CLIMATE-DRIVEN AGRICULTURAL DECLINE INDEX: TECHNICAL REPORT

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Abstract. This document describes the data, methodology, and construction of the Climate-Driven Agricultural Decline Index (CADI). The project quantifies how climate change affects agricultural productivity at high spatial resolution (approximately 9.3×9.3 km) across the globe. We construct a set of indices that translate changes in attainable yield from the Global Agro-Ecological Zones version 5 (GAEZ v5, FAO and IIASA, 2025) into an intuitive metric—*People Fed Yearly* (PFY)—and present results through an interactive website. This codebook documents the full data construction process, from raw GAEZ v5 crop and yield data through to the final index variants.

keywords: Climate Change, Agricultural Productivity, Attainable Yield, Food Security, GAEZ v5

1. Introduction

This codebook documents the construction of the Climate-Driven Agricultural Decline Index (CADI), a global dataset that measures how climate change affects the food production capacity of every agricultural grid cell on the planet at approximately 9.3×9.3 km resolution. The dataset and an interactive visualization website are publicly available to support researchers, policymakers, and advocacy groups.

CADI is built on a simple counterfactual exercise. We take the crops currently grown in each cell, the area they occupy, and the management practices in place, and hold all of these fixed. We then feed observed and projected climate conditions through the mechanistic crop growth model of the Global Agro-Ecological Zones version 5 (GAEZ v5, FAO and IIASA, 2025) to compute attainable yields under each scenario. The result is expressed as *People Fed Yearly* (PFY)—the number of people a cell's agricultural output could sustain at 2,000 kcal/day—for the historical period and for projected horizons up to 2081–2100 under three emission pathways.

Because everything except climate is held constant, CADI does not predict future harvests. It measures the pressure that climate change exerts on food systems in the absence of any adjustment. This quantity can be read in two ways: as the damage that climate change inflicts if nothing else changes, or—more usefully—as the scale of the adaptation challenge ahead. The two readings point in the same direction, toward identifying where action is most urgent.

The no-adaptation assumption is strong, but Burke and Emerick (2016) show that even US farmers—with deep capital markets and access to frontier technology—have offset at most half,

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and more likely none, of the negative effects of rising temperatures over two decades. In lower-income, agriculture-dependent settings the scope for autonomous adjustment is likely far smaller, making CADI a plausible benchmark rather than a worst case.

This document is structured as follows. Section 2 describes the data sources: GAEZ v5 yields, climate scenarios, and soil inputs and explains how the GAEZ model computes attainable yields. Section 3 presents the construction of the CADI, including the caloric conversion, the PFY metric, and the three index variants. Section 4 discusses the empirical motivation for reporting SSP3-7.0 and SSP5-8.5, with SSP3-7.0 as the primary scenario.

2. Data

Our primary data source is the Global Agro-Ecological Zones version 5 (GAEZ v5), developed jointly by FAO and IIASA (FAO and IIASA, 2025). It represents a major update over version 4 (Fischer et al., 2021), incorporating CMIP6 climate projections (O'Neill et al., 2016), updated soil data from the Harmonized World Soil Database v2.1 (HWSD v2, FAO and IIASA, 2023), consolidated land cover data circa 2020, terrain data from ALOS, and historical climate forcing from the AgERA5 reanalysis (Copernicus Climate Change Service, 2020). We extract attainable yield estimates—the agronomically feasible upper bound of crop production under given climatic, soil, and terrain conditions for a specified management level—for each grid cell, crop, and time period.

GAEZ v5 provides spatially explicit estimates of crop suitability and attainable yields at a resolution of 5 arc-minutes (approximately 9.3×9.3 km at the equator) for over 50 crop groups (in the Module V output we use), under multiple input levels and water supply systems (rainfed and irrigated).

2.1. Time periods and climate scenarios.

2.1.1. Time periods. GAEZ v5 provides yield estimates for two historical periods—**1981–2000** and **2001–2020**—and four projected 20-year windows: **2021–2040**, **2041–2060**, **2061–2080**, and **2081–2100**.

2.1.2. Climate inputs. For historical periods, GAEZ v5 uses daily climate data from the AgERA5 dataset (Copernicus Climate Change Service, 2020), interpolated to the 5 arc-minute grid. Six variables are employed: daily minimum and maximum temperature, solar radiation, vapour pressure, wind speed, and precipitation. Year-by-year daily data covering 1981–2020 are combined into two 20-year averages.

For future periods, climate projections are derived from five bias-corrected CMIP6 global climate models processed through the ISIMIP3b framework: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL. We use the *ensemble* (multi-model mean) projections, which average across all five models for each scenario.

Crucially, the future climate inputs are not raw GCM outputs. GAEZ v5 applies a delta (change-factor) method anchored to the 1981–2000 historical baseline: (i) the ISIMIP3b output is interpolated to the 5 arc-minute grid; (ii) for each climate variable, the monthly difference between the GCM's 1981–2000 simulation and the future scenario is computed; (iii) this delta is added to the observed AgERA5 data for 1981–2000; (iv) the daily distribution from the GCM disaggregates the adjusted monthly signal into daily values.[1]

This construction means that all future attainable yields reflect climate change *relative to the observed 1981–2000 climate*. The delta method preserves the spatial detail and statistical properties of the observational record while removing systematic GCM biases, since only the *change* between historical and future simulations enters the calculation.

2.1.3. Climate scenarios. GAEZ v5 provides estimates under three Shared Socioeconomic Pathways (SSPs), which pair socioeconomic narratives with end-of-century radiative forcing targets (O'Neill et al., 2016). SSP1-2.6 (Sustainability) describes a world that prioritises well-being over growth, reduces inequality, and limits warming to approximately 1.8°C by 2100. SSP3-7.0 (Regional Rivalry) envisions rising nationalism, declining investment in education and technology, and growing inequality, leading to roughly 3.6°C of warming. SSP5-8.5 (Fossil-fueled Development) assumes rapid economic growth driven by intensive fossil-fuel exploitation, reaching approximately 4.4°C of warming despite progress on local environmental problems. Together, these three pathways span the plausible range of future climate impacts on agriculture, from ambitious mitigation to continued high emissions.

2.2. Soil and terrain inputs. Soil data are sourced from the Harmonized World Soil Database version 2.01 (HWSD v2, FAO and IIASA, 2023), providing information on over 29,000 soil mapping units globally. Terrain slope data are derived from the ALOS global digital surface model at 1 arc-second resolution, aggregated into slope gradient classes at 30 arc-seconds and then to the 5 arc-minute GAEZ grid.

2.3. Input levels and water management. GAEZ v5 provides attainable yield estimates at two management levels: low-input (subsistence farming with no external nutrients, pesticides, or improved varieties) and high-input (full nutrient application, improved high-yielding varieties, chemical plant protection, and optimal agronomic practices). We use the high-input scenario throughout, primarily because it offers the most complete crop coverage and therefore allows us to construct a consistent caloric aggregate across all crops and periods. The low-input scenario, by contrast, is available only for a subset of crops and only for the observed periods (1981–2000 and 2001–2020). Since our analysis exploits changes in attainable yields between periods rather than yield levels, this choice is less consequential than in a level-based setting. The main climatic drivers of yield change—heat stress on photosynthesis, changes in water availability, and shifts in

[1] For details, see the GAEZ v5 Model Documentation, Chapter 2, at https://github.com/un-fao/gaezv5/wiki/02.-GAEZ-input-datasets.

growing-season length—operate under both low- and high-input management regimes, implying broadly similar proportional climate sensitivities across input assumptions.

For each crop and grid cell, GAEZ provides yield estimates under rainfed (**HRLM**) and irrigated (**HILM**) conditions. We retain this distinction, assigning to each cell the water supply corresponding to its current irrigation status. Cells classified as irrigated use the irrigated attainable yield; all others use the rainfed estimate. This captures the climate sensitivity of yields *conditional on existing water supply infrastructure*, without accounting for potential future changes in irrigated area or water availability.

2.4. What varies across periods and what is held constant. A central feature of the GAEZ framework for interpreting temporal changes in attainable yields is the distinction between inputs that change across periods and those that remain fixed:

- **Changes across periods:** Climate variables (minimum and maximum temperature, precipitation, solar radiation, wind speed, vapour pressure) and atmospheric CO_2 concentration. These flow through the ecophysiological model in Modules I–III, altering biomass accumulation, water stress, growing-season length, and the optimal crop calendar.
- **Held constant:** Soil and terrain properties (Module IV) are fixed across periods. Crop parameters (Land Utilisation Type definitions, including growth cycle duration, harvest index, and maximum leaf area index) are also fixed, as are the management-level assumptions and the harvested-area shares used in our caloric aggregation (Section 3).

Consequently, differences in attainable yield between periods are driven by the climate signal filtered through a mechanistic crop growth model, with soil, terrain, and management held constant. This makes the GAEZ output well suited for isolating the biophysical impact of climate change on food production capacity.

2.5. Attainable yields. The GAEZ model computes attainable yields through a sequential modular framework. Starting from the theoretical maximum yield a crop could achieve given radiation and temperature, each module progressively applies reduction factors—for water stress, pests and diseases, and soil and terrain constraints—arriving at the attainable yield for each cell-crop-period combination. We summarise the key steps below.

2.5.1. Step 1: Climate indicators (Module I). Module I processes raw climate variables into agronomically meaningful indicators, including thermal regime classifications, moisture availability indices, and the Length of Growing Period (LGP)—the number of days per year in which both temperature and moisture conditions permit crop growth.

2.5.2. Step 2: Potential biomass and yield (Module II). This is the core ecophysiological engine. For each Land Utilisation Type (LUT)—a combination of crop species, cultivar group, management level, and cultivation practices—the model:

(1) Computes **constraint-free biomass** using an eco-physiological crop growth model (Kassam, 1977) driven by temperature, radiation, and (for rainfed conditions) soil moisture. Each LUT is characterised by crop-specific parameters including growth cycle duration, harvest index, and maximum leaf area index.
(2) **Optimises the crop calendar** by testing multiple planting dates and selecting those producing the highest yield, separately for rainfed and irrigated conditions.
(3) For rainfed conditions, computes the **water-limited yield** via a daily soil water balance. When actual evapotranspiration (ET_a) falls below maximum crop evapotranspiration (ET_m), a water stress reduction is applied. For irrigated conditions, water supply is assumed non-limiting.
(4) Converts total above-ground biomass to **harvestable yield** through a crop-specific harvest index.

2.5.3. Step 3: Agro-climatic constraints (Module III). Module III applies additional yield reductions for climate-related hazards not fully captured in Module II, including estimated losses from pests, diseases, and weeds (derived statistically from climatic conditions) and workability constraints on field operations.

2.5.4. Step 4: Soil and terrain constraints (Module IV). Module IV evaluates soil and terrain suitability for each crop using attributes from the HWSD (texture, depth, drainage, fertility, pH, salinity, sodicity) and terrain slope information. Each soil quality factor yields a rating between 0 and 1, combined into an overall edaphic reduction factor.

2.5.5. Step 5: Integration and final attainable yield (Module V). Module V combines the agro-climatic yield from Modules II/III with the edaphic ratings from Module IV to produce the final attainable yield. Soil and terrain conditions are integrated at the sub-grid-cell level: within each 30 arc-second component, the model assesses edaphic limitations separately before aggregating to the 5 arc-minute grid. Module V also applies a CO_2 fertilisation adjustment: elevated atmospheric CO_2 enhances photosynthesis, with crop-group-specific yield adjustment factors that depend on scenario-period CO_2 concentration and land suitability class. C3 and C4 crops are treated differently, reflecting their distinct physiological responses. **The Module V attainable yield is the variable we use for our main analysis.**

2.5.6. Step 6: Actual production and harvested area (Module VI). Module VI downscales national agricultural statistics (FAOSTAT averages for 2019–2021) onto spatial rainfed and irrigated cropland, providing harvested area, yield, and production for 33 major commodity groups at 5 arc-minute resolution. These data tell us which crops are actually grown in each cell and how much area each occupies. We use the Module VI harvested area data to weight the Module V attainable yields when constructing our caloric production measure.

3. CADI: Climate-Driven Agricultural Decline Index

This section describes the construction of the CADI. The index quantifies how climate change alters the food production capacity of each grid cell by combining attainable yields from GAEZ v5 with crop distributions, caloric conversion factors, and local population data.

3.1. Crop selection and caloric conversion.

3.1.1. Crop mapping. A technical challenge is that GAEZ v5 uses different crop taxonomies across modules: Module II/III contains approximately 100 individual crop varieties, Module V about 70 crop groups, and Module VI uses 33 harvested area groups. We constructed a mapping table linking each Module II/III variety to its Module V group and Module VI category through exact name matching and manual expert assignment.

We classify the Module VI crop groups into *caloric* and *noncaloric* categories (Table 1). Noncaloric crops—cocoa, coffee, tea, cotton, tobacco, rubber, and fodder—are assigned zero caloric value. Fruits and Nuts (FRT) are excluded due to the excessively wide range of caloric values within this group, which prevents meaningful aggregation. Our indices focus on food production for direct human consumption, and caloric measures are robust against market dynamics, unlike price-based measures (Gilbert and Morgan, 2010).

3.1.2. Caloric conversion. Following Galor and Özak (2016), we convert physical yields into caloric equivalents using crop-specific data from the USDA National Nutrient Database (U.S. Department of Agriculture, Agricultural Research Service, 2018; Haytowitz et al., 2019). Let κ_c denote the caloric content of crop c (kcal per kg). The caloric yield of crop c in cell i under scenario s in period t is:

$$\hat{y}_{icst} = y_{icst} \times \kappa_c \tag{1}$$

where y_{icst} is the attainable yield in tonnes per hectare from GAEZ v5.

3.2. From attainable yields to People Fed Yearly.

3.2.1. Crop distribution. We define the crop distribution through a harvesting matrix H, where h_{ic} denotes the harvested area (hectares) of crop c in cell i, drawn from the GAEZ v5 Module VI spatial representation of crop areas (based on FAOSTAT statistics for 2019–2021). We hold H fixed throughout, so the only source of variation across periods is the climate signal. This counterfactual design asks how many people today's agricultural landscape could feed under the climatic conditions of each period, attributing any change to climate rather than to adaptation or land-use change.

We work with the subset C that contains the 24 "caloric" crop groups in Table 1.

Table 1. GAEZ v5 Module VI Crop Groups: Caloric Yields and Classification

Module VI Code	Crop Name	kcal/100 g	Type
WHE	Wheat	377	caloric
RCW	Rice	413	caloric
MZE	Maize	407	caloric
SRG	Sorghum	375	caloric
MLT	Millet	413	caloric
BRL	Barley	391	caloric
OCE	Other cereals (oats, rye, buckwheat, etc.)	404	caloric
POT	White potato, Sweet potato	363	caloric
CSV	Cassava	397	caloric
ORT	Yams and other minor root crops	388	caloric
SUB	Sugar beet	387	caloric
SUC	Sugarcane	387	caloric
PLS	Pulses	393	caloric
SOY	Soybean	488	caloric
RSD	Rapeseed	810	caloric
SFL	Sunflower seed	613	caloric
GRD	Groundnuts (with shell)	618	caloric
SES	Sesame seed	601	caloric
OLP	Oil palm fruit	810	caloric
OOC	Olives and other minor oil crops	810	caloric
CON	Coconut	668	caloric
BAN	Banana and Plantain	394	caloric
OVG	Other vegetables	365	caloric
TOM	Tomato	415	caloric
FDD	Fodder crops	0	noncaloric
COC	Cocoa	0	noncaloric
COF	Coffee	0	noncaloric
TEA	Tea & Mate leaves	0	noncaloric
COT	Seed cotton	0	noncaloric
TOB	Tobacco leaves	0	noncaloric
RUB	Para rubber	0	noncaloric
NES	All other crops n.e.s.	0	noncaloric
FRT	Fruits & Nuts	—	excluded

Notes: Caloric values are per 100 g dry weight, sourced from the USDA National Nutrient Database (U.S. Department of Agriculture, Agricultural Research Service, 2018). FRT is excluded because the wide spread in caloric values across underlying crops prevents meaningful aggregation.

3.2.2. Food production capacity. Total caloric production in cell i under scenario s in period t is:

$$Y_{ist} = \sum_{c \in C} \hat{y}_{icst} \times h_{ic} \tag{2}$$

We express this as the number of people that can be sustained for one year at $c_{\min} = 2{,}000 \times 365 = 730{,}000$ kcal per person per year:

$$PFY_{ist} = \frac{Y_{ist}}{c_{\min}} \tag{3}$$

We call this **People Fed Yearly** (PFY): the number of people the agricultural output of cell i could feed for a year at subsistence level (Cassidy et al., 2013).

Three features deserve emphasis. First, because we use attainable yields rather than actual yields, our measure reflects the biophysical production frontier—the maximum output achievable given climate, soil, and terrain at a specified input level—rather than realised production. Changes in our measure are therefore attributable to climatic factors rather than to socioeconomic conditions. Second, the fixed crop distribution isolates the pure climate effect. Third, PFY assumes all calories go to human consumption; in practice, diversions to animal feed mean the implied number of people fed is an upper bound.

3.3. The CADI index variants. We define three complementary variants, each capturing a different dimension of climate-driven agricultural change. We construct two sets of comparisons: *observed* changes (baseline t_0^{obs} = 1981–2000, comparison t_1^{obs} = 2001–2020) and *projected* changes (baseline t_0^{proj} = 2001–2020, future periods $t \in \{2021\text{–}2040, 2041\text{–}2060, 2061\text{–}2080, 2081\text{–}2100\}$). Climate scenarios are indexed by $s \in \{\text{SSP1-2.6, SSP3-7.0, SSP5-8.5}\}$. Note that 2001–2020 serves a dual role: end period for observed changes and baseline for projections.

3.3.1. CADI (absolute). The absolute index measures the change in food production capacity in PFY terms:

$$CADI^{\text{A}}_{it,\text{obs}} = PFY_{it} - PFY_{it_0^{\text{obs}}} \tag{4}$$

$$CADI^{\text{A}}_{ist,\text{proj}} = PFY_{ist} - PFY_{it_0^{\text{proj}}} \tag{5}$$

A negative value indicates that cell i can feed fewer people under the climatic conditions of period t. This variant naturally highlights major foodsheds where absolute losses are largest (Kinnunen et al., 2020).

3.3.2. CADI (percentage change). The relative index captures proportional change, revealing where the shock is severe relative to local capacity:

$$CADI^{\text{R}}_{it,\text{obs}} = \frac{PFY_{it} - PFY_{it_0^{\text{obs}}}}{PF_{it_0^{\text{obs}}}} \tag{6}$$

$$CADI^{\text{R}}_{ist,\text{proj}} = \frac{PFY_{ist} - PFY_{it_0^{\text{proj}}}}{PFY_{it_0^{\text{proj}}}} \tag{7}$$

A cell with modest baseline output that loses a large fraction registers a high $|CADI^{\text{R}}|$ even if the absolute loss is small, identifying vulnerable communities facing proportionally large climate shocks.

3.3.3. Population-adjusted CADI. To connect agricultural change to food security, we incorporate gridded population counts n_i from WorldPop (Bondarenko et al., 2025) (year 2020). We define the share of local population sustained by local production:

$$\sigma_{ist} = \min\left\{\frac{PFY_{ist}}{n_i},\ 1\right\} \tag{8}$$

The population-adjusted CADI is:

$$CADI^{\text{P}}_{it,\text{obs}} = \min\left\{(\sigma_{it} - \sigma_{it_0^{\text{obs}}}) \times n_i,\ 0\right\} \tag{9}$$

$$CADI^{\text{P}}_{ist,\text{proj}} = \min\left\{(\sigma_{ist} - \sigma_{it_0^{\text{proj}}}) \times n_i,\ 0\right\} \tag{10}$$

This captures the number of people who lose local food self-sufficiency due to climate-driven yield changes. The $\min\{\cdot, 0\}$ operator ensures that only cells experiencing a decline are flagged, focusing attention on populations directly exposed to local production shortfalls.

The three variants are complementary. $CADI^{A}$ identifies where the largest absolute losses occur. $CADI^{R}$ reveals where the proportional shock is most severe, often in regions with low baseline production. $CADI^{P}$ identifies populations at risk of losing local food self-sufficiency. Together they provide a multi-dimensional picture of climate-driven agricultural change.

4. Scenario selection

We report results under two scenarios: **SSP3-7.0** and **SSP5-8.5**. In our key findings we present SSP3-7.0 as the primary scenario, with SSP5-8.5 shown alongside as an upper bound. SSP1-2.6 is available in the dataset but not featured in the main analysis.

This choice is empirical rather than normative—it does not imply an endorsement of either emissions pathway. The motivation rests on the structure of the GAEZ climate inputs and on a comparison of projections with already-observed agricultural change.

As described in Section 2.1, all future attainable yields in GAEZ v5 are constructed using a delta method anchored to the 1981–2000 observed climate. The GCM-projected change relative to 1981–2000 is added to the historical AgERA5 record, and the resulting climate is fed through the crop growth model. The 2001–2020 period, by contrast, is driven directly by AgERA5 observations and therefore reflects the climate change that has actually materialised over the past two decades.

This creates a natural validation exercise: we can compare the productivity changes that GAEZ projects for the 2001–2020 window under each SSP scenario with the changes actually observed in the AgERA5-driven data. When we perform this comparison, a clear pattern emerges. The observed deterioration in agricultural productivity over the past two decades tracks between SSP3-7.0 and SSP5-8.5. Both scenarios produce broadly plausible near-term changes, and they yield very similar outcomes through mid-century—for example, the number of countries with net agricultural losses at 2041–2060 is identical (101 of 166) under both.[2] The scenarios diverge more sharply toward the end of the century, where SSP5-8.5 produces deeper losses.

This near-term similarity likely reflects two factors. First, CMIP6 models in the ensemble tend to underestimate the pace of recent warming at regional scales, particularly in tropical and subtropical agricultural zones. Second, internal climate variability over a single 20-year window can produce realised changes that exceed the forced signal projected by any individual scenario over a comparable horizon—and the past two decades appear to have been characterised by unfavourable realisations in many key agricultural regions. The divergence between scenarios

[2] A country is counted as experiencing net agricultural losses in a given period if the population-weighted sum of $CADI^{A}$ across its cropped grid cells is negative relative to the 1981–2000 baseline. The denominator (166) is the set of countries with non-zero cropped area in the Module VI harvested-area data.

narrows for later time horizons (2041–2060 onward), as the forced climate signal increasingly dominates over natural variability and the pathways separate more clearly.

Why not SSP1-2.6? Under SSP1-2.6, the projected changes from the 1981–2000 baseline are smaller than what has already been observed by 2001–2020. Using SSP1-2.6 as the basis for forward projections would paradoxically suggest an *improvement* relative to the 2001–2020 baseline in many regions—not because conditions are expected to improve, but because the observed damage has already exceeded what this scenario anticipates. Beyond this technical issue, SSP1-2.6 assumes rapid and coordinated global mitigation that current emissions trajectories have not yet begun to deliver, making it the least informative scenario for near-term planning.

We emphasise that the scenario choice is a statement about empirical plausibility, not about the likelihood of different emissions futures. SSP5-8.5 is increasingly regarded in the climate science literature as an unlikely long-run trajectory, while SSP3-7.0 reflects a pathway of fragmented development and moderate-to-high emissions that is broadly consistent with current trends.

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