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Bio-physical climate change risk assessment for current and innovative production systems in Tanzania

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Deliverables

D4.3.1 Bio-physical climate change risk assessment for current and innovative production systems in Tanzania, including an analysis on the transferability of Tanzanian solutions to other regions (month 36, 58) (**PIK, IFPRI**, IUW, SUA, ZALF)

D4.3.2 Economic climate change risk assessment for current and innovative food value chains in Tanzania, including an analysis on the transferability of Tanzanian solutions to other regions (month 36, 58) (IFPRI, PIK, IUW, SUA, ZALF)

BIO-PHYSICAL AND ECONOMIC CLIMATE CHANGE RISK ASSESSMENT – Bio-physical climate change risk assessment for current and innovative production systems in Tanzania

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Abstract

Weather-related yield losses endanger food security and inhibit the establishment of a resilient farming system for more than 30 million people working in the agricultural sector of Tanzania. If these losses were quantified, this information could be used for risk transfer instruments to stabilize smallholder farmers' incomes in Tanzania. Here, we develop a combined application of a process-based and statistical crop model and demonstrate that this approach significantly improves the yield assessment accuracy by 74% at district level. Furthermore, it allows to separate weather-related yield losses (covered by the risk transfer instruments) from the management-related losses. Using our approach, we calculate that only 27% of the actual maize yield losses in Tanzania are directly attributable to weather. Considering this and the model uncertainty, the economic costs for weather-related yield losses are 71 million US$ p.a. (23 US$ ha^{-1}) for maize production in Tanzania.

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Abbreviations

AYI	Adjusted maize yield index
°C	Degrees Celsius
EPIC	Environmental Policy Integrated Climate (crop model)
Eq.	Equation
ETP	Potential evapotranspiration
Fig.	Figure
GRF	Crop growth regulating factor
ha	Hectare
i	Individuals (districts) with $i = 1, \ldots, N$
j	Vector of exogenous variables, with $j = 1, \ldots, J$
kg N	Nitrogen fertilization
kg P_2O_5	Phosphorus fertilization
LAI	Leaf area index
m	Meter
nw	non-weather-related impacts in yields
NSE	Nash–Sutcliffe efficiency
p	Significance level
PM	Process-based crop model
PDM	Panel data model
PREC	Precipitation
r	Correlation coefficient
R^2	Coefficient of determination
RCM	Random coefficient model
RESET	Regression equation specification error test
SI	Supplemental information
SM	Statistical model
SR	Solar radiation
SSD	Semi standard deviation
SSA	Sub-Saharan Africa
STSM	Separate time-series model
SWIM	Soil and Water Integrated Model
t ha^{-1}	Metric tons per hectare
t	Time (years), with $t = 1, \ldots, T$
Tab.	Table
TMP	Temperature
u	Error term
p.a.	Per annum
VPD	Vapor pressure deficit
we	Weather impacts on yields
x	Exogenous variable
y	Maize yield (endogenous variable)
β	Parameter
ε	Residuals of observed and SWIM yields

Introduction

In Sub-Saharan Africa (SSA), crop yields commonly have high variability on a very low average yield level. This hinders smallholder farmers investing in agronomic management to stabilize and increase their crop yields and keeps them in the loop of poverty and food insecurity. Often, these smallholder farmers do not have the financial capacity to adjust their agronomic management when extreme weather conditions strike *(1, 2)*. An improved agronomic management could contribute to stabilize smallholder farmers' incomes and make their agricultural production less vulnerable to weather extremes. Besides these farm-individual perils, widespread weather perils (termed *systemic risk*) strongly harm the agricultural sector as it was the case during the El Niño drought of 2014–15 and 2015–16 in eastern and southern Africa. Without proper risk transfer instruments, systemic risks make smallholder farmers highly vulnerable to crop yield losses *(3)*. Risk transfer instruments (like micro insurances) have high potential as an adaptation strategy towards climate change and systemic weather perils *(4, 5)*, because they can stabilize smallholder farmers' incomes, prevent indebtedness, and indemnify their livelihoods. However, widespread implementation of such insurance schemes is hindered by uncertain and unreliable assessments of crop yield losses, notably for cropping conditions in SSA.

In Tanzania, maize (*Zea mays* L.) is the most widely cultivated crop. Cropping conditions are characterized by high spatial and temporal heterogeneity *(6, 7)*. The average annual precipitation ranges in the south–west lowlands from 700 to 2,000 mm and in the northern semi-arid highlands from 400 to 700 mm. The monthly average temperature is between 18 and 28 °C throughout the year. Despite this favorable climate, the mean Tanzanian maize yield is rather low at 1.3 t ha^{-1}. Typically for SSA, yields are more often influenced by agronomic management than by weather impacts *(8, 9)*. In comparison, the impact of agronomic management on yield variability is smaller in regions with a high-input agronomic management *(10)*. In SSA, a low and unbalanced fertilizer supply characterizes the agronomic management and represents the major yield limitations *(11, 12)*. Besides weather and fertilization, several other factors influence maize yields *(13)*. Among these factors are, notably, limited access to arable land *(14)*, labor, credits, markets, and technology *(11, 15)*, pests, weeds, and diseases *(16)*, or fertilizer subsidies *(17–19)*.

Crop models can contribute to gaining insights about the impacts of weather, soil, agronomy, and socio-economy on crop yields. These insights of the crop models make it possible to separate the weather-related yield losses from the total yield losses. In most global and regional crop yield assessments, process-based *(20–22)* and statistical models *(6, 10, 23, 24)* are used alternatively. Estes et al. *(25)* show the advantages and weaknesses of these two model types for South-African crop yield assessments. Lobell et al. *(26)* and Lobell and Burke *(27)* separately use a statistical model to corroborate process-based yield assessments. Liu at al. *(28)* and Lobell and Asseng *(29)* show in an inter-comparison the similarities of both model types. However, to our knowledge no combined application of both model types has so far been published. Here, we use a process-based model to identify purely weather-attributable yield variability, while our statistical model captures the remaining non-weather-related yield variability. The ability of statistical models to account for non-weather-related impacts allows us to identify those yield impacts beyond the weather-attributable yield impacts. We combine the advantages of both model types to enhance the robustness of yield assessments and to integrate scarce observed yield data efficiently. This makes our approach suitable for other regions of SSA with also limited observed yield information.

Results and discussion

The combination of a process-based and statistical model increases the assessment accuracy of yield variability. The combined application of both model types significantly ($p < 0.01$, Fisher z-transformation, 796 observations) increases the reproduction of annual yield variability (Fig. 1). While the solely process-based assessment attains $r = 0.05^{NS}$ ($R^2 = 0.00$), the goodness of fit increases to $r = 0.86^{***}$ ($R^2 = 0.74$) for the combined assessment (Pearson correlation; ^{NS} $p > 0.1$, * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$) [all correlation coefficients and the corresponding R^2 are in SI Tab. S.1, S.2, and Fig. S.7]. Moreover, the out-of-sample validation achieves a correlation of $r = 0.38^{***}$ ($R^2 = 0.15$) and the corresponding statistical tests show that the model provides robust and valid results (see SI S.2.3.2 for details). However, the solely application of a statistical model to identify the weather-attributable yield variability significantly ($p < 0.01$, Fisher z-transformation) reduces the goodness of fit to $r = 0.77$ ($R^2 = 0.59$) for the estimation and to $r = 0.10$ ($R^2 = 0.01$) for the validation (see SI S.2.3.3 and Fig. S.8 for further details). This demonstrates that the information of the process-based and the statistical model are complementary. Since weather has often nonlinear and more complex impacts on crop yields, linear and log-linear statistical models are only limitedly able to capture the weather-attributable yield variability and therefore, often underestimate the weather impacts.

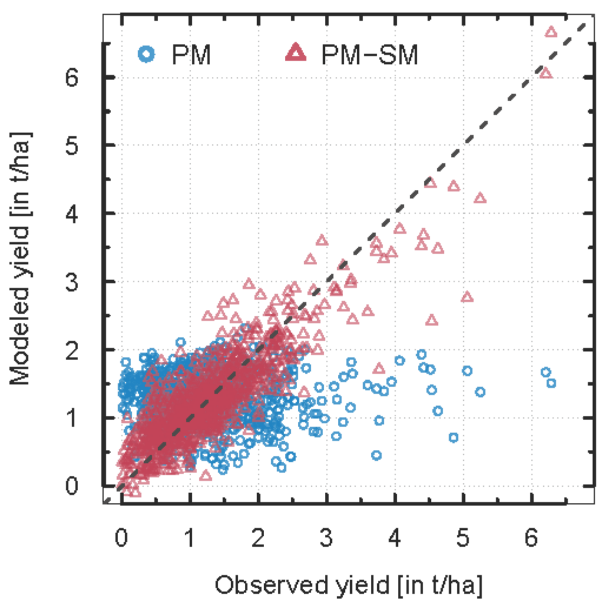

Fig. 1. Increase in goodness of fit due to the combined application of a process based (PM) and a statistical model (SM). The blue points show the accuracy of a solely application of the PM. The red points show the accuracy of a consecutive application of PM and SM (PM-SM).

Our process-based model satisfactorily captures the average national maize yield (modeled: 1.29 t ha^{-1} and observed: 1.27 t ha^{-1}) between 2003 and 2010. The process-based modeled yields show regional yield patterns of low and high yields similar to the observed district yields (Fig. 2). Aggregated to agro-ecological zones (see SI S.1.2 Fig. S.2), the modeled yields correlate spatially with the observed yields at r = 0.57 ^{NS} ($R^2 = 0.32$). The semi-arid regions in the center and the north–eastern regions as well as the sub-humid regions in the south are clearly distinguishable in the modeled and observed yield maps. However, the annual yield variability is insufficiently reproduced by the process-based model for entire Tanzania, a result also found for other regions and process-based crop models *(30)*. Nevertheless, the water scarce regions are reproduced with higher accuracy than the regions with sufficient water supply (SI Fig. S.5 and S.6). Since process-based models consider only a limited number of processes in their model set-up, they may neglect possibly relevant ones *(31)*. In particular, socio-economic impacts on agronomic management practices, which are important in SSA *(14, 32)*, are usually not considered by process-based models. Our consecutively applied statistical model resolves the residual yield variability by using the non-weather variables *maize acreage*, *paid subsidies on crop production*, and *urea application* (see SI S.1.4 for further information). As a result, our combined modeling approach is able to reproduce the actual yield variability; this justifies the separation of weather and non-weather-related yield losses.

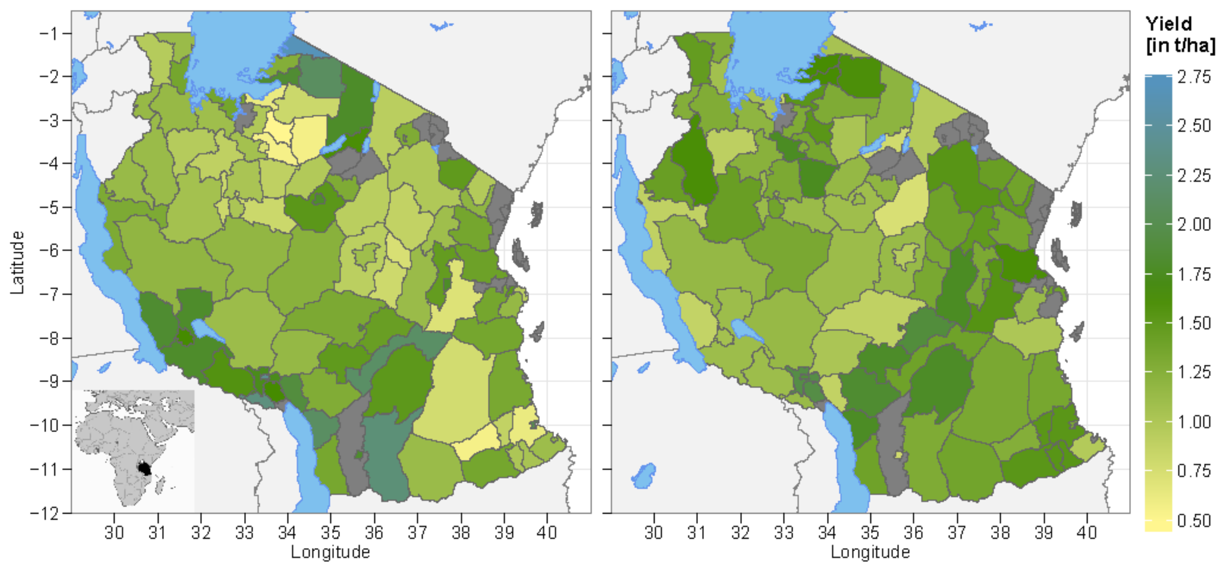

Fig. 2. Observed (left) and process-based modeled (right) average maize yields for Tanzanian districts in the period 2003-2010. No data is marked in dark gray.

Generally, our combined approach explains 74% of the total observed yield variability ($R^2 = 0.74$). Considering process-based models alone might cause them to be rejected as of limited use, if they fail to satisfactorily explain total yield variability. However, as shown, statistical models can be used to explain the remaining yield variability due to agronomic management and socio-economic factors. This demonstrates the general relevance and usability of process-based models. However, the aggregation of farm yields to the district level by the Tanzanian statistical office might have a filtering effect *(33)*. Nevertheless, our combined approach contributes a pragmatic solution to cover both agronomic management and socio-economic yield impacts in addition to weather impacts. Moreover, the process-based model in our combined approach allows assessments of yield losses for changed agronomic management practices and altered weather conditions, which are in agreement with plant-physiological processes.

Indirect weather-triggered effects are negligible for Tanzania. Besides both impact factor groups, we also investigate whether indirect weather-triggered effects (like pests and diseases) explain the remaining yield variability. Similar to the combination of the two model types, we estimate a consecutive weather-driven statistical model with the residuals of the non-weather-driven statistical model as the endogenous variable (see SI Fig. S.4). The weather-driven statistical model explains the residual yield variability by *precipitation*, *vapor pressure deficit*, and *solar radiation* of the district-specific growing season. This consecutive weather-driven statistical model explains yield variability with $r = 0.92^{***}$ ($R^2 = 0.84$). However, the validation decreases from $r = 0.38^{***}$ ($R^2 = 0.15$) [only process-based and non-weather-driven statistical model] to $r = 0.33^{***}$ ($R^2 = 0.11$) [process-based, non-weather, and indirect weather-triggered statistical model]. In a further step, we remove the non-weather-driven statistical model. Considering only the indirect weather-triggered effects significantly ($p < 0.01$, Fisher z-transformation) reduces goodness of fit to $r = 0.78^{***}$ ($R^2 = 0.60$) for the estimation and to $r = 0.04^{NS}$ ($R^2 = 0.00$) for the validation, respectively. Hence, we conclude that the indirect weather-triggered effects do not contribute model robustness. In the following we only consider the non-weather-related impacts to explain the residual yield variability. The results indicate that indirect weather-triggered impacts only have a minor influence on crop yields at the district scale. However, since process-based crop models are calibrated to field trials with a prevalent pest, disease and weed pressure, it is possible that these impacts are already implicitly included in our model. This could be the reason for the indirect weather-triggered impacts appearing insignificant. If there were a significant and robust influence of these indirect weather-triggered effect (due to pest and diseases), it would be allocated to the weather-related part (because of the correlation with the weather) and thus, be indemnified.

Weather-related yield losses constitute only one-third of total maize yield losses in Tanzania. To stabilize smallholder farmers' incomes if yield losses – here defined as yield anomaly below the mean yield level according to Eq. 2 and Finger *(34)* – occur which are attributable to weather impacts. Our separation of maize yield loss factors shows dissimilar shares of weather-related (27%) and non-weather-related (73%) yield losses for Tanzania on average. Across districts, weather-related yield variability varies between 4% (in sub-humid south–east Tanzania) and 57% (in the semi-arid central and north–

west, see Fig. 3). In total, the average and maximum weather-related yield losses are 0.11 and 0.41 t ha^{-1} and the non-weather-related yield losses are 0.34 and 1.70 t ha^{-1}, respectively. In line with the results of Lesk et al. *(8)*, this indicates that agronomic management and socio-economic factors have a substantially higher impact on maize yields in Tanzania (see also pre-analysis of significant non-weather-related yield effects in SI 2.3.1).

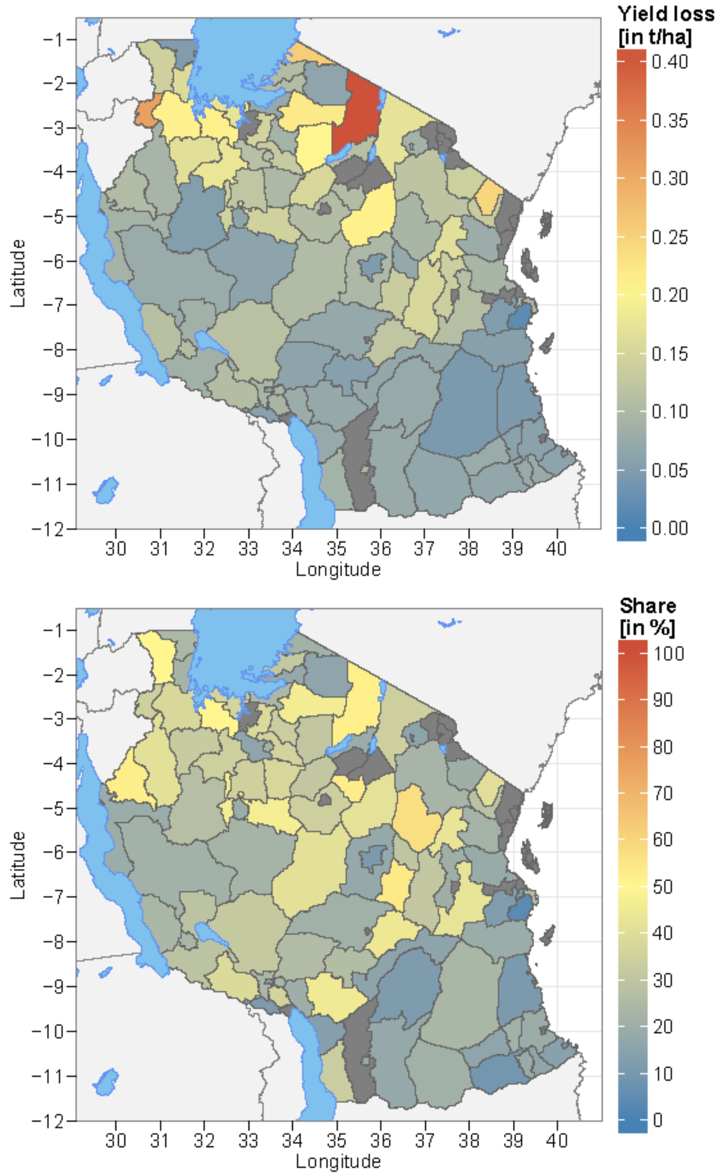

Fig. 3. Weather-related yield losses in t ha^{-1} p.a. (top), the share of weather-related yield losses in comparison to the total yield losses in % (bottom).

Our weather-attributable yield losses are directly usable to calculate costs weather induced yield variability on the Tanzanian crop production at district scale. The costs are the product of the annual and district-specific weather-related yields losses (i), its corresponding maize acreage (ii), and the Tanzanian annual maize prices (iii). For the Tanzanian maize production, we calculate that the costs of weather-related yield losses are 71 million US$ p.a. (23 US$ ha^{-1}). In comparison, the costs of the total yield losses are 212 million US$ p.a. (85 US$ ha^{-1}). This means that 66% (141 million US$ p.a.) of the loss costs are attributable to non-weather-related yield.

Our adjusted crop yield index considers the uncertainty of the modeling approach. Since both crop model types still have limitations, we consider the model uncertainty of our modeling scheme. On the basis of weather-related yield variability, we calculate an adjusted yield index, which is adjusted to the district-specific accuracy of the model approach (see *methods* for further information). Depending on the district scale model accuracy (R^2), we use weighted shares of modeled weather-related and observed yields for our adjusted yield index (Eq. 3). Where the model is able to fully explain actual yield variability (by weather and non-weather-related impacts), the adjusted yield index only uses the modeled weather-related yield variability of the process-based model (see Arusha, Kilimanjaro in Fig. 4). The share of observed yield variability increases in the index (for instance in Dodoma or Dar es Salaam) by decreasing the goodness of fit of our combined modeling approach. Due to the consideration of the model uncertainty, the economic costs increase to 141 million US$ p.a. (49 US$ ha^{-1}).

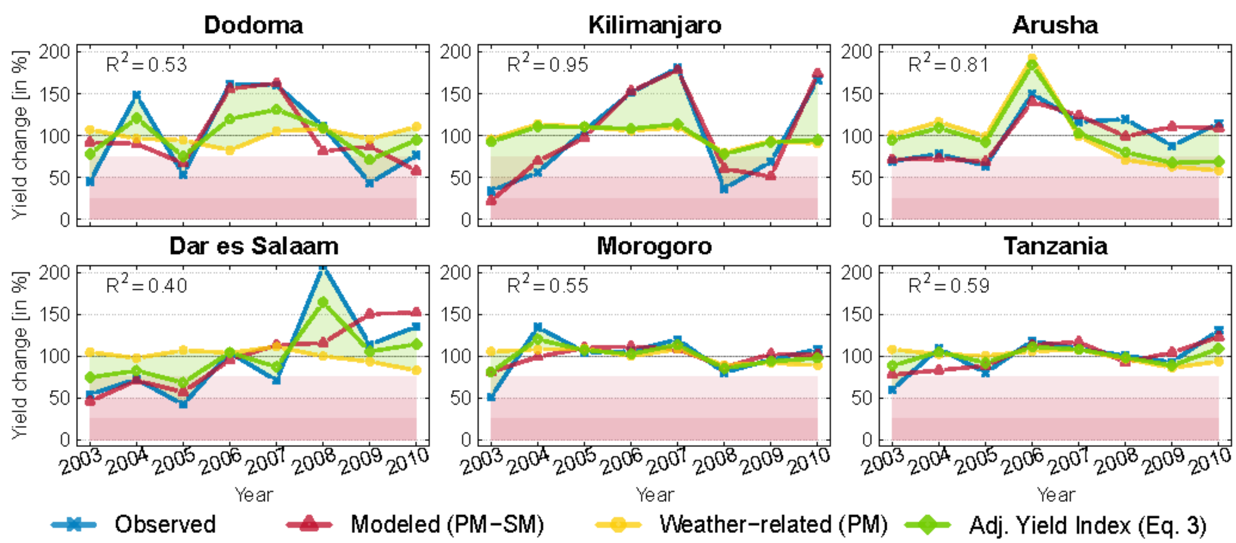

Fig. 4. Observed and modeled yields for agro-ecological zones. The weather-related part is represented by the PM and the combination of weather and non-weather-related by the PM-SM modeling approach. The adjusted yield index is calculated as R^2-weighted product of the observed and modeled yield variability. The R^2 is the goodness of fit for the modeled and the observed yields.

Conclusions

The combination of the statistical and process-based crop modeling increases the accuracy of assessing actual yield variability. In our approach, we capture the plant-physiological yield development within the process-based model and large amounts of the remaining, unexplained yield variability by using a statistical model. The improvement in accuracy and robustness makes our approach suitable for crop production risk assessments on a district scale.. We show that the suggested approach can contribute assess the weather and non-weather related production risk in Tanzania. This can reduce the vulnerability to severe yield losses for smallholder farmers and enhance farmers' ability to cope with climate change and altering weather patterns and contribute to long-term food security by incentivizing higher investments into agricultural production techniques.

Materials and methods

We apply a combined process-based (PM) and statistical (SM) modeling approach (PM-SM) to capture weather-attributable and non-weather-related yield variability. The PM captures influences on yield variability directly attributable to weather. The residual, non-weather-related yield variability of the process-based model is then modeled by a SM (see also SI Fig. S.3).

Process-based modeling of the weather-attributable yield variability

As PM we use the Soil and Water Integrated Model (SWIM). SWIM is an eco-hydrological model to capture river discharge, land use, and agricultural crop yield development *(35, 36)*. The crop module of SWIM is a modified approach of the Erosion Productivity Impact Calculator (EPIC) model (see also SI S.1.3 for further description). SWIM computes crop yields as a product of total above-ground biomass and the harvest index. Any divergence from the optimal growing conditions reduces biomass growth by stress factors within a minimum function. Considered stress factors are heat stress and water, nitrogen, and phosphorus scarcity. SWIM considers several agronomic management measures like fertilization, planting and harvest dates, and crop variety selection by maturity groups.

Statistical modeling of the non-weather-related yield variability

For our statistical model, we use a similar statistical approach to the approach used by Gornott and Wechsung *(37)*. The SM captures spatial and temporal heterogeneity in the residual yield variability of the PM. The SM estimates district-specific yield influences within a logarithmic function (Eq. 1). We use the statistical model with the residuals (ε_{it}) between the observed (y_{it}) and the process-based modeled yields (y_{it}^{PM}) as the endogenous variable and a vector of J exogenous variables (x_{jti}). The exogenous variables are maize acreage (in ha), paid subsidies on crop production (in US$), and urea application (in tons for entire Tanzania). Time-constant effects like land tenure security or market access (see SI S.1.4.3) are captured by the district-individual intercept (β_{0i}).

$$\varepsilon_{it} = \log \beta_{0i} + \sum_{j=1}^{J} \beta_{ji} \log\, x_{jit} + \log u_{it}, \tag{1}$$

with β as parameters and u_{it} as error term for T years ($t = 1, \dots, T$) and N spatial units ($i = 1, \dots, N$).

Maize yield losses and adjusted yield index

The mean weather and non-weather attributable yield loss (average yield anomaly below mean yield level) is calculated as semi-standard deviation (SSD_i^{below}, Eq. 2) for each district:

$$SSD_i^{below} = \sqrt{(T-1)^{-1} \sum_{t=1}^{T} \min\big((y_{it} - \bar{y}_i), \quad 0\big)^2}, \tag{2}$$

with $\bar{y}$ as arithmetic average yield across the T years.

The average indemnity claims are the product of SSD_{below}, maize acreage and maize price. In our case, the critical value for indemnity payments is the average yield. But other critical values, like the 25%-percentile and 10%-percentile, are also applied.

The maize yield adjusted yield index (AYI) is calculated by Eq. 3. As adjusted maize yield index (AYI), we use a weighted product of process-based modeled weather-related and observed yield variability. Depending on the accuracy of the combined model approach to explain the total yield variability, we weigh the share of modeled weather-related and total observed yield variability by the model R^2. Where the model is able to fully ($R^2 = 1$) explain total yield variability (by weather and non-weather-related impacts), only the weather-related modeled yield variability is used as the index. With decreasing R^2, the share of observed yield variability increases in the index (Eq. 3). The adjusted yield index is normalized with the average yield and the factor 100.

$$AYI_{it} = 100\left(\left(\frac{y_{it}^{PM}}{\bar{y}_i^{PM}}\right)\mathrm{R}_i^2 + \left(\frac{y_{it}}{\bar{y}_i}\right)\left(1 - \mathrm{R}_i^2\right)\right) \tag{3}$$

Supplemental information

S.1 Materials and methods

S.1.1. Data

S.1.2.1 Yield information

We use observed farm maize yields supplied by the Ministry of Agriculture, Food Security and Cooperatives *(38)* for Tanzanian districts ($N = 116$) and the period 2003 to 2010. These observed yield data contain some implausible outliers, which are far beyond the genetic yield potential of maize. Schlenker and Lobell *(11)* show that the direct use of such observed yields can amplify the uncertainty of yield assessments. Thus, we eliminate implausible outliers in the observed yield dataset by using reasonable upper yield ceilings. The ceiling is 25% above the local yield calculated by our process-based model assuming a fertilization of 120 kg N and 40 kg P_2O_5 ha^{-1}. After adjusting the yield dataset (removing implausible outliers or too short time series), we still work with $\mathrm{N} = 104$ districts. Since this dataset has also some missing values, in total our dataset contains 796 observed yield values. The average of the original dataset is 1.5 t ha^{-1} and the standard deviation is ±2.0 t ha^{-1}, while the average of the adjusted dataset is 1.3 t ha^{-1} with a standard deviation of ±0.9 t ha^{-1}.

S.1.2.2 Weather information

We use reanalyzed weather information (WFDEI ERA-Interim) of 319 grid points across Tanzania from 1979 to 2012 *(39)*. To justify the usability of the dataset, we compare the reanalyzed weather dataset with nearest weather data from 16 stations *(40)* of the period 1970 to 2006. The plots in Fig. S.1 exemplarily show the comparison of the yearly-averaged, intra-annual precipitation distribution for five reanalyzes points and observed weather stations. In general, the seasonality of the observed weather data is reproduced by reanalyzed weather data for all weather stations. The 6-day moving average shows that the reanalyzed weather data satisfactorily represent the measured data: The Nash–Sutcliffe model efficiency coefficient (NSE, see also Chipanshi et al. *(41)* for the calculation) for precipitation (*PREC*) is: 0.77, NSE for minimum temperature (TMP_{min}): 0.74, and NSE for maximum temperature (TMP_{max}): 0.31.

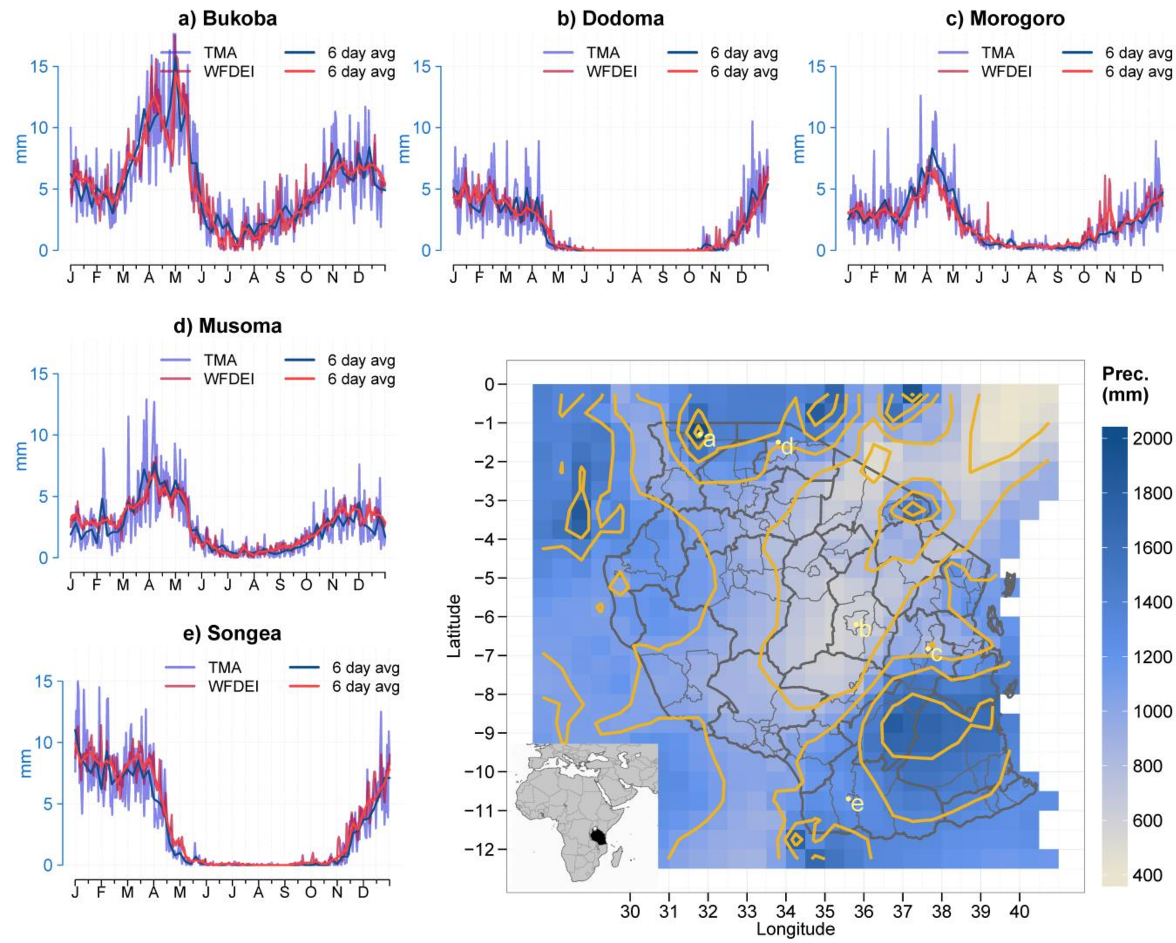

Fig. S.1. Spatial and intra-annual distribution of reanalyzed and observed precipitation patterns. The iso-precipitation lines are yellow; the black boundaries are the regions (thick lines) of Tanzania with its districts (thin lines). The weather stations are the white points a–e. The acronym WFDEI stands for the reanalyzed and TMA for the observed weather data.

S.1.2.3 Soil and agronomic management information

The soil information for the 319 weather grid points is taken from the FAO-74 soil classification according to Dewitte et al. *(42)* and the ILRI *(43)* soil map. We use the fertilization amounts according to Thornton et al. *(44)* as input for the process-based model. For the statistical model, we use the variables acreage maize (district scale), paid agricultural subsidies, and urea application (both on national scale) provided by the Ministry of Agriculture, Food Security and Cooperatives *(38)*. Finally, we use agro-ecological zones *(45)* for the classification of semi-arid and sub-humid regions (Fig. S.2). The division of the maize growing season (planting to harvesting periods) is taken from FAO Crop Calendar *(46)*. For maize prices, we use the national price statistics from the FAO Stat *(47)*.

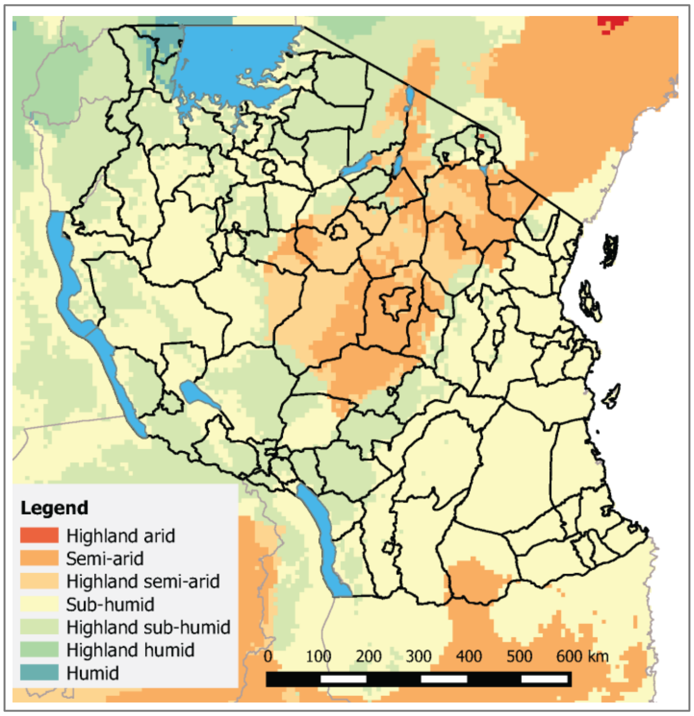

Fig. S.2. Agro-ecological zones and Tanzanian districts.

S.1.2. Process-based crop modeling

We use the Soil and Water Integrated Model (SWIM) as process-based model. The processes of SWIM are calculated on a daily time step for spatial points, which are representative for larger regions (sub-national boundaries, hydrotopes, field trials, or grid cells) *(36, 48)*. For our investigation, we apply SWIM on grid cell information of 0.5° (approximately 50km at the equator).

S.1.3.1 Crop yield modeling by SWIM is based on the EPIC crop module

EPIC is a worldwide applied process-based crop model *(21, 49)*, which is able to reproduce the cropping conditions in SSA *(20)*. The model computes crop yields as a product of the total above-ground biomass and the harvest index. While the harvest index increases until harvesting, the above-ground biomass growth is calculated as the product of the crop-specific parameter for converting energy to biomass and the photosynthetic active radiation. The photosynthetic active radiation is a function of the incoming solar radiation and the leaf area index (LAI) of the corresponding crop. Any divergence of these optimal growing conditions reduces the biomass growth by the stress factors heat stress and insufficient water, nitrogen, and phosphorus supply within a minimum function. The plant water supply is determined by precipitation and water withdrawn by evaporation, surface runoff, infiltration, and plant water uptake, respectively. The EPIC crop module embeds a nitrogen and phosphorus cycle. The nitrogen cycle includes mineralization, nitrification, and denitrification. The phosphorus cycle includes phosphorus adsorption and mineralization. The nitrogen and phosphorous supply is added by organic and mineral fertilization.

S.1.3.2 Modifications in the EPIC crop module

In the EPIC crop module within SWIM, we use mostly the standard maize parametrization of the EPIC model *(36)*. For Tanzanian maize yield assessments, we adjust the temperature sensitivity, harvest index, maximum LAI, and required heat units to maturity. Folberth et al. *(20, 50, 51)* show that this parametrization is valid for the cropping conditions in SSA. The crops in SWIM are not parametrized on one or more individual crop varieties. Information about crop varieties would be very helpful for an accurate representation of local or regional cropping conditions. However this information seems to be unavailable for Tanzania. The temperature sensitivity is corrected according to Rötter and van de Geijn *(52)* to 8 °C basic and 28 °C optimum temperature. According to Gaiser et al. *(53)* and McClung *(54)*, the harvest index of local, unimproved crop varieties is lower than for improved varieties. Since seed saving of local varieties is common in Tanzania *(55, 56)*, we take a HI of 0.35 *(53)*. Folberth et al. *(50)* show that a HI parameter of 0.35 leads to reasonable results for entire SSA. Depending on the environmental and crop genetic conditions, the maximum LAI varies highly in SSA *(57)*. Following Gaiser et al. *(53)*, we use a maximum LAI of 6.0 m^2 (leaf) m^{-2} (ground). The maize maturity groups are covered by the heat units. The heat units are the accumulated growing temperature (actual temperature reduced by the basis temperature) sum from seeding to maturity of the crop. For Tanzania as a whole, we use medium-maturity varieties with 2800 °C heat units *(20, 58)*. In our model, the management is uniform for all grid points. The variables harvesting dates, nitrogen dynamics in the soil (e.g., leaching), or other soil properties (e.g., water holding capacity, rooting depth) vary across space (grid-specific) in our process-based model. Planting dates and fertilizer application are uniform across districts. The planting date is set relatively early (December 10^{th}). In the process-based model, the plant germination starts with the first rains and the plant will not die within the first 30 days also with insufficient water supply. Due to this, we implicitly account for differences in the planting dates. The harvest date is 6 days after maturity (or after this, the next day without precipitation). According to the World Bank *(59)* survey, the average Tanzanian maize fertilization is 23.0 kg N and 0.0 kg P_2O_5 ha^{-1}. For smallholder farmers, Thornton et al. *(44)* describe an inorganic fertilization of 5.0kg N and no phosphorus fertilization. Following the later, we apply an inorganic fertilization of 5.0 kg N and 0.0 kg P_2O_5 ha^{-1}, because the fertilization is rather poor than sufficient *(60, 61)*. In particular in semi-arid, tropical regions, the nutrient uptake is highly influenced by the soil moisture. According to Folberth et al. *(20)* and Harmsen *(62)*, we included in the Liebig minimum function an interaction between water and nutrient stress to calculate the crop growth regulating factor (*GRF*, Eq. S.1). The fertilization is applied 13 days after sowing.

$$GRF = \min(TMP^{Stress}, Water^{Stress}) \quad \min\left(N^{Stress}, P_2O_5^{Stress}\right) \tag{S.1}$$

S.1.4. Statistical crop models

We use an approach, which is similar to the statistical regression model introduced by Gornott and Wechsung *(37)* for the case of Germany. For our approach, we use the same conceptual framework for the variable selection and the same statistical methods and consider both non-weather and weather impacts on maize yields. However, we use a different functional form and variable transformation, which fits better to the Tanzanian weather and agronomic conditions.

S.1.4.1 Statistical method

We use three different statistical regression methods to capture the spatial and temporal heterogeneity among N districts and T years: separately estimated time-series models (STSMs), panel data models (PDMs), and random coefficient models (RCMs). The STSMs estimate independently a separate time-series model for all districts. Each STSM explains the yield variability by a district-individual intercept and district-individual parameters. The PDMs capture directly temporal and spatial variability by one parameter set valid for N considered districts. RCMs contain both one parameter set for all N districts and district individual parameters. Since these parameters depend on each other, the RCMs are estimated by the restricted maximum likelihood method instead of the ordinary least squares method used for STSMs and PDMs.

S.1.4.2 Modeling approach

Combined process-based and statistical modeling approach to assess weather and non-weather-related yield variability by using a logarithmic function (PM^{we}-SM^{nw}-SM^{we2}): The process-based model (PM) is supposed to explain the direct weather-related yield variability (we). The residual yield variability ($\varepsilon_{it} = y_{it} - y_{it}^{PBM}$) of the observed ($y_{it}$) and process-based modeled yields (y_{it}^{PM}) is explained by (i) non-weather-related (nw) and (ii) indirect (second-order) weather-triggered yield influences (we2) like pests and diseases. (iii) Since our dataset only has limited degrees of freedom ($T = 8$), we estimate non-weather-related and indirect weather-triggered impacts in two consecutive statistical models. This means that the non-weather-related statistical model uses the residuals of the process-based model. In the consecutive step, the weather-driven statistical model uses the residuals of the non-weather-related statistical model as the endogenous variable. This approach enables the consideration of both impact factor groups without the risk that any impact factor is considered twice. While the STSMs are directly estimated on district scale, the PDMs are estimated on regional scale. Due to this, PDMs have more available degrees of freedom. (iv) This allows the consideration of both non-weather-related and indirect weather-triggered impacts in a single PDM. RCMs require the same amount of degrees of freedom as the STSMs, thus, they are applied like the STSM for approach i–iii. In total, we compare four approaches to explain the PM residuals (ε^{we}): (i) only i non-weather-driven, (ii) only weather-driven, (iii) non-weather and weather-driven (in two consecutive statistical models), and (iv) non-weather and weather-driven in one model:

(i) PM^{we}-SM^{nw} (ε^{we}): one statistical model to capture the non-weather-related impacts on ε^{we} (Fig. S.3),
(ii) PM^{we}-SM^{we2} (ε^{we}): one statistical model to capture indirect weather-triggered impacts on ε^{we},
(iii) PM^{we}-SM^{nw} (ε^{we})-SM^{we2} (ε^{nw}): two consecutive statistical models to captures non-weather-related impacts on ε^{we} and the residuals of that model (ε^{nw}) by indirect weather-triggered impacts (Fig. S.4),
(iv) PM^{we}-SM^{nw}&SM^{we2} (ε^{we}): one statistical model to capture both non-weather-related and indirect weather-triggered impacts on ε^{we} (only investigated with PDMs).

We use a logarithmic function as the basic functional form with the residuals (ε_{it}) as endogenous variables (Eq. S.2). The exogenous variables are either the non-weather-related or indirect weather-triggered variables. The J exogenous variables are transformed to logarithmic values. The terms β are the parameters, u is the error term, t (with $t = 1, \ldots, T$) is the time-index, and i denotes the spatial index (with $i = 1, \ldots, N$). The endogenous variable is considered in untransformed values, because the negative residual values allow no logarithm. We use exogenous variables as logarithmic values, because this transformation achieves better results than the untransformed ones. We also investigate several other transformations (see S.2.3.3), however, the fixed effects transformation achieves the best goodness of fit.

$$\varepsilon_{it}^{id/we2} = \log \beta_{0i} + \sum_{j=1}^{J} \beta_{ji} \log\ x_{jit} + \log u_{it} \tag{S.2}$$

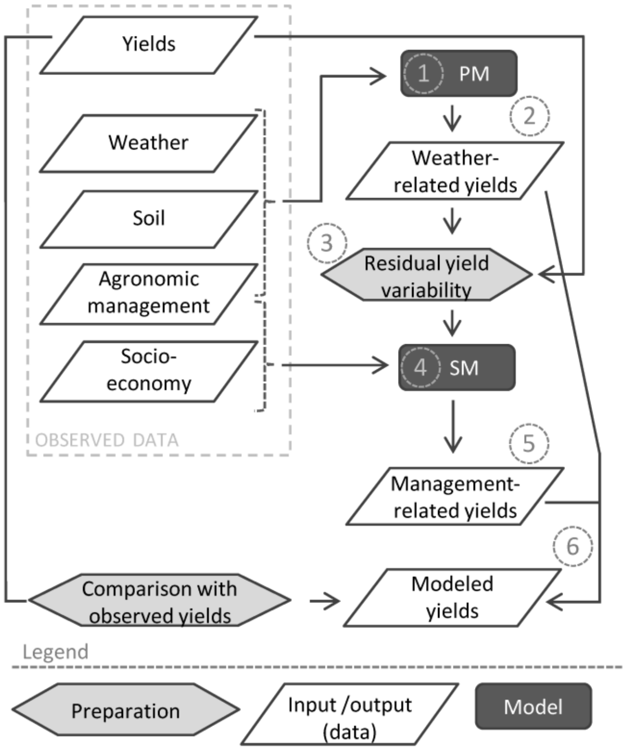

Fig. S.3. Flowchart of the combined model approach (PM^{we}-SM^{nw}): (1) Application of the process-based crop model (PM) for the region-specific agro-ecological conditions. (2) Separation of weather-related yield variability and (3) calculation of residual yield variability. (4) Application of the statistical crop model (SM) to capture the residual, non-weather-related yield variability by agronomic and socio-economic impacts. (5) Separation of non-weather-related yield variability. (6) Combination of weather-related and non-weather-related yield variability to compare the modeled yields with the observed yields.

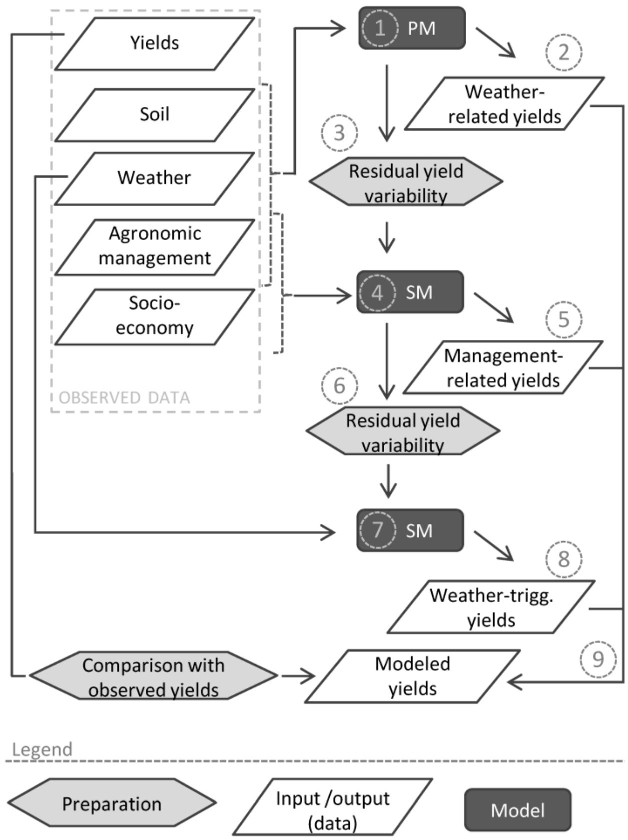

Fig. S.4. Flowchart of the combined model approach (PM^{we}-SM^{nw}-SM^{we2}): (1) Application of the process-based crop model (PM) for the region specific agro-ecological conditions. (2) Separation of weather-related yield variability and (3) calculation of residual yield variability. (4) Application of the statistical crop model (SM) to capture the residual, non-weather-related yield variability by agronomic and socio-economic impacts, (5) separation of non-weather-related yield variability. (6) Calculation of residual yield variability (from the SM). (7) Application of the statistical crop model (SM) to capture the residual, indirect weather-triggered yield variability (5) separation of indirect weather-triggered yield variability. (9) Combination of weather-related, non-weather-related and indirect weather-triggered yield variability to compare the modeled yields with the observed yields.

S.1.4.3 Variable selection

In general, we use the same weather and non-weather exogenous variables for our statistical model approaches. The approaches are driven with a set of either non-weather or weather variables. As non-weather exogenous variables, we use *maize acreage* (in ha per district), *urea application* (in metric tons for entire Tanzania), and *paid subsidies on crop production* (in US$). The *maize acreage* is thought to capture agronomic management decisions, land use and land availability *(14)*. This includes crop rotation preferences (for more maize) and the economic suitability of maize production. Moreover, yield can be interpreted as land productivity *(63)* and changes in acreage might go ahead with changes in soil quality, because farmers plant on marginal soils in case of an acreage expansion *(64)*. This will have a direct impact on crop yields. *Urea application* (in metric tons for entire Tanzania) should cover fertilizer availability and application *(65)*. The application of fertilizer is already modeled by the process-based model. However, because information about annual variation of fertilizer application is not available at district level, fertilizer application is kept constant over time and only used to reproduce the average yield level. As a result annual yield variation attributable to fertilizer application cannot be reproduced by the process-based model. Thus, the statistical model is needed to explain also the yield variability attributable to changes in fertilizer application. For SSA, Ward et al. *(32)* use as economic variables nitrogen and phosphorus fertilizer as well as irrigation. Since only 1.8 – 3.3% of the Tanzanian cropland is irrigated *(66, 67)*, we haven't included this variable. Other production factors, e.g., machinery *(68)*, also seems to be of lower importance for Tanzania. Pauw and Thurlow *(69)* show that agricultural growth stagnates since the 1990s, because of low investments in infrastructure and machinery. The variable *paid subsidies on crop production* (in US$) addresses the efficiency of the fertilizer and seeds' subsidy system and the socio-economic behavior of farmers *(19)*. Fertilizer and seed subsidies tripled the maize yields in Malawi within three years *(18)*. Such subsidies are also disbursed in Tanzania, however, with a smaller yield increase *(17)*. Tanzania has launched an input subsidy program in 2003 with the main objective to facilitate fertilizer and improved seeds' use in remote areas. This program was changed in 2008 with the aim to raise maize and rice production. The program was designed to increase Tanzania's household and national food security and to response to the fertilizer prices spikes in 2007 and 2008. Because of the disbursed subsidies for improved seeds and fertilizer, the farmers have adjusted their agronomic management with direct implications on crop yields *(70)*.

Since market access, land tenure security or access to extension are rather time-constant in Tanzania *(71, 72)*, the impact of these variables is captured by the intercept of our statistical model and the other parameters are not biased (no omitted variable bias). The spatial heterogeneity of these variables is also captured by the district-individual intercepts. Thus, our model accounts for time-invariant and spatial heterogeneous impacts of market access, land tenure security or access to extension.

As weather variables, we use *solar radiation*, *precipitation,* and the *vapor pressure deficit*. The solar radiation (*SR*) maps the potential growth. The variables *PREC* and vapor pressure deficit (*VPD*, Eq. S.3 for calculation) should capture deviations from the optimal water supply. The *VPD* is calculated by TMP_{max} and TMP_{min} *(73)*. As indirect weather-triggered impacts, these variables should address plant health (pests, weeds, and diseases) and agronomic management, which is collinear with the weather variables *(16)*.

$$VPD = 6.11\left(\exp^{\left(\frac{17.269\,TMP_{\text{max}}}{237.3\,+\,TMP_{\text{max}}}\right)} - \exp^{\left(\frac{17.269\,TMP_{\text{min}}}{237.3\,+\,TMP_{\text{min}}}\right)}\right) \tag{S.3}$$

The Tanzanian maize growing season lasts approximately from December to June. Within Tanzania there is a high heterogeneity of the planting and harvesting dates *(46)*. Therefore, the weather variables are aggregated by the district-specific maize growing season. Because of limited degrees of freedoms, the variables are not further divided in sub-parts of growing season.

S.1.5. Validation

To test the robustness of the process-based and statistical models, we conduct a validation with observed yields, which are not considered in the model calibration. Process-based models endogenously compute crop yields (without the consideration of observed yields). This allows for a direct comparison of the observed and modeled yields. Statistical models require observed yields for their estimation. To validate statistical models with unconsidered observed yields, we apply an out-of-sample cross-validation. This validation reduces the estimation dataset by the values of the year t subsequently for all years T. For each year, the parameters are estimated for the reduced dataset (validation parameter). Finally, the yields of the removed years are calculated by the validation parameter and the exogenous variable values of the removed years *(41)*.

S.1.6. Aggregation of results

The yields of the process-based model are calculated on grid scale and aggregated from grid-cell scale to district scale to make them comparable with the observed yields. For the comparison of spatial patterns, we aggregate the district yields to agro-ecological zones. The humid areas of Tanzania are neglected, because these areas only cover tiny parts of the Tanzanian land surface. Due to the aggregation, the goodness of fit increases retrospectively, because district individual yield anomalies are filtered out *(33)*. All statistical models are applied on district level; we did not aggregate the exogenous variables, because this would lead to information losses due to a reduced variability of the estimation dataset *(74)*. To show the adjusted yield index, we aggregate the yield index from district to regional scale by the arithmetic average (main article Fig. 4).

S.1.7. Software

Our statistical models are estimated with the software *R*. We use the package *plm* for the PDMs, the package *lme4* for the RCMs and the package *lmtest* for the statistical tests. The maps are generated with the *R* package *ggplot2*. The process-based model SWIM is written in *fortran*.

S.2 Further results and discussion

S.2.1. Crop physiological yield assessment by SWIM

The yield level of 1.3 t ha^{-1} is satisfactorily captured by the process-based model SWIM. However, the patterns of low and high yield regions and the inter-annual variability are only poorly ($r = 0.05$) captured by our process-based model (district-level correlation map in Fig. S.5 and yield levels for each year and district in Fig. S.6). Since process-based models consider only a limited number of processes in their model set-up, they may neglect possibly relevant processes like intercropping, tillage practices. Moreover, an important additional shortcoming of these models might be the lack of management information – e.g., growing season settings, fertilizer application – *(30)*. This might be one reason for our unexplained residual yield variability. Another reason might be that the development of these models lags behind the rapidly changing agricultural sector – caused by climate change or technological development – *(31)*. However, Fig. S.5 shows that the water scare regions are covered with higher accuracy than the regions with sufficient water supply. This shows that the model is sensitive for the weather-related influences on crop yields.

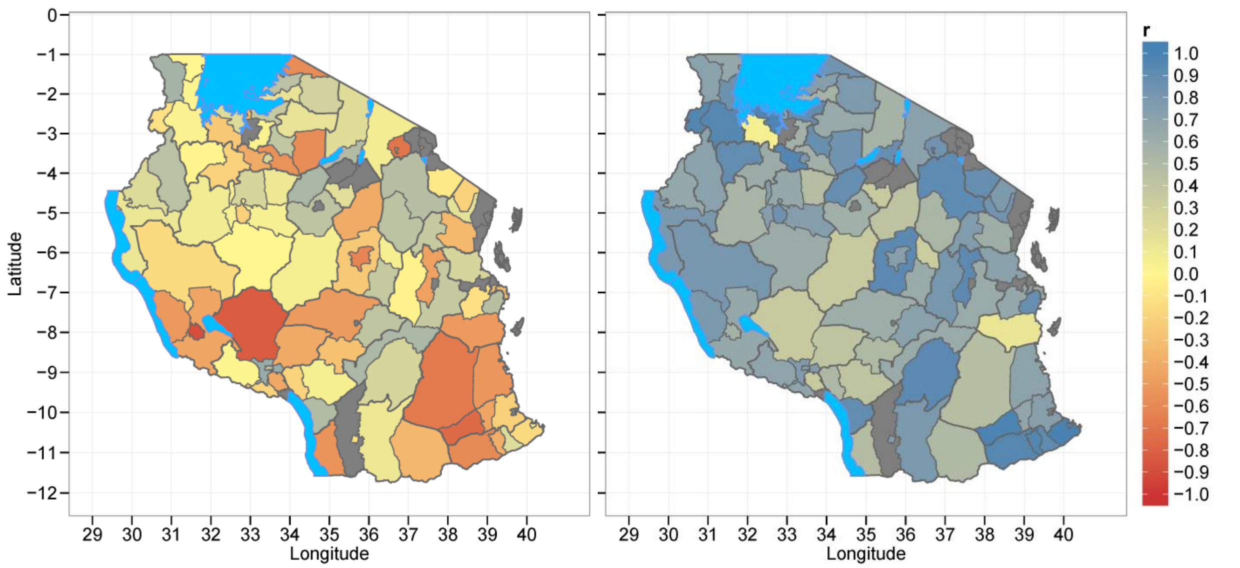

Fig. S.5: Correlation (Pearson's r) of observed maize yields and only process-based modeled yields (left) or process-based and statistical modeled yields (right) at district scale.

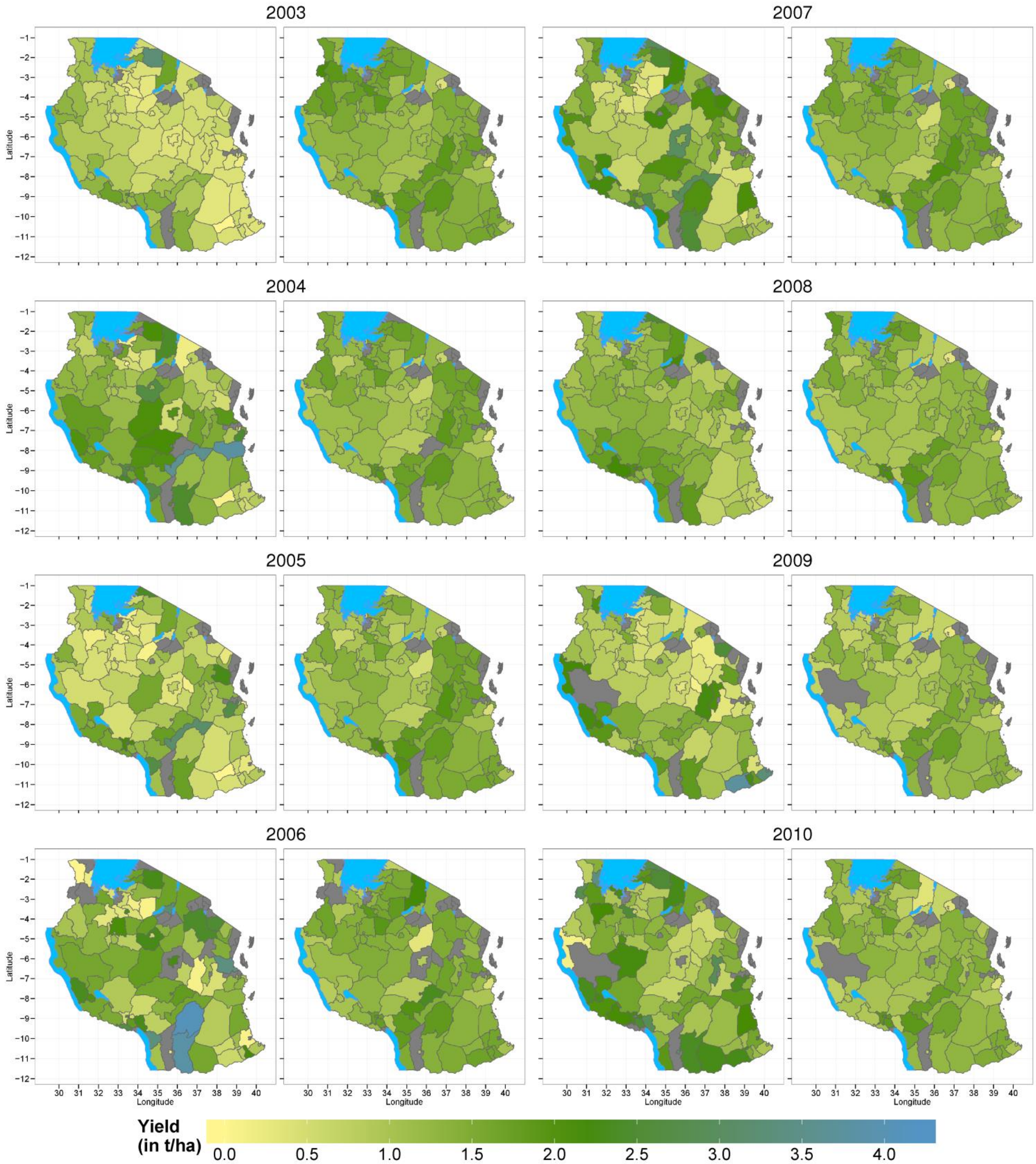

Fig. S.6. Observed (first and third column) and process-based modeled (second and fourth column) yields on district scale for each year of the period 2003-2007.

S.2.2. Results for the statistical modeling approach

S.2.2.1 Model robustness and selection

The results of the PM^{we}-SM^{nw}-SM^{we2} approach (Eq. S.2) are shown in Tab. S.1 and S.2. For our modeling scheme, we use the results of the STSMs row i. The non-weather-related and indirect weather-triggered STSMs (iii) achieve the highest goodness of fit for the estimated yields ($r = 0.92$). The goodness of fit for the STSM with solely non-weather-related impacts (i) is slightly lower ($r = 0.86$), as is also the case for the solely indirect weather-triggered impacts (ii) ($r = 0.78$). The STSMs show stronger indirect weather-triggered impacts on district scale than the PDM on national scale. This can be explained by the fact that weather-triggered effects (like pest outbreaks or plant diseases) appear rather locally than on a national scale. The generally lower goodness of fit in the validation can be explained by the short (8 years) and sometimes incomplete observed yield time series. Remarkably, the validation results decline when the weather-triggered impacts are also considered. While the STSMs attain a correlation of $r = 0.33$ by including the weather-triggered impacts, by excluding these impacts the correlation rises to $r = 0.38$. This is similar for PDMs and RCMs. Consideration of the solely weather-triggered impacts decreases the validation correlation to $r = 0.04$ for the STSMs, to $r = 0.22$ for the PDMs, and to $r = -0.04$ for RCMs. Thus, we conclude that weather-triggered impacts do not contribute any model robustness. The consideration of both impact factor groups in single PDMs leads also to decreasing estimation and validation power in comparison to the sole consideration of either non-weather-related or weather-triggered factors. The RCMs' goodness of fit is close to that of the STSMs. While the STSMs estimation is higher than for the RCMs, the validation results of the RCMs are slightly higher in comparison to the STSMs. For our risk calculation, we use the STSMs with only non-weather-related impacts. However, the PDMs with both factor groups are suitable in the case of strong multicollinearity.

Tab. S.1. Correlation of the observed and estimated or validated yields. The columns (STSMs, PDMs, and RCMs) refer to the three statistical methods. All statistical models (SM) are applied on the residuals of the process-based model (PM). The SM considers either only non-weather-related (i) or indirect (second-order) weather-triggered impacts (ii), non-weather-related and indirect weather-triggered impacts in two consecutive models (iii) or in single PDM (iv). The non-weather-driven statistical model is applied without the process-based model (v). The non-weather variables are *maize acreage*, *urea application*, and *paid subsidies on crop production*, while the weather-triggered variables are *SR*, *PREC*, and *VPD*.

	Approach	STSM	PDM	RCM
	Estimation			
i	PM^{we}-SM^{nw}	0.86	0.55	0.80
ii	PM^{we}-SM^{we2}	0.78	0.49	0.68
iii	PM^{we}-SM^{nw}-SM^{we2}	0.92	0.62	0.85
iv	PM^{we}-$SM^{nw\text{-}we2}$	–	0.65	–
	Validation			
i	PM^{we}-SM^{nw}	0.38	0.31	0.43
ii	PM^{we}-SM^{we2}	0.04	0.22	–0.04
iii	PM^{we}-SM^{nw}-SM^{we2}	0.33	0.30	0.40
iv	PM^{we}-$SM^{nw\text{-}we2}$	–	0.17	–

Tab. S.2. R^2 of the observed and estimated or validated yields. The other terms similar to Tab. S.1.

	Approach	STSM	PDM	RCM
	Estimation			
i	PM^{we}-SM^{nw}	0.74	0.30	0.64
ii	PM^{we}-SM^{we2}	0.60	0.24	0.47
iii	PM^{we}-SM^{nw}-SM^{we2}	0.84	0.39	0.72
iv	PM^{we}-$SM^{nw\text{-}we2}$	–	0.42	–
	Validation			
i	PM^{we}-SM^{nw}	0.15	0.10	0.19
ii	PM^{we}-SM^{we2}	0.00	0.05	0.00
iii	PM^{we}-SM^{nw}-$SM^{we2\text{-}log}$	0.11	0.09	0.16
iv	PM^{we}-$SM^{nw\text{-}we2}$	–	0.03	–

In general, our results show that most of the yield variability can be explained by our approach. Sole consideration of the process-based model might initially challenge its usability. However, by consecutively applying the statistical model (Eq. S.2), we are able to explain the remaining yield variability by agronomic management and socio-economy. This justifies the use of the process-based model to calculate weather-attributable impacts. As a result, our combined approach contributes an important tool for the crop modeling community to cover agronomic management and socio-economic impacts and control the non-weather-related yield variability. Our approach allows us to replace district-specific agronomic management information, which is frequently unavailable in particular in SSA *(75)*, by a set of regionally available agronomic management and socio-economic variables. Moreover, weather-related yield anomalies coming from other process-based crop models, its ensemble results, or additional observed yield data can be easily incorporated.

S.2.2.2 Variable parameters

The parameters of the statistical models driven by the non-weather and indirect weather-triggered variables are shown in Fig. S.7 (PM^{we}-SM^{nw}-SM^{we2}-approch). The non-weather variable *urea supply* has on average a positive yield impact. This means that additional fertilization is positive for the yields. The impact of the *maize acreage* is negative. This is also reasonable since an expansion of the maize acreage is achieved through the cultivation of less suitable land. The impact of *paid agricultural subsidies* is also positive. This is also reasonable, because the increase in improved seeds and fertilizer is positive for the maize yield *(18)*. However, the *paid agricultural subsidies* parameter is with 6% added explained yield variability smaller than the other two non-weather-related parameters. This could be interpreted as an indication that these subsidies have a relatively small impact (this is in line with the literature, e.g., Benson et al. *(17)*). While the weather variables *VPD* and *SR* have on average a positive yield impact, the *PREC* yield impact is on average close to zero. Moreover, the range of the district individual parameters is higher for the statistical model with indirect weather-triggered variables than for the statistical model with non-weather-related variables. This can be explained by the significantly lower explained yield variability by the statistical model with indirect weather-triggered variables.

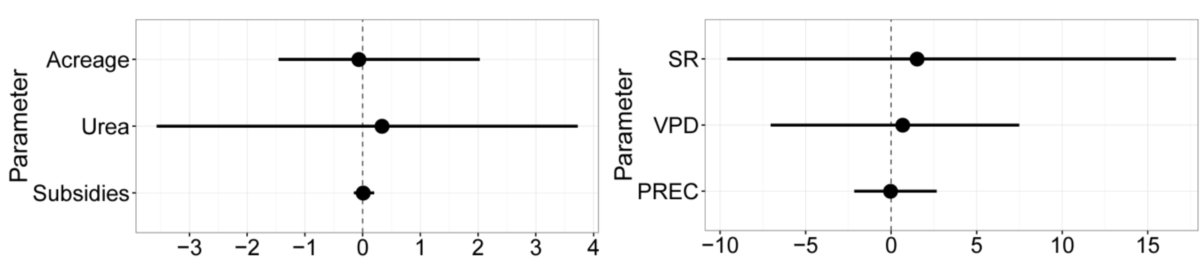

Fig. S.7. Estimated parameters of the non-weather (left) and weather-driven (right) separate time-series model (Eq. S.2). The point is the arithmetic average parameter size of all district models; the lines are the 5% and 95% percentile.

The consideration of a further exogenous variable increases the goodness of fit of the estimation, independently of whether there is an actual contribution by the variable. However, this does not necessarily hold true for the goodness of fit of the validation *(e.g., 14)*. The variable selection *SR*, *VPD*, *PREC*, TMP_{min} leads to poorer validation results than for the validation with the variables *SR*, *VPD*, *PREC*. This can be explained by the limited degrees of freedom. The variable selection *SR*, *VPD*, *PREC* archieves the best validation goodness of fit. The validation goodness of fit decreases by using the variables selection TMP_{min}, *SR*, *PREC*, and further by the selection TMP_{min}, *VPD*, *PREC*.

Furthermore, we also analyze several other weather and non-weather variables, however, with lower goodness of fit. The additionally tested variables are evapotranspiration (ETP_{TI} by Turc-Ivanov and ETP_H by Haude), *growing degree days* (≥ 8 °C, < 30 °C), *heat degree days* (≥ 30 °C), *temperature normalized solar radiation*, national fertilizer application (*diammonium phosphate* and *calcium ammonium nitrate*), *sprayed area against red locust*, and the Tanzanian *maize price*.

S.2.3. Model robustness and uncertainty

S.2.3.1 Pre-analysis of significant non-weather-related yield effects

We apply two PDMs on national scale to investigate whether indirect weather-triggered and socio-economic effects are in the residuals (unexplained yield variability) of the process-based model. These residuals are used as the endogenous variable. The exogenous variables of the first PDM are year dummies (to capture year-dependent systemic effects), maize acreage and the weather variables *SR*, ETP_{TI}, and *PREC* (to capture collinear or omitted weather-triggered effects). As result, all year dummy parameters and the acreage are significant with $p \leq 0.01$ and the models provide significant correlation coefficient of $r = 0.40^{***}$ (Pearson correlation; $^{NS}\,p > 0.1$, $^{*}\,p \leq 0.1$, $^{**}\,p \leq 0.05$, $^{***}\,p \leq 0.01$). The consideration of only weather variables, after removing year dummies and the acreage, reduces the r to 0.07^{*} and leaves no significant variables $p \leq 0.01$. Thus, we conclude that only a small effect from weather-triggered impacts remains in the residuals on the national scale. The significant impact of the year dummies indicates an uncontrolled impact of non-weather-related variables.

S.2.3.2 Model validity and statistical tests

For statistical models, the estimation method is permissible if the ordinary least squares assumptions are fulfilled and if no explaining variables are neglected (problem of omitted variable bias). Thus, we conduct several statistical tests to verify the permissibility of the statistical models, which consider the socio-economic yield impacts. The statistical tests are described by Croissant and Millo *(77)* and Baltagi *(78)*. No statistical test exists for the problem of omitted variable bias; however, the regression equation specification error test (RESET) investigates whether quadratic variables are omitted in the model. The RESET shows that quadratic variables are not neglected. Only in 4% of the models, quadratic terms would be beneficial for the model goodness of fit. We also tested several other variable transformations. The chosen $\log y_t$-transformation achieves the highest goodness of fit. The first differences and fixed-effects transformation as well as the untransformed terms achieve lower goodness of fit. The Breusch–Godfrey and the Breusch–Pagan test are applied to test against autocorrelation and heteroscedasticity. In some cases the model residuals are autocorrelated (29%), but mostly they are not (Breusch–Godfrey test). However, autocorrelation can be a problem in macro panels with $T \geq 60$ and $N > T$, but is rather unproblematic in micro panels *(90, p. 102-103)*. Since our panel has only a time series length of 8 years and more spatial than the temporal observations, autocorrelation (Breusch–Godfrey test) seems not relevant for our case. Heteroscedasticity appears in 0% (Breusch–Pagan test) of the models. The normal distribution of residuals is tested using the Shapiro–Wilk test. In 4% (Shapiro–Wilk test) of the models, the residuals are not normal distributed. The weather-driven statistical model is not tested, because the results are not further used.

If both weather and management-related factors are estimated in one statistical model, there might be an overlap of these factors due to multi-collinear and/or not clearly assignable processes. These are for instance, temperature and pests & diseases *(16)* or precipitation and fertilizer efficiency *(79)*. In particular, pests & diseases are (at least partly) manageable, but also depend on weather conditions. If such factors are included in a statistical model, this model might not be able to disentangle these collinear processes without a certain uncertainty. Due to the design of our approach, the weather-related part is assessed in the first step (by the process-based model) and only the remaining yield variability is further used for the statistical model assessment. Since process-based models do not face the problem of statistical multicollinearity and its outputs are calculated independently from statistical model outputs, the fraction of overlap should be relatively small in our analysis. For the claim calculation, our approach solely relies on the process-based model, while the statistical model is used to justify the usability of the process-based component. Thus, a limited robustness of the statistical model influences neither the weather-attributable yields nor claim payouts.

S.2.3.3 Functional form and variable transformation

The limited degrees of freedom do not allow separating the non-weather and weather-related yield variability within one statistical model. However, we can separately estimate models for both parts. Therefore, we apply the Cobb–Douglas function as a further functional form. The Cobb–Douglas function has been well tested for agronomic and economic applications. To linearize the Cobb–Douglas function, all variables are used as a logarithm. We apply the function to capture either the (first-order) weather (which are assessed by the process-based model in the main approach) or non-weather-related yield impacts. The different variable transformations have been tested previously. The fixed-effects transformation $\left(\log \ddot{y}_t = \log\left(\frac{y_t}{\bar{y}}\right)\right)$ works best, followed by logarithmic transformation ($\log y_t$), followed by first differences $\left(\Delta \log y_t = \log\left(\frac{y_t}{y_{t-1}}\right)\right)$, followed by untransformed values (y_t).

$$\log \ddot{y}_{it} = \log \beta_{0i} + \sum_{j=1}^{J} \beta_{ji} \ \log \ddot{x}_{jit} + \log \ddot{u}_{it} \,, \qquad \text{with } \ddot{y} = \frac{y_{it}}{\bar{y}_i}, \tag{S.4}$$

$\bar{y}$ as arithmetic average of y_t, and respectively for $\ddot{x}$, $\bar{x}$, $\ddot{u}$, and $\bar{u}$.

The utilization of the Cobb–Douglas function with the fixed-effects transformation (Eq. S.4) leads to significantly ($p < 0.01$, Fisher z-transformation) lower goodness of fit in comparison to our used modeling approach (Tab. S.1 row i). The weather-driven statistical model (SM^{we}) attains a correlation of 0.77 (0.10) for the STSMs estimation (validation), 0.64 (0.27) for the PDMs, and 0.72 (0.22) for the RCMs. Fig. S.8 (left) shows that the weather-driven STSM attains a lower goodness of fit than the main (PM^{we}-SM^{nw}) approach. The average deviation from the observed yields (root mean square error) is for the solely weather-driven statistical model 0.53 t ha^{-1} and for the main approach 0.41 t ha^{-1}.

The non-weather-driven statistical model (SM^{nw}) attains a correlation of 0.83 (0.29) for the STSMs, 0.71 (0.50) for the PDMs, and 0.79 (0.49) for the RCMs. Fig. S.8 (right) shows that this modeled yields (STSM, r = 0.83) scatter slightly more around the observed yields than the yields of the main approach (r = 0.86). The root mean square error is 0.46 t ha^{-1} for the solely non-weather-driven statistical model and 0.41 t ha^{-1} for the main approach. The small differences between the non-weather--driven statistical model and the main approach can be explained by the dominate yield impacts of non-weather effects (see also Fig. 3 of the main article: share of weather-related yield losses). The high correlation of non-weather and weather-driven statistical models illustrates a statistical overlap between weather- and non-weather-determined yield variability. This can only be resolved by using a process-based model to capture beforehand the weather-related yield variability, notably under these low degrees of freedom.

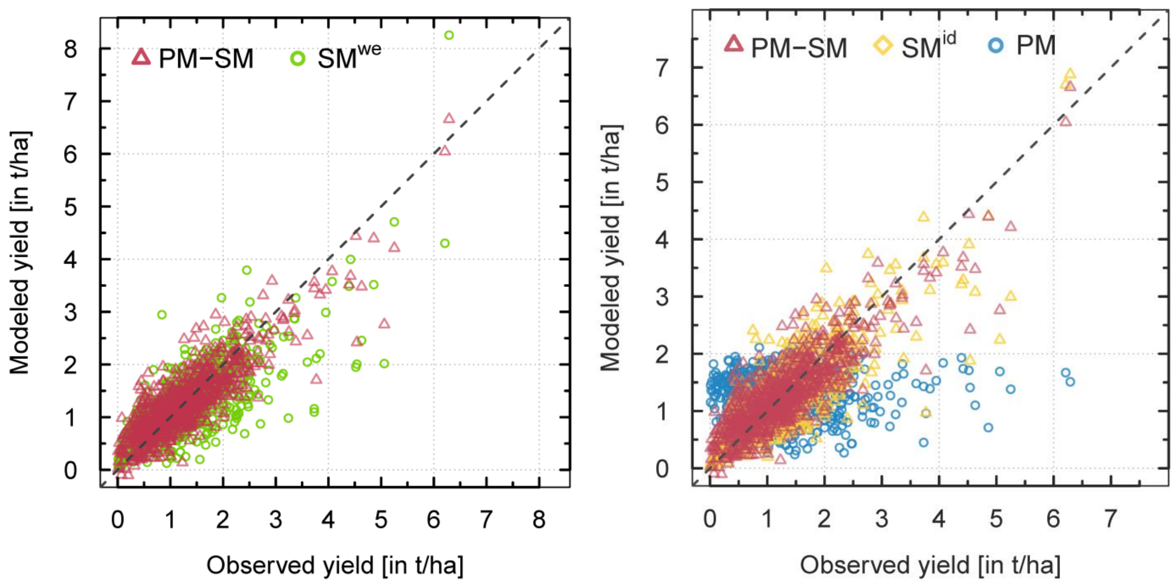

Fig. S.8. Goodness of fit due to the combined application of a process based and a statistical model (PM-SM, red points). Left: the green points show the sole weather-driven statistical model (SM^{we}, Eq. S.4). Right: the yellow points show the sole application of the non-weather-drive statistical model (SM^{nw}, Eq. S.4) and the blue points show the solely applied process-based model (PM).

We also apply our main approach (PM^{we}-SM^{nw}) with the Cobb–Douglas function instead of the logarithmic function as the functional form. The process-based model is used to capture the (first-order) weather-attributable yield impacts and a consecutive statistical model to capture non-weather and indirect weather-triggered influences as in the PM^{we}-SM^{nw}-SM^{we2} approach. The exogenous variables (right side of Eq. S.5) are similarly transformed as in the approach of Eq. S.4. As the endogenous variable, we take the difference of the transformed observed and process-based modeled yields. As transformation, we use the logarithmic fixed-effects. However, this approach achieves the lowest goodness of fit. The correlation of the non-weather-driven statistical models achieve an r of 0.33 (0.18) for the STSMs, of 0.42 (0.33) for the PDMs, and of 0.31 (0.18) for the RCMs (validation results in parentheses). The models for indirect weather-triggered impacts achieve as correlations 0.30 (0.03) for STSMs, 0.34 (0.21) for PDMs, and 0.28 (0.19) for RCMs. Thus, we conclude that the Cobb–Douglas function is less suitable for the cropping conditions in Tanzania.

$$\log \ddot{y}_{it} - \log \ddot{y}_{it}^{PM} = \log \beta_{0i} + \sum_{j=1}^{J} \beta_{ji} \, \log \ddot{x}_{jit} + \log \ddot{u}_{it} \qquad (S.5)$$

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