital sector.

**Figure 8. Benefits of Agricultural Insurance**


When farmers have insurance coverage, they can invest confidently in their operations. Knowing that losses are mitigated, they can adopt better practices, purchase quality inputs, and improve productivity. Extreme weather shocks can also lead to significant budget volatility for governments. By transferring some of the risk to the private sector through insurance, governments can stabilize their fiscal expenditures related to agriculture. Also, by defining cash transfer crisis support or premium contribution, governments engage in proactive rather than reactive social protection. When farmers are protected by insurance, they are more likely to invest and expand their operations, potentially leading to employment opportunities. By promoting transparency and accountability, agricultural insurance can minimize fiscal leakages and corruption (e.g., misappropriation of support funds). When insurance payouts are fair and timely, it strengthens trust in the system and discourages unethical practices.

The agricultural insurance industry in Latin America has been growing, but slower than expected a decade ago.[14,15] According to Cognitive Market Research, the Latin America's agricultural insurance market size was estimated at more than USD 2 billion (5 percent) of total global market in 2024 against USD 1.6 billion in 2015 and USD 780 million in 2009. Insurance, while relatively developed in some countries, exhibits significant variability across different countries within Latin/South America in terms of product types, coverage and premium distribution, and the degree of collaboration between the public and private sectors.

The main insurance policies offered are Multi-Peril Crop Insurance (MPCI), crop-named perils, and index-based insurance (Annex I).[16] MPCI is most common and prevalent type of insurance.[17] Two thirds of premiums are written for crop, named-peril and individual-farmer multiperil crop. An NDVI crop insurance scheme was first introduced in 2006 in Mexico. Index-based agricultural insurance and crop revenue insurance, which

14 In 2015, Swiss Re forecasted that the market would grow to USD 3.7 billion by 2025 which is almost double the current estimated level.

15 Granular country data is not readily available. Latin America represents South American countries plus Mexico.

16 In this paper we only discuss crop insurance.

17 Hess and Hazell (2016) estimated that about 198 million farmers were insured in 2014 (3.3 million in Latin America and the Caribbean), approximately 650,000 in Africa, and about 194.2 million in Asia, of which 160 million were in China and 33.2 million in India. ISF Advisers (2018) estimated that the regional gap in smallholder insurance coverage was 67 percent in Latin America, 97 percent in Africa and 78 percent in Asia.

protects the policyholder from shortfalls in yield of the insured crop (MPCI) and from adverse movements in the price of the insured crop, are leading the way in innovative insurance products (Box 1).[18]

### Box 1. Index-Based Agricultural Insurance

This approach settles claims based on local weather conditions rather than on the specific damages suffered by an individual, including for losses that are often excluded by traditional insurance, while significantly reducing the expenses associated with claim underwriting and processing. The use of modelled data for index-based insurance enables its introduction in markets lacking historical claims data for accurate actuarial evaluations. The simplicity, transparency, objectivity, and quicker disbursement of index-based insurance payments make these products more appealing to low-income individuals who previously may have been deterred from purchasing insurance due to a lack of experience, awareness of risks, or trust.

However, the challenge of basis risk remains a concern. This risk involves the possibility of a claim not being activated by the index despite an actual loss occurring, resulting in calls for aligning triggers with actual losses[1]. Continuous innovation in index development and advancements in satellite technology are crucial for expanding the reach of index-based insurance. Additionally, increasing education and awareness among clients is essential for promoting adoption while regulatory transparency and support are also vital for successfully implementing parametric insurance.

1/ See FSI Insights (2024): Uncertain waters: can parametric insurance help bridge NatCat protection gaps?

The agricultural insurance market remains very small (only about 2 percent of regional non-life premiums), with quite low an uneven penetration (around 0.6 percent of agricultural output, comparing to 1 percent in Europe and 5 percent in North America). In Paraguay, penetration is low and estimated at 0.03 percent of GDP and 0.6 percent of agriculture output (World Bank (WB), 2023). In Brazil, by contrast, about 20 percent of farming activity is covered by insurance on average (Superintendência de Seguros Privados (SUSEP)). In Colombia, although agricultural insurance schemes are being implemented, their current penetration and geographical coverage are still limited, and some of the schemes have not yet been scaled up beyond pilot stage (Country Climate and Development Report (CCRD), WB, 2023). In Peru, non-life insurance penetration is one of the lowest (Figure 9), and agriculture's share is even lower; and of the 18 active insurance companies in Peru, only five offer catastrophic insurance (CCRD, WB, 2023).[19]

Premium distribution is dispersed unevenly among the different agricultural insurance business sub-lines and across the region, with Brazil, Argentina (and México) accounting for 90 percent of gross written premiums (GWP). Furthermore, the cost of insurance is higher compared to other regions. While more granular and recent data is not available, a decade ago, the total expenses for the provision of agricultural insurance in the Latin America and Caribbean was estimated to be 11 percent higher than average expenses in other regions, and they would be rising. The severe 2021-22 drought showed that losses have exceeded premiums by 42 percent in Paraguay and resulted in a significant increase in premiums in Brazil (Figure 10).

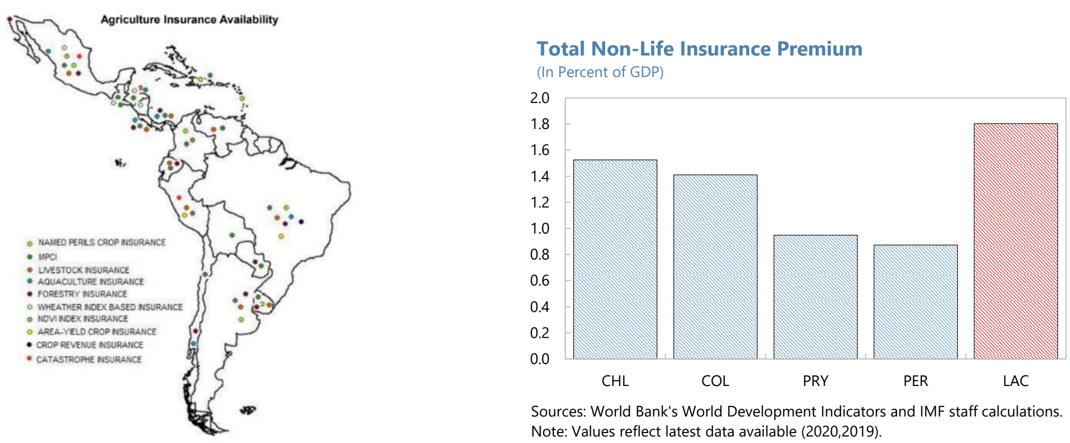
The size of the insurance market reflects a host of demand- and supply-side constraints. Insurers face issues with the high fragmentation of rural clients, the complexity of the value chains in which they operate, and the

[18] According to representatives from the industry, the main challenge facing the implementation of crop revenue insurance is the lack of developed local commodity futures markets with enough open interest for the forward positions that would have to be taken by the insurance industry to implement this type of product.

[19] The SAC, a catastrophic insurance instrument that insures low-income growers (mostly subsistence farmers) against all relevant hazards,50 covers only 8 of 25 regions and about 8.9 percent of small and medium-sized farmers on average.

lack of granular public data on agricultural and weather trends in most countries. To create insurance products that meet the needs of both insurers and farmers, underwriters must possess extensive knowledge of agriculture and its risks. Established insurance companies typically develop specialized technical units focused on agriculture or outsource underwriting to firms with expertise in the field. For smaller insurers, acquiring this expertise involves a lengthy process of trial-and-error, with negative experiences potentially deterring further engagement in the agricultural sector. This is not exclusive to South America and affects most developing countries. Significant technical demands contribute to high administrative and transaction costs. On the demand side, limited incomes of small- and medium-sized farms make insurance premiums relatively expensive. Furthermore, farmers often have a limited grasp of the advantages offered by insurance, resulting in reactions that vary from confusion to outright skepticism. Finally, there are some weaknesses in legal and regulatory framework on the domestic level, including in application of international regulatory standards.[20]

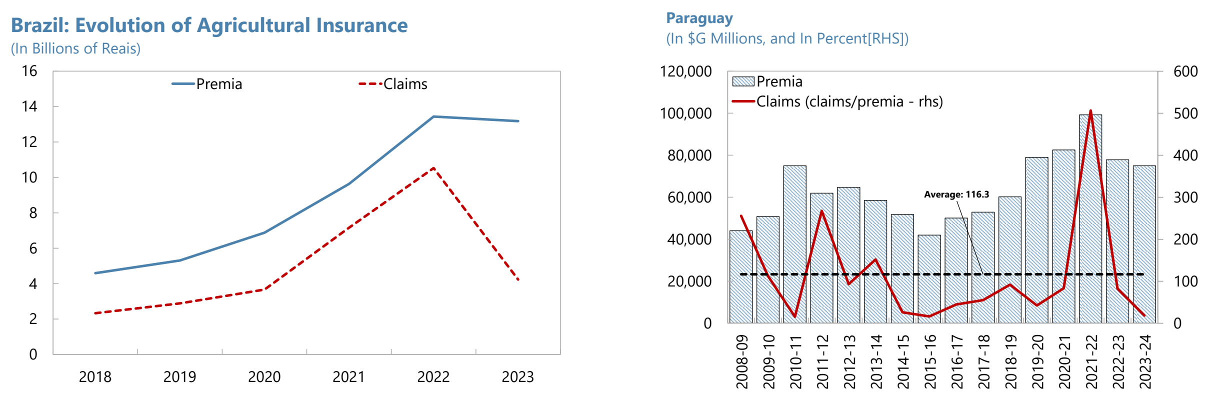
**Figure 9. Agricultural Insurance: Availability and Penetration[1]**




Sources: World Bank's World Development Indicators and IMF staff calculations.
Note: Values reflect latest data available (2020,2019).

1/ Recent data is scarce but given the still low share on insurance coverage in the region, these maps appear representative.
Sources: World Bank (2010); and Aspen Re (2014), updated from (Iturrioz R & Arias D. 2011); and (Mahul & Stutley, 2010).

**Figure 10: Premia and Claims in Brazil and Paraguay**



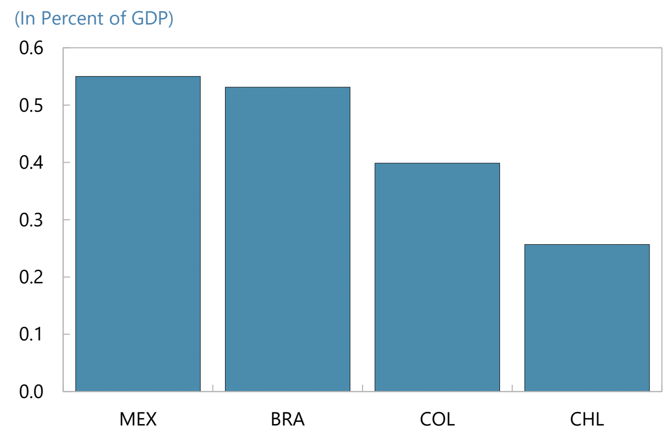

Source: SUSEP.

Sources: Central bank of Paraguay.

[20] There is a need to establish clear regulations for indices, triggers and payout structures, and provide an enabling supervisory framework that sets out clear expectations and guidance (BIS, 2024).

Reinsurers indeed play an active role in agricultural insurance markets with 15 reinsurance companies present in the region. Approximately 65 percent of the total direct written premiums for agricultural insurance in the region are conceded to this market. Crop hail and named-peril crop (specific crop) insurance programs have adequate reinsurance capacity because this business is not subject to catastrophic losses. Accessing reinsurance services is still challenging in developing areas, as global reinsurers usually struggle with the small business volumes and lack of available data associated with these markets, as well as various regulatory impediments. Many international reinsurers are also averse to underwriting MPCI for individual growers because the exposure to systemic risks, such as drought and flood, can accumulate over wide regions, resulting in catastrophic losses. The increasing frequency extreme weather events over the years has prompted reinsurers to adjust their risk and exposure management strategies, leading to higher premiums.

**Figure 11. Total Fiscal Support to Agriculture**




Sources: Organization for Economic Co-operation and Development (OECD); Haver Analytics; and IMF staff calculations.

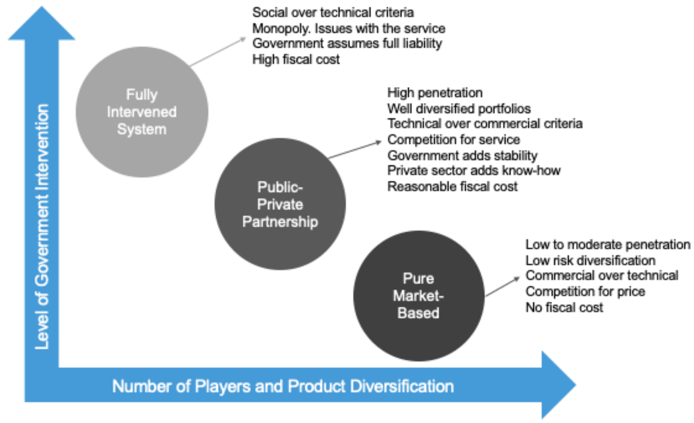
Governments in the region are contributing to the growth of agricultural insurance markets to some extent (Figure 11). Systemic risk and the constraints on the capacity of reinsurers to underwrite it is one of the core reasons for governmental participation, while other reasons being (a) the absence of insurance infrastructure in rural areas and the absence of private sector agricultural insurance services; (b) the prohibitively high start-up costs in developing agricultural insurance products; (c) the high administrative costs of underwriting insurance; and (d) farmers' affordability issues due to high costs of premiums. Therefore, public sector support usually (but not exclusively) takes the following forms: (a) funding of premium subsidies, (b) research and development of insurance products, (c) direct purchase or provision of insurance and reinsurance, and (d) the setup of specific insurance programs targeted to small and marginal farmers.[21] Some governments, like in Peru, transitioned from ad hoc natural disaster compensation schemes to formal crop and livestock insurance programs that are executed by the private sector but supported by the government through the provision of subsidies for premiums or reinsurance protection (Annex III). Some governments still offer public sector disaster relief, especially to small and medium-sized enterprises, alongside subsidized crop insurance, as seen in Brazil (Annex II). In Paraguay, there is no direct government involvement in insurance provision or subsidization, but there have been some post-disaster or emergency outlays financed by post-disaster loans. During the recent severe droughts of 2021-22 and 2024, administrative forbearance has been exercised allowing banks to relax loan service obligations to the affected clients while the necessary liquidity to banks was available from the central bank.[22]

Integrating the above information, below are several models of public-private cooperation that have been observed in practice with varying cost-benefit outcomes (Figure 12).

[21] Agricultural insurance was provided in many countries by public sector insurance companies from the 1950s up to the end of the 1980s but were terminated by 1990 on account of their poor results.

[22] "Drought: APR celebrates BCP support measures": [Sequía: ARP celebra medidas de apoyo del BCP - Economía - ABC Color]

**Figure 12. Models of Support for Agricultural Insurance**




Source: Iturrioz (2009).

# Agricultural Insurance and Productivity

To study how risk influences decision making in agriculture, we closely follow Donovan (2021) and outline a dynamic general equilibrium model that emphasizes the intricate relationship between agricultural risk and productivity. While the model does not allow for a one-to-one mapping of our empirical findings above, it highlights how risk influences the use of intermediate goods in agriculture, leading to variations in labor productivity and total factor productivity across different market structures. Using both country specific aggregate data and exploiting the granular empirical analysis of agricultural risk above, we then calibrate the model to our country sample to quantify the impact of introducing insurance on agricultural productivity.

## The Equilibrium Impact of Insurance: A Dual-Sector Analysis of Agricultural Risk and Intermediate Goods Use

### Model Overview and Key Mechanisms

The model is built upon a dual-sector framework consisting of agriculture and manufacturing. The key distinguishing feature of the agricultural sector is its exposure to random productivity shocks reflecting the uncertainty in agricultural output due to factors like weather conditions, which are not fully insurable due to incomplete markets. In line with the chronological order of agricultural decisions, intermediate inputs are selected prior to the realization of the shocks. Therefore, this inherent risk component of agricultural production influences farmers' optimal decisions regarding the use of intermediate goods such as fertilizers, pesticides, and machinery. Furthermore, farmers face a subsistence requirement implying that they exhibit decreasing relative risk aversion and allowing the equilibrium price of agricultural output to directly influence risk aversion through the cost of subsistence. Thus, farmers have an incentive to use fewer intermediate inputs, as this limits their exposure to risk and allows for self-insurance. Hence, risk leads to misallocation, disproportionately impacting poorer households.

## Production technology

### Manufacturing

The output of manufacturing, serving as the numeraire, can be allocated for consumption or as an intermediate input in the agriculture sector. The production process in period $t$ is encapsulated by a representative profit maximizing firm that relies solely on labor services, denoted as $\mathrm{N}_{mt}$, to generate output. This process adheres to a production function with constant returns to scale, expressed as $Y_{mt} = A\, N_{mt}$, where $A$ signifies a sector neutral TFP parameter which is specific to each country and represents the overall efficiency of the economy.

### Farming

Each household possesses a single farm, which utilizes intermediate inputs $x$ and labor $n_a$ for production. This process is governed by a production function with decreasing returns to scale, formulated as $y_{at} = z_t A\, x_t{}^{\gamma} n_{at}^{\zeta}$, where $\gamma + \zeta < 1$. The productivity shock $z_t$, specific to each household, is derived from a stationary distribution and spans the interval $[\underline{z}, \bar{z}]$. The occurrence of $z_t$ is independent and identically distributed across both households and over time. Intermediate inputs are acquired from the manufacturing sector at a price $p_x \geq 1$, which is subject to variation across different countries.

### Households

Households derive utility from consuming goods produced in both the agricultural and manufacturing sectors, aiming to maximize their expected utility $E_0 \sum_{t=0}^{\infty} \beta^t u(c_{at}, c_{mt})$, where $\beta$ is the discount factor. The flow utility for period is defined as $u(c_{at}, c_{mt}) = \alpha\, log(c_{at} - \overline{a}) + (1 - \alpha) log(c_{mt})$, with $c_{jt}$ denoting consumption from sector $j \in \{a, m\}$ and $\overline{a} > 0$ indicating the minimum subsistence level of agricultural consumption. In the absence of insurance markets, households can only employ self-insurance strategies against risks. Savings are measured in agricultural goods and are subject to a country-specific depreciation rate $\delta$, reflecting the variance in agricultural saving technologies across countries, such as differing spoilage rates in crop storage.

### Timing

At the preceding time period, $t-1$, households allocate $b_t$ units of the agricultural good towards savings. A fraction $\delta$ of these savings depreciates, leaving the household to commence time $t$ with $(1-\delta)b_t$ units of saved resources. The decision-making process for period $t$ is segmented into two distinct phases, namely the ordering phase and the production phase, with the shock $z$ occurring in between them. During the ordering phase, households decide on the quantity of intermediate inputs, $x_t$, to be utilized on their farms. Following this decision, the shock $z_t$ materializes. All activities related to production and consumption are carried out in the subsequent production phase. Initially, households determine the distribution of labor between the agricultural sector, offering the opportunity to work on their own farm, and the manufacturing sector, where employment yields a wage $w_t$ subject to a tax rate $\tau \geq 0$. Once labor allocation is finalized, the production activities are executed. The presence of a centralized marketplace ensures a singular equilibrium price $p_a$ for transactions. Profits are generated, payments for all production inputs are disbursed, and choices regarding consumption and future savings $(c_{at}, c_{mt}, b_{t+1})$ are made. This timing implies that the household state variable is savings $b$, and the aggregate state is the distribution of savings across all households.[23]

[23] For more details, including the definition of the recursive problem and the stationary equilibrium, a discussion on modelling choices, as well as a formal characterization of the mechanics of the model, see Donovan (2021).

## Calibration and Model Fit

To examine the quantitative effects of risk within our general equilibrium framework, we initiate by calibrating our baseline model for Brazil, Paraguay, and Uruguay. The calibration process integrates both aggregate statistical and micro-level data such as the cell-level variation in NDVI, which we use as a proxy for variation in harvest income. The calibration procedure is structured as follows: certain parameters are determined externally, some are derived from our preceding empirical analysis, while others adhere to commonly accepted values found in existing literature. The remaining parameters are jointly calibrated to align with specific micro and macroeconomic indicators of the respective countries. This involves computing the stationary equilibrium of the model economies and iteratively refining the parameter values until there is a match with the observed empirical moments. Table 4 summarized the calibration and model fit.

### Parameters set exogenously

Seven parameters are determined externally in the model. The utility function parameters are assigned as follows: $\beta$ is set to 0.96 to reflect the annual model period, and $\alpha$ is determined to be 0.005, in alignment with the findings of Restuccia et al. (2008) and Lagakos and Waugh (2013). Secondly, the coefficients for the Cobb–Douglas production function are set in line with Donovan (2021), i.e., $\zeta$ is chosen as 0.42 and $\gamma$ as 0.40. The values for $p_x = \{1.17, 2.28, 1.50\}$ are chosen based on data regarding fertilizer and pesticide inputs from the Food and Agriculture Organization (FAO). The tax on manufacturing labor income, denoted by $\tau$ is calibrated using microdata from household surveys in the respective countries. Specifically, we run the following regressions for our sample countries: $log(w_{isct}) = \alpha X_{ict} + \theta_{ct} + \psi 1_{isct\ \mathbb{I}[s=m]} + \epsilon_{isct}$ where $w_{isct}$ represents the wage earned by household $i$ in county $c$ in year $t$ for sector $s \in \{a, m\}$. Here, $X$ accounts for variations in household composition, education, and age that might influence wages but are not included in the model. $\theta_{ct}$ is a county-year fixed effect. The focal point of this analysis is the coefficient $\psi$, which estimates the wage change if the income is from the manufacturing sector, as indicated by $\mathbb{I}[s = m]$. The derived estimates $\hat{\psi} = \{0.36, 0.44, 0.34\}$ are subsequently employed as the measure for $\tau$. Finally, we calculate the variation in individual-level harvests using NDVI data. However, this data encompasses variations stemming from heterogeneity in specific cell characteristics that are not accounted for in our model. To the degree that these variations are predictable, attributing them directly to variance in the data would incorrectly classify them as unanticipated shocks. Consequently, we adopt the approach of Kaboski and Townsend (2011) among others, employing regressions that include cell and year fixed effects to eliminate these factors from the data. The standard deviation of the residuals from these regressions is then aligned with the income variation observed in the model's stationary equilibrium. This process results in $\sigma_z = \{0.419, 0.499, 0.438\}$.

### Parameters calibrated jointly

Armed with the parameters set externally, we are left with calibrating four remaining parameters. The shock distribution is presumed to be a mean-zero truncated log-normal distribution, necessitating the determination of bounds $\{\underline{z}, \overline{z}\}$ in addition to the standard deviation $\sigma_z$, which is predefined externally as described above. Although these parameters are selected in conjunction, each aligns naturally with specific target moments. Thus, we will elucidate each target alongside its corresponding model analogue, bearing in mind that their selection is a collective process aimed at matching moments in equilibrium. Specifically, the subsistence requirement $\overline{a}$ is calibrated to align with the agricultural employment share observed in our sample countries, in accordance with the World Bank's development indicators. We then adjust the sector- neutral TFP $A$ to reflect the real GDP per worker ratio between that of the U.S. and our sample countries. The final two moments, $\underline{z}$ and $\overline{z}$, are chosen to match the top and bottom 1% of observations within the cross-sectional NDVI distribution.

**Table 6. Calibration and Model Fit**

| Parameter | Parameter Value | | | Target Value | | | Model Value | | |
|---|---|---|---|---|---|---|---|---|---|
| | BRA | PRY | URY | BRA | PRY | URY | BRA | PRY | URY |
| $\alpha$ | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |
| $\beta$ | 0.960 | 0.960 | 0.960 | 0.960 | 0.960 | 0.960 | 0.960 | 0.960 | 0.960 |
| $\overline{a}$ | 0.023 | 0.026 | 0.025 | 0.087 | 0.170 | 0.080 | 0.047 | 0.154 | 0.082 |
| $\gamma$ | 0.400 | 0.400 | 0.400 | 0.400 | 0.400 | 0.400 | 0.400 | 0.400 | 0.400 |
| $\zeta$ | 0.420 | 0.420 | 0.420 | 0.420 | 0.420 | 0.420 | 0.420 | 0.420 | 0.420 |
| $\sigma_z$ | 0.419 | 0.499 | 0.438 | 0.419 | 0.499 | 0.438 | 0.419 | 0.499 | 0.438 |
| $\underline{z}$ | 0.760 | 0.725 | 0.780 | 0.777 | 0.732 | 0.813 | 0.815 | 0.786 | 0.796 |
| $\overline{z}$ | 0.900 | 0.875 | 0.930 | 1.148 | 1.111 | 1.152 | 1.091 | 1.117 | 1.185 |
| $\tau$ | 0.360 | 0.440 | 0.340 | 0.360 | 0.440 | 0.340 | 0.360 | 0.440 | 0.340 |
| $p_x$ | 1.170 | 2.280 | 1.500 | 1.170 | 2.280 | 1.500 | 1.170 | 2.280 | 1.500 |
| $A$ | 0.140 | 0.226 | 0.150 | 3.750 | 4.550 | 2.320 | 4.073 | 4.893 | 2.773 |

## Results

We employ the model to analyze the equilibrium effects of risk by contrasting two types of economies in each of our sample countries: one without insurance and one with insurance. Through this comparison, we aim to elucidate the mechanisms by which risk suppresses productivity in relatively poor countries.[24]

Table 5 presents aggregate data from the sample economies, comparing outcomes under a baseline model with incomplete markets to those under a hypothetical model with complete markets. The inclusion of insurance is observed to elevate the nominal intermediate share by 2.66% in Brazil, 9.34% in Paraguay, and 4.50% in Uruguay, indicating significant distortions induced by risk with considerable implications for productivity and employment. Specifically, the employment percentage in agriculture declines by 1.30% in Brazil, 5.89% in Paraguay, and 2.18% in Uruguay. Meanwhile, labor productivity sees an uplift both in the agricultural sector and overall. Agricultural labor productivity increases by 2.67% in Brazil, 7.45% in Paraguay, and 3.60% in Uruguay, while GDP per capita rises by 0.99%, 2.85%, and 1.51% in these countries respectively.

What drives the enhancement in productivity following the introduction of insurance? Two primary mechanisms are at play: the influence of insurance on both the mean and variability of the real intermediate share distribution among households. Insurance boosts the average real intermediate share, directly elevating agricultural labor productivity. The second mechanism operates through risk elimination, which enhances allocative efficiency among farmers, even when keeping the mean realization constant.

[24] As mentioned previously, insurance is not completely lacking in the sample economies under consideration. Nonetheless, due to the absence of an explicitly modeled and calibrated insurance sector (or specific types of insurance products) and constraints posed by data availability, our analysis is centered on contrasting the two polar scenarios of no insurance and complete insurance. Consequently, our findings can be viewed, to some extent, as representing an upper bound.

**Table 7. Model Results**

| Economy | Agricultural Productivity | GDP per capita | Intermediate Input Share | Agricultural Labor Share |
|---|---|---|---|---|
| **Brazil** | | | | |
| %-change | 2.67 | 0.99 | 2.66 | -1.30 |
| **Paraguay** | | | | |
| %-change | 7.45 | 2.85 | 9.34 | -5.89 |
| **Uruguay** | | | | |
| %-change | 3.60 | 1.51 | 4.50 | -2.18 |

This reduction in misallocation further augments agricultural productivity by increasing what is effectively measured as agricultural TFP. These dynamics also elucidate the more pronounced effects observed in Paraguay, a country that is not only poorer and less productive compared to Brazil and Uruguay but also contends with less advantageous input costs and higher, more dispersed agricultural risks and therefore more misallocation.

# Conclusions

By using satellite data, we can map the effect of a weather shock (drought) on agricultural output. Our analysis reveals that regional influences significantly impact agricultural output, displaying considerable variation: on average, droughts result in a close to 2 percent reduction in soy output in Argentina and Brazil, whereas the decrease is substantially larger in other countries, reaching 8 percent in Uruguay and 19 percent in Paraguay. This disparity could be attributed to the timing of droughts, as they occur at different stages of the crop cycle across countries, as well as to differences in the adoption of drought-resistant seeds and technologies. Furthermore, the potential benefits of other adaptation measures, such as broadening insurance coverage, are substantial. Specifically, agricultural productivity could see an enhancement of 7.5 percent in Paraguay, 2.7 percent in Brazil, and 3.6 percent in Uruguay.

As compounding shocks are more present, the need for innovative insurance solutions is becoming even more critical.[25] Global market agricultural insurance is projected to grow from the current USD 40 to 60 billion by 2030. How can South American countries benefit from this expected growth? Despite some progress, there are multiple impediments to further and more broad development and penetration of insurance in the region. There is a lack of analytical capacity at a local level, including limited knowledge and information systems required to monitor and evaluate agricultural risks appropriately, and expensive reinsurance at the international level, dampening insurers’ capacity to offer crop insurance products at the national level.

Agricultural insurance should not be seen as a one-size-fits-all solution to farmers' weather-related challenges. And here is no one-size-fits-all strategy for overcoming the challenges facing the development of agricultural insurance. Yet, enhanced private-public efforts could help the private insurance industry overcome some of the latter. However, calibrating and targeting public policies is crucial (Obolensky, 2024). Furthermore, proactive social assistance to most vulnerable farmers with a long-term view should be in place of reactive policies.

[25] See, for example, Brookings: Agricultural insurance the antidote to many economic illnesses.

In general, a public-private partnership model should include efforts towards achieving the following objectives:

**Spread the risk**: Farmer groups, insurance companies, and governments could examine the possibility of pooling agricultural risks, including on a regional level, guided by international examples such as African Drought Insurance and Caribbean Catastrophe Risk Insurance Facility [26], and possibly orient the insurance industry's approach from a focus on farmers to a broader focus on the agribusiness value chain. Governments could participate in risk financing on top of catastrophic risk layers to complement reinsurance markets while redefining the role of agricultural insurance premium subsidies and other public support mechanisms to avoid moral hazard or indirect support (e.g., regulatory forbearance), constituting a proactive rather than reactive approach.

**Improve data availability**. Governments have a vital role in enhancing data availability for insurers and other key stakeholders (such as modeling and forecasting companies) by investing in public infrastructure.[27] This requires the establishment of agricultural and weather databases, including at a regional level, that provide regular, up-to-date, granular, and historic data on average yields and rainfall. These databases would enable enhanced risk modeling and would provide the basis for potential index insurance solutions.

**Strengthen regulations:** Governments should work on strengthening regulatory regimes, including contract enforcement, and facilitating access to international good practices on underwriting, policy terms and conditions, and loss adjustment procedures. The regulators should ensure stability, fairness, and transparency of the insurance sector. This increases the chances that local insurers can access international reinsurance services to offset some of their risk. The legal and regulatory frameworks will need to keep up with ongoing changes in product design and delivery mechanisms to maintain a healthy retail and reinsurance market.

**Reduce costs:** For agricultural insurers, establishing efficient distribution networks and leveraging technology are essential strategies for reducing administrative and claims settlement costs. Recent success stories in Latin America highlight the effectiveness of mobile technology and automated weather stations. Experimentation with remote sensing technology for index-based insurance shows promise for reducing operational costs by streamlining risk assessment.

**Improve access and build trust:** Expanding insurance coverage to include remote regions, particularly in the Andean countries, is crucial. Technologies, including mobile and internet-based solutions, are increasingly important for delivering insurance. Further growth of mobile money technology in premium collection and settlement will require a well-functioning telecommunication infrastructure, which would have to be a public-private cooperation as well. Awareness campaigns, financial literacy training, etc., can help build trust in and awareness of insurance as a financial product among small farmers.

[26] Drought Models | African Risk Capacity Group (arc.int); Home | CCRIF SPC.

[27] BIS, 2024.

# Annex I. Literature Review

This annex lists the various papers measuring the link between the greenness index and actual yield. For each paper, we report the years, the country and the crop studied. We also report which data and which methodology were used to derive the correlation between the NDVI and actual yield on the ground (statistical data or local measures).

| Paper | Year | Country | Crop | Data | Correlation / Main Finding |
|---|---|---|---|---|---|
| Alam, Shamm & Meng (2021) | 2000-2018 | US | Soy | Crop yield from USDA, NDVI | $R^2$ =0.95 |
| Basso et al. (2001) | 2001 | Durand, MI | Soy | Local measures of crop yield, NDVI | Very high ($R^2$= 0.9) |
| Bolton & Friedl (2013) | 2004-2009 | US | Maize and soybean | Crop yield from USDA, NDVI | $R^2$ ~ 0.7 but need to account for the seasonality as they are good predictors around green-up time |
| Franch et al.(2019) | 2001 - 2017 | US and Ukraine | Wheat | Historical yield statistics and NDVI | Very high ($R^2$ between 0.81 and 0.86) |
| Johnson (2016) | 2008-2013 | US | 11 crops including soybeans | County level data on crop yield, annual and NDVI | Strong correlation between two-week lagged NDVI and yield |
| Kogan et al. (2018) | 2018 | Australia | Wheat | Official yield statistics, NDVI | $R^2$>0.7 |
| Mkhabela et al. (2011) | 2000-2006 | Canada | Barley, canola, field peas and spring wheat | Census Agricultural Region from Statistics Canada, NDVI MODIS Data | Regress NDVI on shock variables. Strong predicting power of NDVI for crop yield for most crops. |
| Quarmby et al. (1991) | 1986-1988 | Northern Greece | Wheat, cotton, rice, maize | NDVI and yield | Strong degree of accuracy but estimates stabilize 50-100 before harvesting |
| Wall et al. (2007) | 1987 - 2002 | Canada | Wheat | Land-based measurement of yield and NDVI | NDVI has strong explanatory power for yield |
| Zhang et al. (2014) | | China | Maize | Official statistics and NDVI from MODIS | $R^2$ = 0.82 |

# Annex II. Agricultural Insurance Products by Type

**Agricultural insurances Sub-lines of Business**

| | |
|---|---|
| **Crops & horticulture** | Privately-provided insurance cover is available for all types of crops, fruits, flowers and vegetables, in the following formats:<br>▪ Named-peril crop insurance – indemnifies owners of certain crops, or tenant farmers having an interest in such crops, for loss or damage due to a specific peril named in the policy.<br>▪ Multi-peril crop insurance (MPCI) – provides crop insurance protection for growers of certain kinds of crops. Coverage is written on specific cause-of-loss or all-risk basis.<br>▪ Revenue coverage (price and yield) – revenue protection for an insurable crop when low prices, low yields or a combination of both cause a producer's revenues to fall below a guaranteed level.<br>▪ Parametric or index covers, including weather derivatives – covers yield losses due to a readily observable variable that is highly correlated with the particular crop yield, normally rainfall, irrigation water flow, or number of days with temperature above/below a certain threshold. Could also be determined by the performance of an insurance-related index (eg, on claims development for certain risks related to specific weather conditions).<br>▪ Quality guarantee – covers commercial standards established by the reference markets. |
| **Greenhouse** | Comprehensive coverage for material damage to structure, glass, equipment and plants due to fire, windstorms, snow weight and equipment failure. |
| **Livestock** | Generally protects the owner against losses resulting from death or involuntary destruction of livestock due to disease or accidental injury. Business interruption covers have been developed for large-scale cattle, pig and poultry operations. |
| **Horses, bloodstock and pets** | Covers individual animals of the most varied species, but in most cases equines, whether pleasure horses or bloodstock. The cover is triggered by disease or accident causing death or permanent disability. |
| **Forestry** | Insurance for timber and plantations, most importantly for fire and windstorm . Extended covers are becoming increasingly popular and may include flood, hail, snow weight, insect infestation, and damage caused by domestic and wild animals. |
| **Aquaculture** | Insurance cover for the breeding and raising of aquatic animals, whether in inland ponds or offshore. It covers mortality or loss of fish stock due to meteorological events, disease, pollution, algae blooms and escape from damaged installations. |

Source: Swiss Re Economic Research & Consulting.

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Working Paper No. WP/2025/052