RISK MODEL SENSITIVITY & ROBUSTNESS

Analysis Framework & Application to Africa RiskView

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EXECUTIVE SUMMARY[1]

This note sets forth a methodology for the evaluation of uncertainties related to the precision of a risk model. It is based on sensitivity and robustness analyses (assessment of output level variability from—respectively—one or multiple input parameters variations). The methodology is illustrated through the application to Africa RiskView (ARV), African Risk Capacity's (ARC) risk model, for which a five-day support mission took place between November 2016 and January 2017.

Overall, the study concludes that whilst the analysis contained in this report only paves the way to further, more comprehensive studies, some preliminary results can already be extracted and provide orders of magnitude of the uncertainty involved in the modelling of Maize in Malawi, Millet in Niger and Rangeland in Mauritania. It identifies specific areas where uncertainty can be understood, controlled, and reduced. A number of limitations are raised and recommendations on future follow-up studies provided.

As expected, the observations made here exemplify the fact that the complex nature of a large-scale generic modelling platform being customized to the specificities of various countries and assets, requires well-informed decision making. It also implies a very close cooperation between in-country teams and developers, as both contribute effectively to the overall precision and accuracy of the modelling process.

Specifically, the study concludes with the following short- and medium-term recommendations:

1. Refining the review by:
    a. complementing it with more *exhaustive* cases, making sure the entire spectrum of uncertainties is properly reflected;
    b. extending it to *other countries/assets* (to ideally produce a list of *top three–four uncertainty parameters* for each country/asset, so as to alert end users/Technical Working Groups (TWG) on the high-impact potential of those inputs, as well as identify *hypersensitive combinations*);
    c. incorporating *TWG's insight* into the definition of realistic inputs, uncertainties and variations;
2. Implementing lessons learnt from the above *into decision-making processes;*
3. Extending the analysis to other perils (flood, wind);
4. *Raising awareness* of end users/TWG on sensitivities identified and managing risks accordingly.

In the long term, it is recommended that the following be considered:

5. Addressing uncertainty through *communication and capacity building:* raising awareness on overall criticality of input parameters selection and risk management practices. Managing expectations from the modelling platform both at user level and risk transfer/insurance level, based on improved quantification of the variability identified, as well as based on clear, visual communication of limitations and confidence intervals.
6. Reviewing *external data sources and index selection* impact. Notably, the variability due to the WRSI index itself is major, and a quantification of its domain of applicability might be required;
7. Addressing uncertainty through *"dynamic" or blended models.*

[1] This note was authored by Antoine Bavandi of the Disaster Risk Financing and Insurance Program at The World Bank Group, with the inputs of Joanna Syroka, Balthazar Debrouwer and Chencheng Du, of African Risk Capacity. The author would like to thank them for their support, availability and invaluable insights, which greatly facilitated the progress made under this analysis. The note is an output of the Disaster Risk Financing and Insurance Program. It benefited from the technical expertise and guidance of Samuel Munzele Maimbo, Olivier Mahul, Julie Dana and Brenden Jongman.

Photo credit: USAID/Tash McCarroll.

1

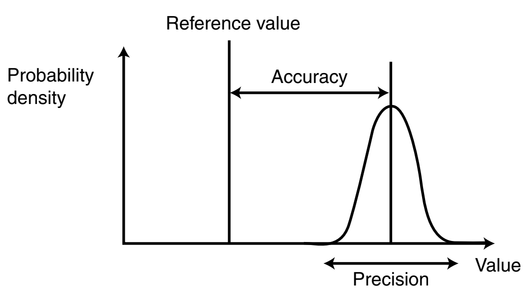
Methodology

1.1 Rationale and Objectives

Risk models can be highly complex. As a result, the relationships between inputs and outputs may be difficult to capture, counterintuitive or poorly understood. In some cases, the model can be viewed as a black box, where outputs are an opaque function of inputs.

Most of the time, inputs are subject to sources of uncertainty, including errors of measurement, poor data quality, natural (aleatory) intrinsic variability, absence of information and partial understanding of the driving mechanisms behind modelled events. Those uncertainties impose a limit on our confidence in the response or output of the model.

This paper focuses on the part of the uncertainties related to the precision of a model. The reliability of a model is indeed the combined result of its accuracy (proximity of a simulation to the actual value observed) and its precision (repeatability or stability of simulations between themselves), as illustrated below.



Precision (stability) of a measure vs. accuracy (conformity to actual value).

Reviewing the accuracy of a model means focusing on the comparison between historical losses and simulated losses, which is not a standard exercise and *requires substantial bespoke analysis and relevant, adequate, historical datasets*. It does not lend itself to generic analysis methodologies.

The precision-related uncertainties, too often considered minimal, can in many cases however drive the overall uncertainty. This is particularly true for sophisticated models which combine complex nonlinear sequences of computations and approximations. The purpose of this note is to set forth a methodology for assessing the uncertainty related to the precision of a model.

In other terms, the questions that are being answered through this methodology specifically are:

- How stable or robust is the modelling chain to uncertainties likely to exist at *input level?*
- How much of an impact does the *utilization* of the software have, on the overall results?
- How much uncertainty can be *reduced or controlled* from unknowns that can be refined or improved?

1.2 Sensitivity Analysis

Sensitivity analysis is a systematic procedure used to explore how an optimal solution responds to changes in inputs—which are typically either known values which might vary over time, or parameters whose values are open to question. The analysis is based around a prior assumption that optimization is center stage, with uncertainty viewed as a potentially disruptive factor. The analysis aims at discovering how sensitive the 'optimal' solution is to changes in key factors. An insensitive solution offers the advantage of behaving in a more "predictable" way (e.g., a risk environment simulated two years in a row should lead to similar loss numbers) and can be referred to as 'robust' (see §1.3).

The objective of a sensitivity analysis is primarily to highlight the most sensitive input data, parameters or modelling assumptions, ordering by importance the strength and relevance of the inputs in determining the variation in the output.

Other objectives include:

- Determining qualitatively the range of variations of the outputs of a model in the presence of uncertainty;
- Increased understanding of the relationships between input and output variables in a system or model;
- Searching for errors in the model (by encountering unexpected relationships between inputs and outputs);
- Model simplification—fixing model inputs that have no effect on the output, or identifying and removing redundant parts of the model structure;
- Enhancing communication between modelers and decision makers (e.g., by making recommendations more understandable, compelling or persuasive).

One of the simplest and most common approaches is that of changing one-factor-at-a-time (OFAT or OAT), to see what effect this produces on the output, which is the method that has been used in this analysis. This approach does not fully explore the input space, since it does not take into account the simultaneous variation of input variables (which is what the robustness analysis is doing, see §1.3). This means that the OAT approach cannot detect the presence of interactions between input variables, but it was preferred to other methods (e.g., scatter plots trending, regression analysis, or other analytical methods) for its simplicity and transparency.

The outcome of a sensitivity analysis will be the sorting out of input parameters and assumptions used in the modelling, by order of importance of the impact they each have, separately, on the output.

1.3 Robustness Analysis

The next step in the methodology used to quantify precision-related uncertainty is the assessment of output variability when combining multiple input variations together. This is the robustness phase of the analysis, aimed at recreating likely conditions of utilization of a model.

The term "robustness" here can be defined as follows: a risk model is said to be robust if small variations in the way the model is being used—resulting either from estimation or mis-specification errors—result in small variations in the estimated losses at the output level.

The robustness analysis is therefore a combinatory analysis aimed at looking at all possible combinations of parameters likely to exist at the input level, in order to define the response of the model for a range of credible applications. For the sake of simplicity (and computational time), the combinatory analysis presented in this methodology focused on the largest drivers of uncertainty identified during the sensitivity analysis. Most of the time, the uncertainty of a model will indeed be driven by a limited number of key factors. Combining variations of these pre-identified parameters within predetermined ranges can provide a faithful picture of the overall variability that exists at the output level.

The objectives of a robustness analysis can be summarized as:

- Uncertainty reduction, through the identification of the combination of inputs that cause significant uncertainty in the output and should therefore be the focus of attention in order to increase robustness or stability;
- Finding regions in the space of input factors for which the model output is either maximum or minimum or meets some optimum criterion (optimization of Monte-Carlo type of analyses);
- To seek to identify meaningful connections between observations, model inputs, and predictions or forecasts, leading to the development of improved models.

Sensitivity and robustness analyses can use a variety of output metrics in order to determine how precision should be defined. In the context of loss modelling, it is particularly important to understand that a model might be robust within a given domain of application (e.g., a given asset type, geographic area or return period), but possibly much less so over another area, application, or frequency range.

To exemplify this, the study case presented hereafter, which is an application of the above methodology to ARV, addressed different assets and geographies, and looked at the stability of outputs from various return period perspectives (all years as well as worst case events only).

Photo credit: Margaret MacDonald/CIFOR.

2

Application to ARV

2.1 Scope and Objectives

2.1.1 Scope

The work presented here is the result of a five-day review and analysis of Africa RiskView (ARV), African Risk Capacity's (ARC) risk model, which took place between November 2016 and January 2017. It was initiated upon the request of ARC's management who asked for a review of: (i) ARV's overall modelling platform and its quality control procedures as well as (ii) the in-country customization process.

Because of the way the ARV modelling chain is constructed (as a combination of a complex generic modelling platform supporting a high-variability customization process), it was jointly decided with ARC to focus the five-day review on the understanding of the tool's robustness by characterizing output variations as a function of inputs selection, and to follow the logic described in §1.

The rationale behind this is to try and illustrate the limitations of a complex model when developers or users are partially aware of the importance of certain critical inputs which can significantly skew the numbers and lead to poorly informed decisions.

The chosen scope was also defined to ensure that the following objectives can subsequently be addressed (all geared towards a better informed decision-making process):

1. The tool's generic framework and default settings are robust enough to minimize the impact of input uncertainties;
2. The tool is made more transparent and accessible so users can engage more and in a constructive way;
3. The tool's overall confidence range can be communicated in simple, qualitative terms, helping manage expectations and avoid misunderstandings;
4. Users are made aware of the largest areas of uncertainty, where uncertainty can be controlled or reduced, and what the impact would be if sufficient resources were to be invested in reducing those uncertainties, to eventually help manage noncorrelation risk;
5. The responsibility of customizing the tool at the in-country level is addressed appropriately (by the right stakeholders, focusing on the right parameters), follows a risk-based approach (i.e., most sensitive parameters require more attention/time/reviews), and its extent is well understood up front;
6. Decisions related to the customization of the tool are made with full knowledge of the facts.

2.1.2 Timeline, Methodology

Three sample countries were selected in order to illustrate the analysis through various concrete examples and to highlight both general trends, as well as country-specific limitations: **Maize in Malawi, Millet in Niger and Rangeland in Mauritania.**

Close cooperation with the Technical Team at ARC allowed progress to be made quickly and the overall support roughly followed the below steps:

1. Overview of all documentation provided, lessons learnt from recent experience;
2. Clarifications, needs and objectives, specifications, draft work plan;
3. Identification of sensitive assumptions, review of realistic scenarios, setting up of a testing framework sequenced as Sensitivity Analysis first (quantification of output variations from single input variations) and Robustness Analysis second (quantification of output variations from relevant combinations of two or more inputs variations), definition of simulations to be performed;
4. Analysis of all test runs and draft reports.

2.1.3 Limitations

The following caveats should be stressed:

1. Findings on potential errors and limitations related to the accuracy of the modelling itself are outside the scope of this analysis, which only focused on the precision of the modelling framework.
2. The analysis does not pretend to be exhaustive: by lack of time, the parameters, scenarios or assumptions simulated do not represent the full picture, but instead, provide an indicative view of the modelling framework robustness. A more thorough review of all inputs is recommended as a follow-up (see recommendations in §2.4 of this report). Then again, some assumptions were pushed to the limit to stress test the model but those might not always reflect likely scenarios: to avoid the confusion between possible and

probable scenarios, ”likely” and “unlikely” inputs were defined and the distinction is reminded when relevant.

3. The *historical* variability (the data) observed and reported throughout this document is only based on a limited sample size (i.e., 1983–2016), and therefore only represents a partial view of what the actual historical variability truly is. The *simulated* variability also only relies on a limited set of scenarios and assumptions and should be considered indicative too (does not represent the full spectrum of possible outputs).
4. The one-parameter excursions simulated (e.g., nominal planting window +/– 4 days) are in practice likely to be compensated by the adjustment of other input variables, and therefore should not be interpreted on an isolated basis. This is why the sensitivity analysis should be considered as purely indicative of the main drivers of uncertainties, in qualitative terms.
5. The major concern behind the ARV modelling platform is uncorrelated deviations: extreme variations of loss estimates which are not systematic biases of the (utilization of the) model but areas of hypersensitivity leading to large, unexpected variations across the years which cannot be predicted or compensated for, statistically or deterministically.
6. The thresholds and triggers of a risk transfer product are likely to reduce some of the volatility shown here, by reducing the number of outcomes possible. Its impact was outside the scope of this study.
7. The statistical behaviors shown were extracted from the Percentile function. Whilst this method offers relative stability for samples of 100 years and more, it is not the most reliable tail event estimator for 30 years of data or less. More work would be required to capture the full potential of extreme loss events from the limited historical base available.
8. The results shown and observations made are only valid for the three countries/assets studied. More work (more countries/crops/assets) would be required to extract more general trends.

2.1.4 Simulation Runs

The selection of scenarios was the critical starting point of this analysis. It was made jointly with ARC to make sure relevant and credible model- and user-related uncertainties could be captured (drawn “from reality”). The steps followed throughout this phase were:

1. Identification of sensitive input parameters and modelling assumptions;
2. Definition of realistic ranges for the above input values and assumptions;
3. Sensitivity Analysis runs, i.e., quantification of output variations from single input variations (i.e., showing what cost estimates look like when one value is significantly off the actual);
4. Robustness Analysis runs, i.e., quantification of output variations from combinations of input-level deviations (i.e., showing what cost estimates look like when two or more values are significantly off the actual), to eventually identify an expectable domain of variability and confidence intervals.

Output variations were expressed in USD terms, as a difference between simulated cost and “default settings” configuration (the configuration currently in use in each of the countries selected).

2.2 Sensitivity Analysis

2.2.1 Experimental Protocol

The objective of the sensitivity analysis is to highlight the most sensitive input data, parameters or modelling assumptions (i.e., those having a large impact on output numbers). Out of all variables (either within the model architecture itself or left to the user to define), 15–20 were selected for each of the three countries. These are parameters which are either subject to inherent variability, interpretation, or judgment call from users, or that are known to represent a partial representation of reality.

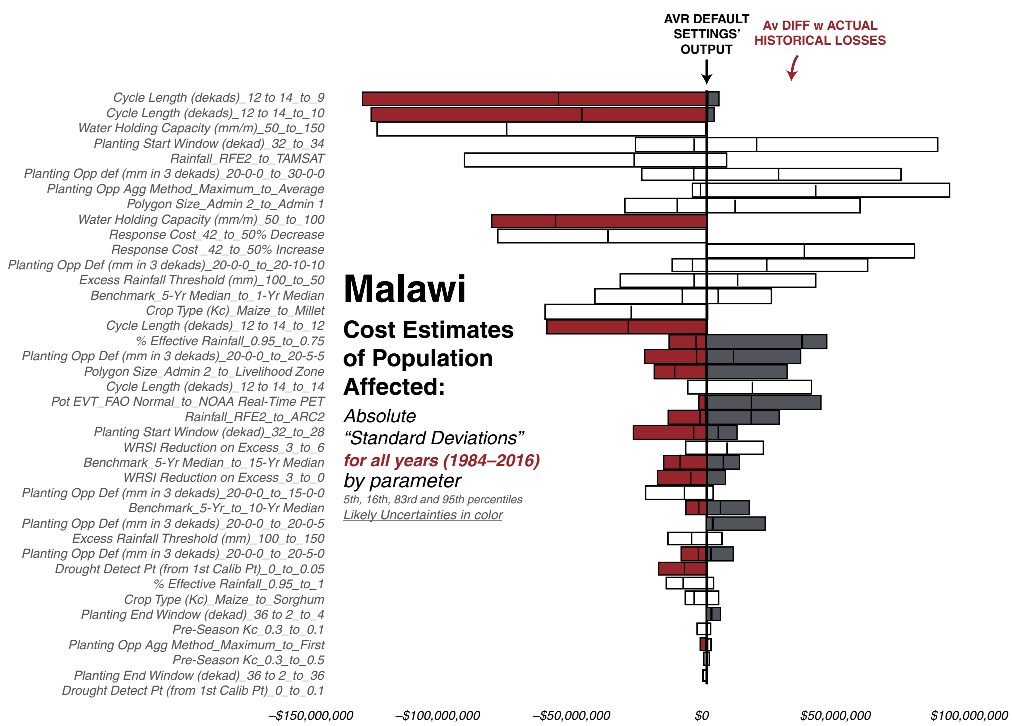
The complete list of parameters selected and simulated for each country is provided in Annex 1.

The results are presented in the form of *absolute* differences, i.e., differences between losses in USD generated from the simulated deviation (e.g., nominal planting window + 2 days) and nominal losses (e.g., default settings with nominal planting window). The results are not presented in relative terms. This is to avoid divisions by zeros (some years have no losses), or disproportionate representations of dispersions around small losses, as it is essentially large absolute variations that are of concern here.

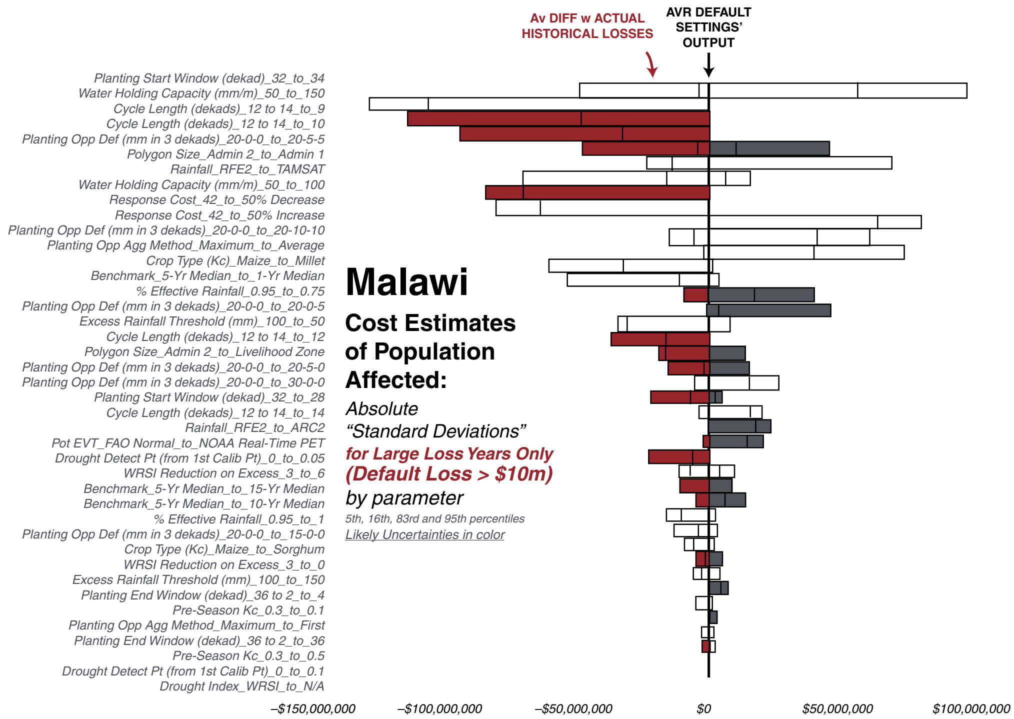
2.2.2 Results

The tornado diagrams below summarize all potential outcomes at the output level (financial losses, in USD) generated from input data/parameters/assumptions variations:

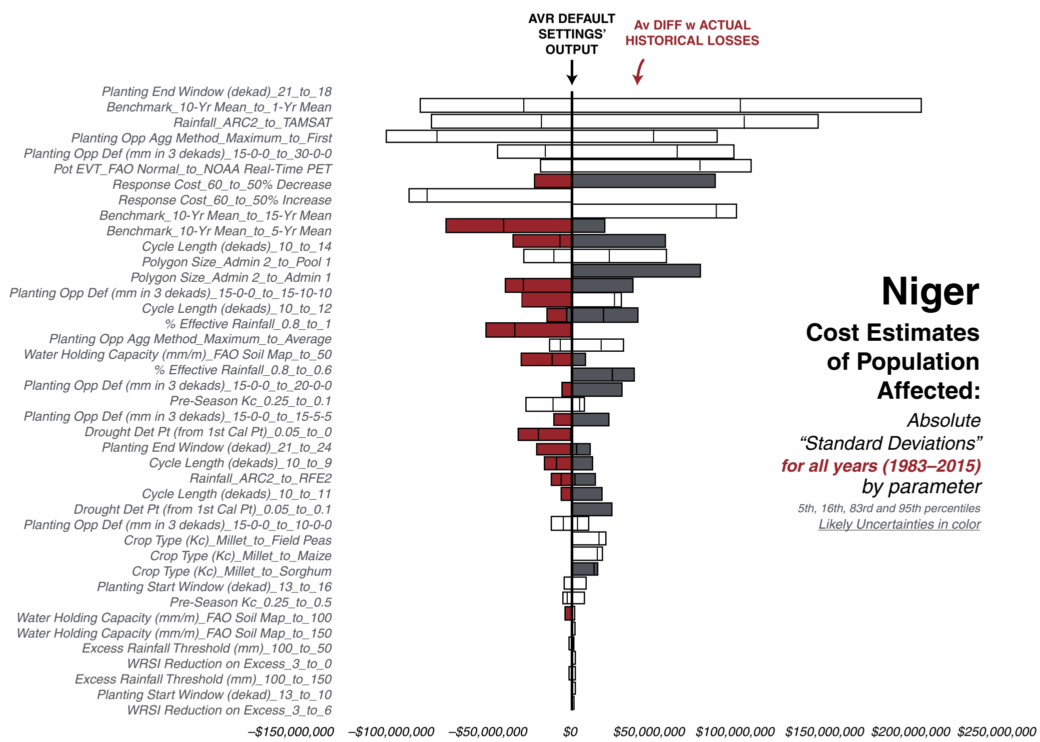
1. The impact of each parameter's variations is shown as a *range;* parameters have been sorted out by (descending order) magnitude of their total impact on financial losses;
2. Likely uncertainties appear as colored bars, less likely or unlikely scenarios in white bars;
3. For likely uncertainties: underestimations with respect to ARV default settings/reference values are highlighted in red, overestimations in grey;
4. For each parameter, the large band represents the statistical spectrum of outcomes for 9 out of 10 years (90% confidence interval, made of the difference between the 95th and the 5th percentiles); the inner band represents 2 out of 3 years (66% confidence interval);
5. At the top and middle of each graph, the vertical nominal (zero line) reference point is highlighted in black (showing that all absolute variations are calculated against the nominal settings), whereas the average difference between actual historical losses (TWG consensus) and ARV default settings over 1983–2016 is shown in red. This is for reference only as again the accuracy of the model per say is outside the scope of this study;
6. For each country, two graphs are presented: for all years combined, and only for large-loss years (ignoring convergence around zeros, and more indicative of the potential for litigation around large claims). *Large-loss years* were defined as years where the *nominal simulated* losses are higher than:
   - 10m USD for Malawi/Maize
   - 15m USD for Niger/Millet
   - 2m USD for Mauritania/Rangeland



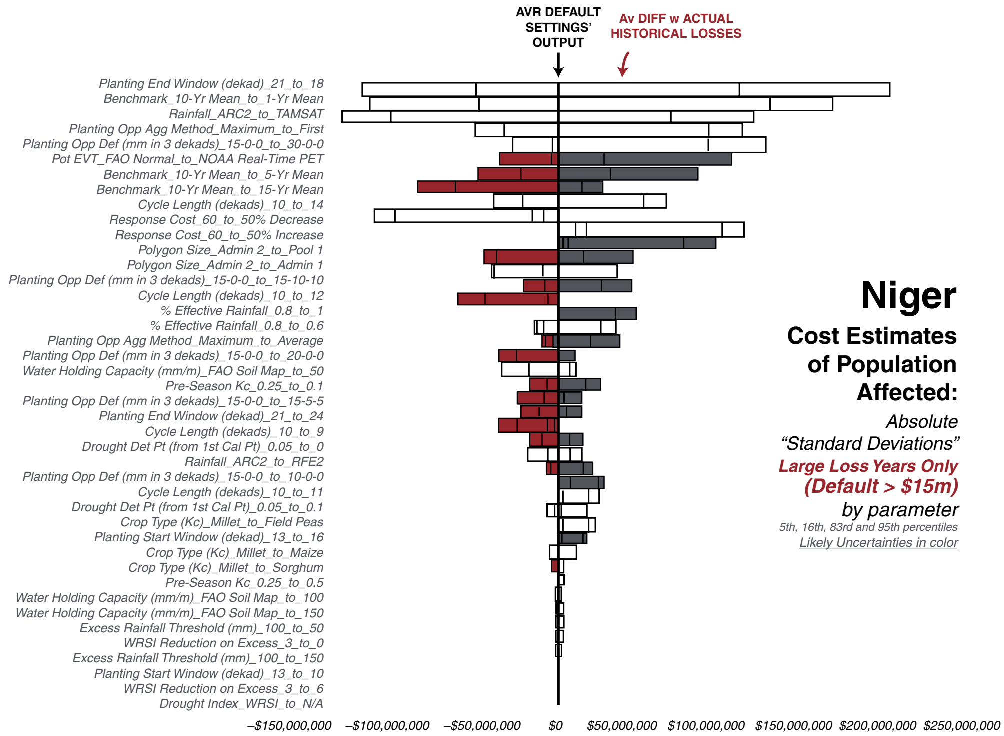
Sensitivity results for Malawi/Maize over 1984–2016.



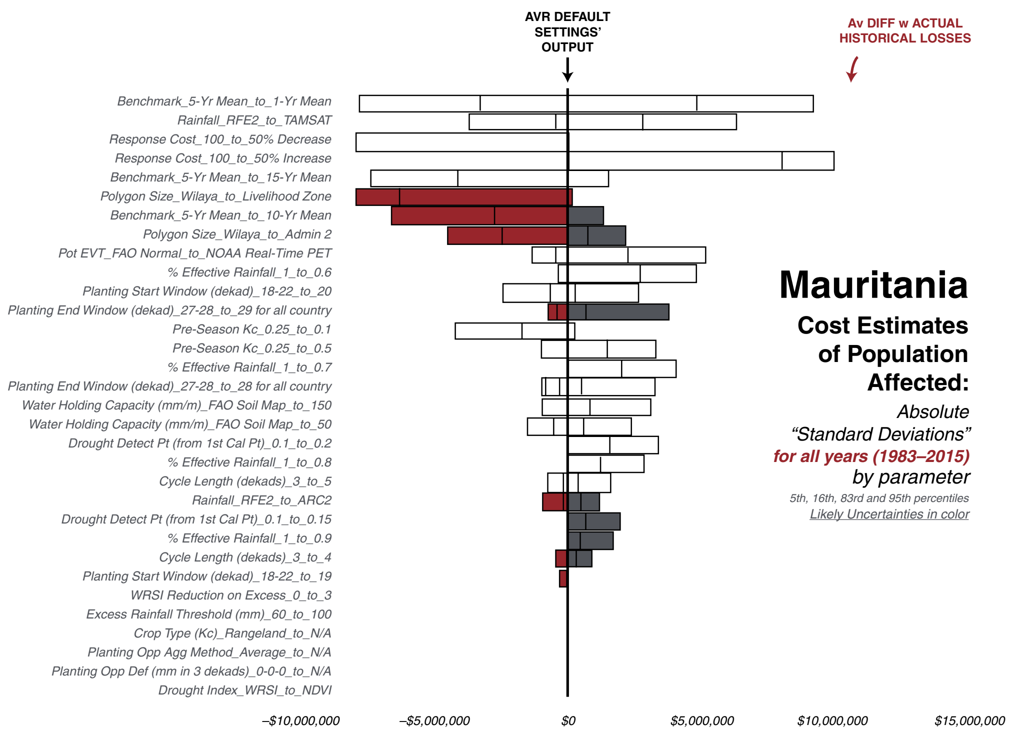
Sensitivity results for Malawi/Maize in 2004–2005–2008–2011–2013–2014–2015.



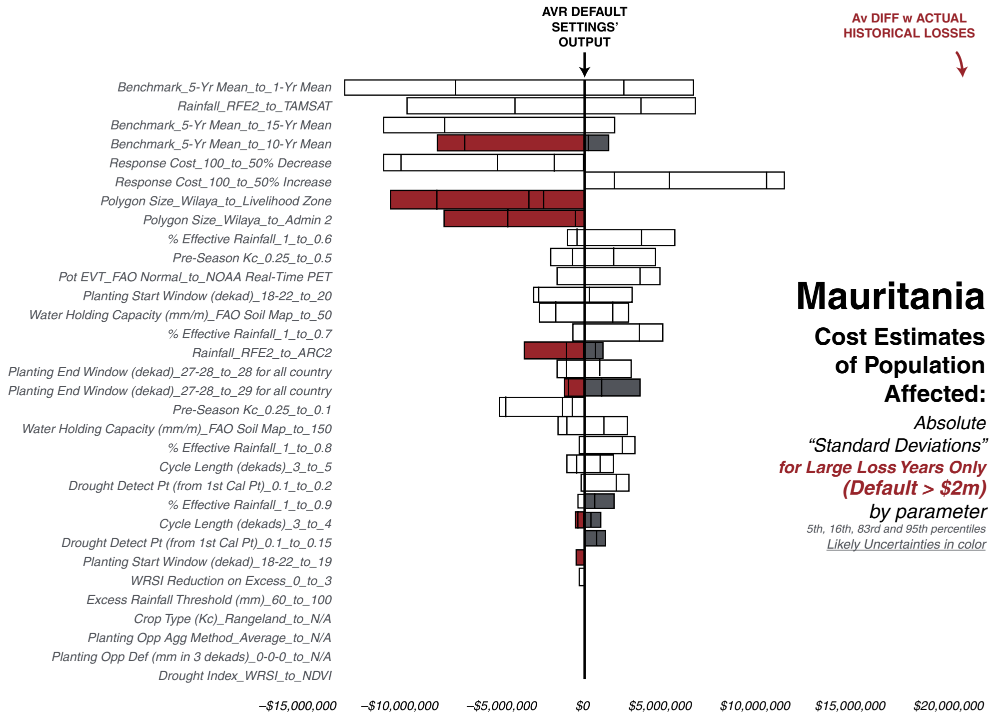
Sensitivity results for Niger/Millet over 1983–2015.



Sensitivity results for Niger/Millet in 2004–2006–2007–2008–2009–2010–2011–2013–2014–2015.



Sensitivity results for Mauritania/Rangeland over 1983–2015.



Sensitivity results for Mauritania/Rangeland in 2002–2004–2005–2011–2014.

2.2.3 Observations

1. Overall, the impact of a single parameter, varied within a reasonable range (likely or less likely) can be significant (e.g., water holding capacity in Malawi when increased from 50mm/m to 100mm/m reduces the overall losses by approximately 50m USD 2/3 of the time). Typical impact by a single likely parameter is in the order of 20% of nominal losses. Typical impact from the top three parameters averages at about 70% of nominal losses (i.e., most of the variability is concentrated over three–four parameters for each of the countries. These parameters vary from country/asset to country/asset, see table on the following page).
2. Most variations are in line with expectations. Some are more obvious (e.g., response cost per capita) than others (e.g., polygon size, determining the way areas are averaged, or time horizon considered for Benchmark Value setting). Uncertainties essentially lie within growing season/cycle (particularly the Length of Growing Period, LGP) and associated triggers, rainfall data and water absorption characteristics.
3. Variations away from the nominal values lead at large to reductions in estimated losses: this is in line with expectations in the sense that most reference settings, even though calibrated to be as close as possible to expected results, tend to be slightly conservative by default. Main exception is for large-loss years in Niger, for which excursions tend to generate slightly higher losses than nominal simulations.
4. The parameters driving uncertainty in all years are for the most part similar to those of large-loss years only: there does not appear to be specific hypersensitivity of parameters when exposed to particular loss environments. Notable exception is, amongst others, the Planting Opportunity Definition (mm of water across 3 Dekads/30 days) when set to 20-5-5 in Malawi (much larger impact in extreme loss years).
5. The sensitivity of the model does not increase for larger losses: between all years and large-loss years only, the variability for all three countries remains similar (and actually slightly reduces in the case of Niger/Millet). This is a positive

For Large Losses and Likely Scenarios Only			
Key Observations	**Malawi/Maize**	**Niger/Millet**	**Mauritania/Rangeland**
ARV average nominal simulated loss	78m USD	81m USD	15m USD
Large loss definition	> 10m USD	> 15m USD	> 2m USD
Average difference between ARV nominal simulation and actual historical	–10m USD or –13%	+10m USD or +12%	+20m USD or +133%
Largest single parameter variability (95th percentile)	–115m USD or –147%	+94m USD or +116%	–11m USD or –73%
Average variability from top 3 parameters (95th percentile)	–60m USD or –77%	+55m USD or +68%	–10m USD or –67%
Top 3 parameters	1. Cycle length 2. Planting opportunity definition triggers 3. Water holding capacity	1. Potential evapotranspiration input data 2. Benchmark time period 3. Polygon size	1. Benchmark time period 2. Polygon size 3. Rainfall data source

finding in the sense that the modelling chain does not exacerbate small input variations for the most severe scenarios. It also means that at financial product level, the inherent (hazard-related) volatility of higher layers is somewhat compounded by a constant model-related variability (making the predictability of higher layers somehow similar to that of lower layers).

6. The table above summarizes some country-specific findings.

7. The above shows that in most cases, the “discrepancies” between nominal and off-nominal simulations can be controlled and improved, as most variation ranges can be reduced by focusing on two to three key parameters which represent most of the uncertainty (at least 2/3 of the likely variability observed originates from three parameters for each of the countries studied).

2.3 Robustness Analysis

2.3.1 Experimental Protocol

The objective of the robustness analysis is to provide a faithful representation of the realistic variability of the model by combining some of the above mentioned likely assumptions into realistic extreme scenarios. It aims at quantifying an expected maximum range of realistic outcomes when developers and users vary the assumptions they are making within the limits of likely, realistic intervals.

Because the impact of a combination of variations is not the sum of each variation taken separately (non-linearity), it is critical to be as exhaustive as possible in the scenarios determination to try and illustrate how certain minor combinations at input level can have significant impact at output level.

To do so, out of the most sensitive parameters identified in §2.2, a subset was created, and combinations were made to reflect realistic settings where some parameters would offset the movement of some other parameters, forming a credible set of simulation scenarios.

The list of combinations selected and simulated for each country is provided in Annex 2.

The results are presented in the form of absolute differences as well, to focus on the identification of large variations in financial loss terms.

2.3.2 Extreme Variations Results

Scenarios tested have been grouped into 4 categories:

1. Season start: this mostly involves parameters related to the LGP, the start of the planting window, the planting opportunity aggregation method.
2. Water stress: this relates to combinations of water holding capacity, percentage of effective rainfall, potential evapotranspiration data source, and LGP as well.
3. Digital jumps: this relates to the way calculations are performed over the entire geography of the country, when converting a simulated WRSI value into number of people affected over various sub-territories or polygons (the smallest scale geographic area used for calculations of vulnerability in ARV). This therefore involves parameters such as the Drought Detection Points (DDPs, which are triggers of vulnerability), and the resolution of the polygons themselves.
4. All combined: this represents the joint influence of the above parameters when simulated into credible scenarios.

The scatter plots below illustrate for the case of Malawi/Maize all potential outcomes at output level (financial losses, in USD) generated from those realistic combinations of input data, assumptions and parameters. The four graphs represent the four categories described above. The main graph of interest is the bottom one (all combined).

Each color represents the variations coming from a given set of likely assumptions over all years (1984–2016).

The following observations can be made:

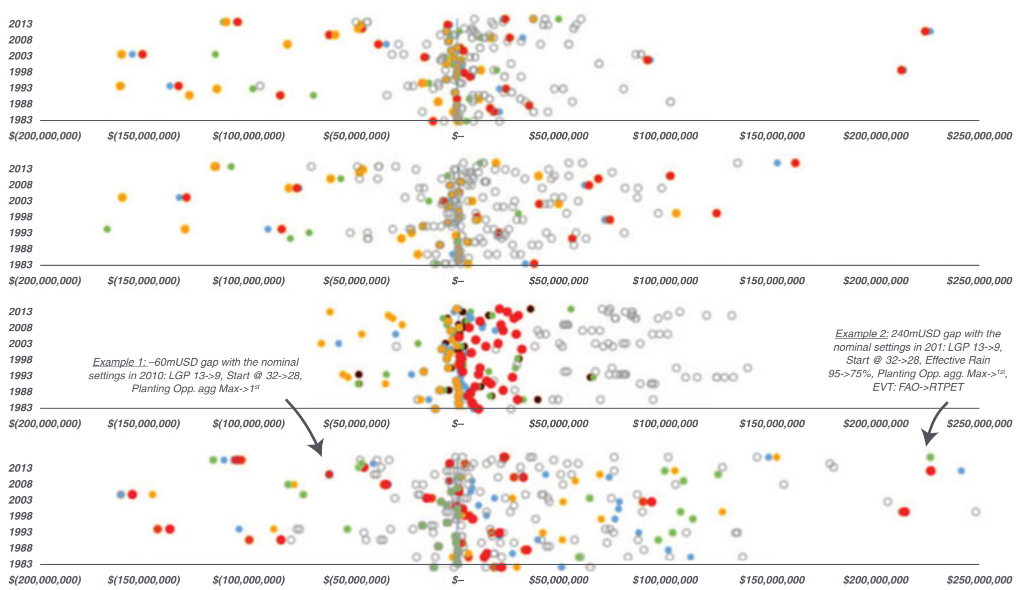
1. The season start and water stress-related parameters are the most uncertain: off-nominal

Malawi

Cost Estimates of Population Affected: Robustness Analysis

Difference in USD between default settings and combined realistic assumptions

Season Start, Water Stress, Digital Jump and Combined



Malawi-Maize: Realistic variability from likely (in color) and unlikely (in grey) sets of assumptions, by category (season start, water stress, digital jump and all combined) over 1984–2016.

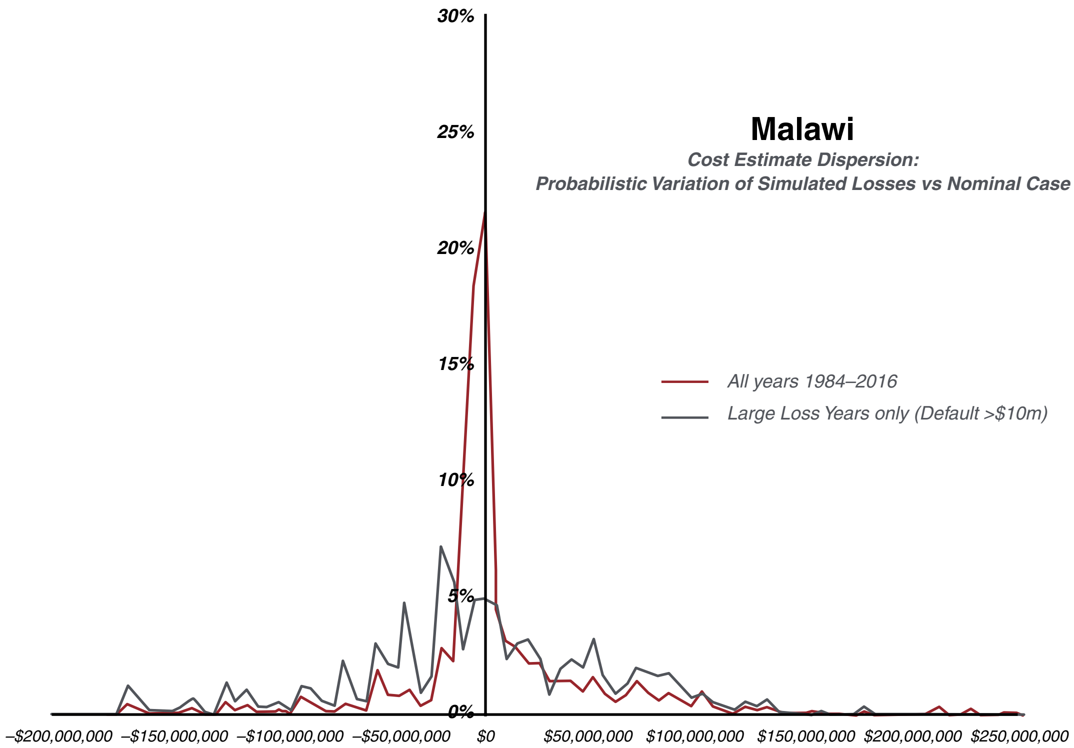
realistic scenarios can move the expected loss numbers by as much as +200m USD or –150m USD (for information, the average nominal simulated loss over 1984–2016 in Malawi is 33m USD—this is therefore significant dispersion) with variations equally spread across the y-axis (i.e., no clear bias, making it difficult to predict or correct from a statistical perspective).

2. Likely “Digital jumps” parameters have a more limited impact (within +/– 50m USD), which is still significant in relative terms. That impact is more predictable in the sense that given combinations (e.g., the red or the orange ones on the third scatter graph) seem to be showing patterns, as expected (these variations are confined to a few, more obvious calculation steps and their effect is well understood).

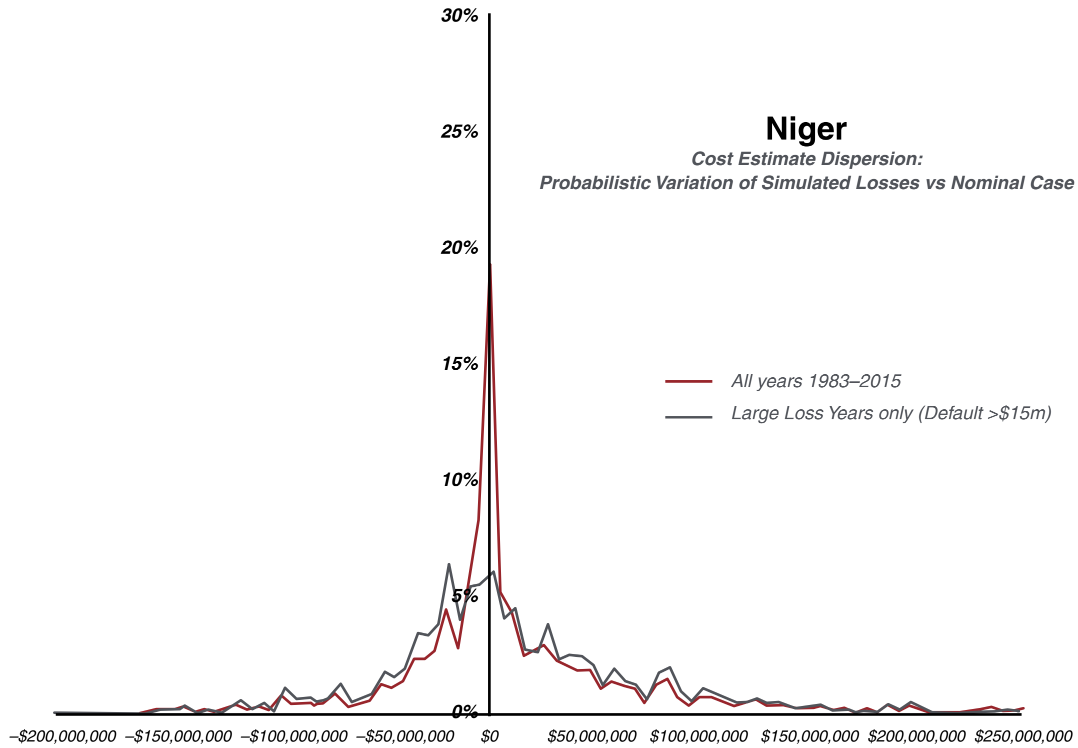
3. The overall, likely dispersion is still relatively well contained around the y-axis: showing that 2 out of 3 simulations fall within a +/–15m USD range (i.e., +/– 50% approx.), for all years combined.

2.3.3 Robustness Results

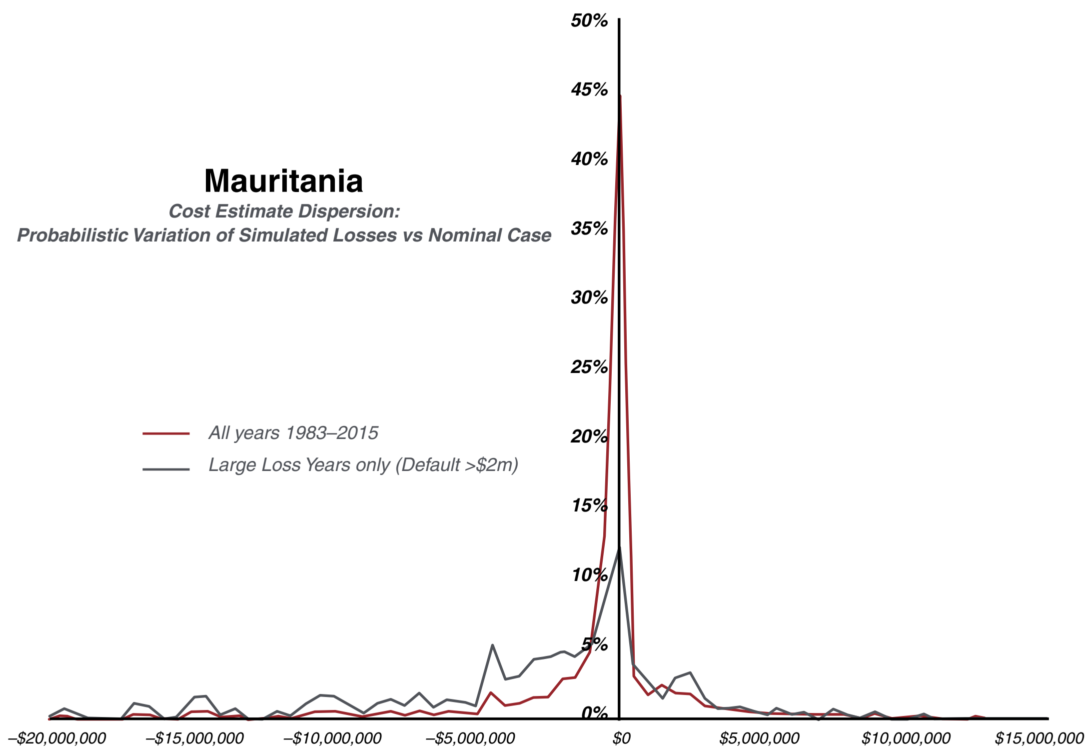
By associating an equal probability to each of the combined scenarios tested, the below graphs display for each country/asset, the probability density function of the model variability. In other terms, they are showing the probability of falling within a specific range away from the nominal output. It is worth noting that both likely and unlikely combinations have been included here (indicative results of dispersion only—the sample size of likely scenarios being too limited to focus the analysis on those scenarios only):



Malawi—Maize: Probability distribution of output variation as a function of input uncertainty (all years in red, large losses only in black).



Niger—Millet: Probability distribution of output variation as a function of input uncertainty (all years in red, large losses only in black).



Mauritania—Rangeland: Probability distribution of output variation as a function of input uncertainty (all years in red, large losses only in black).

The graphs on the previous pages lead to the following observations:

1. All-years curves are relatively well centered around the y-axis, as expected (there is no obvious overall bias), within different ranges: +/–10m USD for Malawi/Maize, +/–20m USD for Niger/Millet, +/–2m USD for Mauritania/Rangeland, which corresponds approximately to their large-loss thresholds defined earlier;
2. When comparing the all-years to large-loss years only curves, the robustness dispersion appears more important for large-loss years, as can be expected: the overall uncertainty increases proportionally with more extreme events;
3. For all three countries/assets, the large-loss years dispersion is slightly shifted to the left of the y-axis, meaning the default/nominal settings tend to be slightly conservative in the case of large losses, as observed previously (with the same exception observed before: Niger/Millet);
4. From the reading of the areas trapped under both curves, the "confidence interval" (in m USD) for each of the three countries/assets can be extracted, qualitatively, as follows (these should be understood as orders of magnitude only considering the assumptions that had to be made in this simplistic analysis):

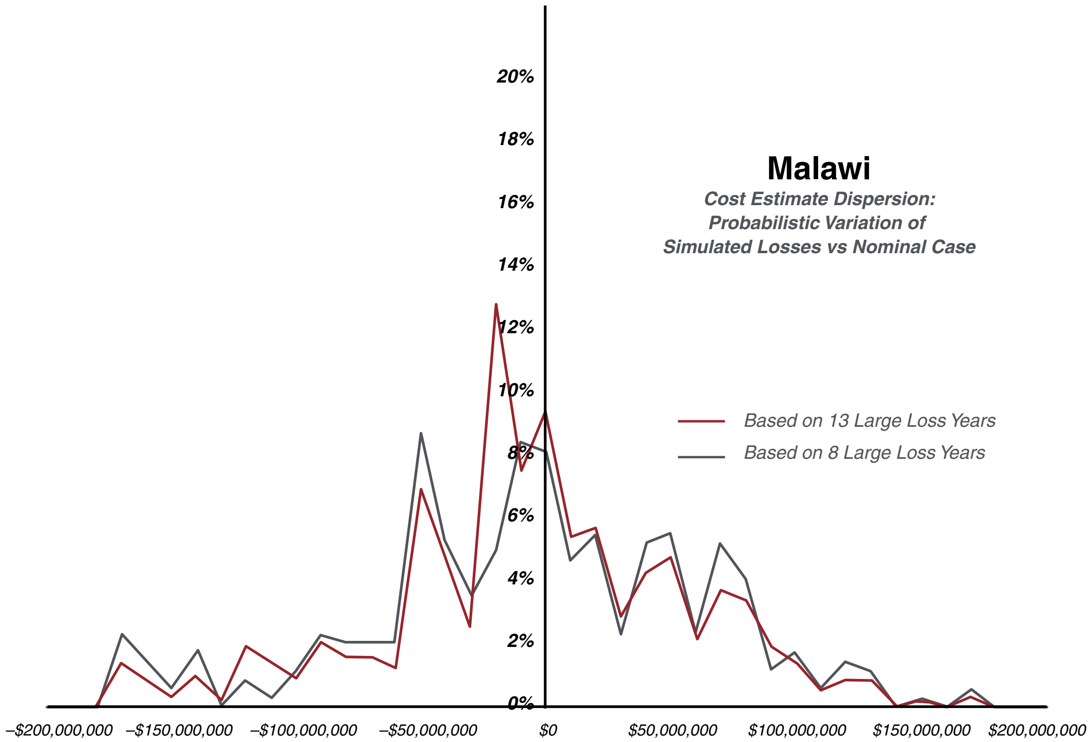
Confidence Intervals (m USD)						
Country/Asset	**Malawi/Maize**		**Niger/Millet**		**Mauritania/Rangeland**	
Years	9 out of 10 years	2 out of 3 years	9 out of 10 years	2 out of 3 years	9 out of 10 years	2 out of 3 years
All years	75	15	85	30	4	1.5
Large losses only	100	50	90	50	5	3

For any given year, 90% of the time, the output will be within 75m USD of its default/nominal value, in Malawi/Maize, all other things being equal

66% of the time in case of a large loss, the output will be within 50m USD of its default/nominal value, in Niger/Millet, all other things being equal

The above shows that, in the specific case of Malawi/Maize, large-loss years (with total cost estimates > 10m USD) are likely to be estimated only within +/–60% (+/–50m USD variation compared against an average nominal of 78m USD) of their nominal value 2/3 of the time (2 out of 3 of those large-loss years). When compared to more mature commercial models—all other things being equal—whose performance over well-monitored/high insurance rate areas is no less than 30% for 1-in-30 events, this is a relatively positive result. The low resolution, lack of exposure profile attributes (e.g., risk modifiers) and very limited reliable historical data are some of the most obvious reasons behind those differences.

Besides, it is also encouraging to see the impact of data quantity (quality and adequacy of the data were outside the scope of this study). Indeed, any additional year of data can potentially reduce the above dispersion by as much as 5%: the chart on the next page shows the improved dispersion when going from a historical base of 8 large-loss years (>10m USD), as was the case in 2006, to 13 large-loss years observed to date in the specific case of Malawi.



Malawi/Maize: impact of increasing historical base on overall robustness (in this particular example, the standard deviation decreases from 68m USD for the grey/as-at-2006 curve down to 55m USD for the red/current curve).

2.4 Suggested Next Steps and Recommendations

2.4.1 Follow-Up to This Analysis

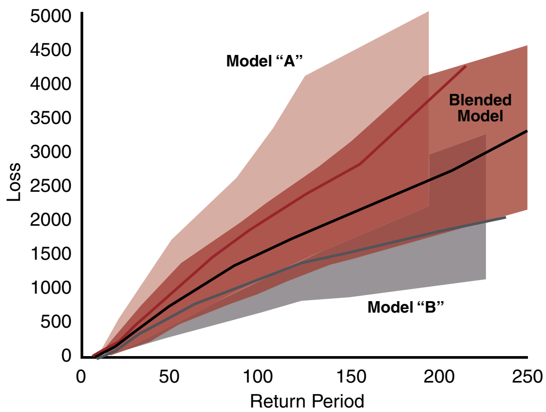
In light of the previous analysis and preliminary results, the recommended next steps could be:

1. Refining the above robustness review by:
    a. complementing it with more *exhaustive* cases (which could not be done here by lack of time), making sure the entire spectrum of uncertainties is properly reflected;
    b. extending it to *other countries/assets* (to ideally produce a list of *top three–four uncertainty parameters* for each country/asset, so as to alert end users/TWG on the high-impact potential of those inputs, as well as identify *hypersensitive combinations)*;
    c. incorporating *TWG's insight* into the definition of realistic inputs, uncertainties and variations (not solely based on ARC and WBG views);
2. Implementing lessons learnt from the above *in the decision-making processes* and documentation;
3. Extending the analysis to other perils (flood, wind);
4. Communication and decision-making support: *raising awareness* of end users/TWG on sensitivities identified and managing associated risks accordingly.

2.4.2 Longer-Term Suggestions

1. *Addressing uncertainty through communication and capacity building*: raising awareness of end users/TWG on overall criticality of input parameters and risk management practices. Managing expectations from the modelling platform both at user level and risk transfer/insurance level, based on improved quantification of the variability discussed here, as well as based on clear, visual communication of limitations and confidence intervals that should be expected;

2. *Reviewing external data sources and index selection impact* (somehow partially tested here). Notably, the variability due to the WRSI index itself is major, and a quantification of its domain of applicability might be required (this is a complex parameter which underpins most of the loss calculations performed under ARV);
3. *Addressing uncertainty through "dynamic" models* (which quantify uncertainty at every stage, make use of trended parameters or provide near-term vs. longer-term forecasts), or *through the blending of multiple indexes or models.*



Blending of Catastrophe Risk Models.
Source: Guy Carpenter.

2.4.3 Conclusion

The above analysis aims at paving the way to further, more comprehensive studies. It quantifies whenever possible uncertainty, dispersion and variability, which, by nature, should be considered indicative orders of magnitude only. It identifies specific areas where uncertainty can be understood, controlled, and reduced. A number of limitations were raised and recommendations on future follow-up studies provided.

As expected, the observations made here exemplify the fact that the complex nature of a large-scale generic modelling platform customized to the specificities of various countries and assets, requires well-informed decision making and a very close cooperation between in-country teams and developers, as both contribute effectively to the overall precision and accuracy of the modelling process.

Annex 1: List of Sensitivity Parameters

MALAWI

Parameter/Value	Likelihood	Default Value	Adjusted Value
Rainfall	Likely	RFE2	ARC2
Rainfall	Unlikely	RFE2	TAMSAT
Pot EVT	Likely	FAO Normal	NOAA Real-Time PET
Planting Start Window (dekad)	Likely	32	28
Planting Start Window (dekad)	Unlikely	32	34
Planting End Window (dekad)	Likely	36 to 2	36
Planting End Window (dekad)	Likely	36 to 2	4
Planting Opp Def (mm in 3 dekads)	Unlikely	20-0-0	15-0-0
Planting Opp Def (mm in 3 dekads)	Likely	20-0-0	20-0-5
Planting Opp Def (mm in 3 dekads)	Likely	20-0-0	20-5-0
Planting Opp Def (mm in 3 dekads)	Likely	20-0-0	20-5-5
Planting Opp Def (mm in 3 dekads)	Unlikely	20-0-0	20-10-10
Planting Opp Def (mm in 3 dekads)	Unlikely	20-0-0	30-0-0
Planting Opp Agg Method	Unlikely	Maximum	Average
Planting Opp Agg Method	Likely	Maximum	First
Cycle Length (dekads)	Likely	12 to 14	9
Cycle Length (dekads)	Likely	12 to 14	10
Cycle Length (dekads)	Likely	12 to 14	12
Cycle Length (dekads)	Unlikely	12 to 14	14
Pre-Season Kc	Unlikely	0.3	0.1
Pre-Season Kc	Unlikely	0.3	0.5
Crop Type (Kc)	Unlikely	Maize	Millet
Crop Type (Kc)	Unlikely	Maize	Sorghum
% Effective Rainfall	Likely	95%	75%
% Effective Rainfall	Unlikely	95%	100%
Water Holding Capacity (mm/m)	Likely	50	100
Water Holding Capacity (mm/m)	Unlikely	50	150
Excess Rainfall Threshold (mm)	Unlikely	100	50
Excess Rainfall Threshold (mm)	Unlikely	100	150
WRSI Reduction on Excess	Likely	3	0
WRSI Reduction on Excess	Unlikely	3	6
Polygon Size	Unlikely	Admin 2	Admin 1
Polygon Size	Likely	Admin 2	Livelihood Zone
Benchmark	Unlikely	5-Yr Median	1-Yr Median
Benchmark	Likely	5-Yr Median	10-Yr Median
Benchmark	Likely	5-Yr Median	15-Yr Median
Drought Detect Pt (from 1st Calib Pt)	Likely	0%	5%
Drought Detect Pt (from 1st Calib Pt)	Likely	0%	10%
Response Cost	Unlikely	$42	50% Increase
Response Cost	Unlikely	$42	50% Decrease

NIGER

Parameter	Likelihood	Default Value	Adjusted Value
Rainfall	Likely	ARC2	RFE2
Rainfall	Unlikely	ARC2	TAMSAT
Pot EVT	Likely	FAO Normal	NOAA Real-Time PET
Planting Start Window (dekad)	Likely	13	10
Planting Start Window (dekad)	Unlikely	13	16
Planting End Window (dekad)	Unlikely	21	18
Planting End Window (dekad)	Likely	21	24
Planting Opp Def (mm in 3 dekads)	Unlikely	15-0-0	10-0-0
Planting Opp Def (mm in 3 dekads)	Likely	15-0-0	20-0-0
Planting Opp Def (mm in 3 dekads)	Unlikely	15-0-0	30-0-0
Planting Opp Def (mm in 3 dekads)	Likely	15-0-0	15-5-5
Planting Opp Def (mm in 3 dekads)	Unlikely	15-0-0	15-10-10
Planting Opp Agg Method	Unlikely	Maximum	First
Planting Opp Agg Method	Unlikely	Maximum	Average
Cycle Length (dekads)	Likely	10	9
Cycle Length (dekads)	Likely	10	11
Cycle Length (dekads)	Likely	10	12
Cycle Length (dekads)	Unlikely	10	14
Pre-Season Kc	Unlikely	0.25	0.1
Pre-Season Kc	Unlikely	0.25	0.5
Crop Type (Kc)	Unlikely	Millet	Maize
Crop Type (Kc)	Likely	Millet	Sorghum
Crop Type (Kc)	Unlikely	Millet	Field Peas
% Effective Rainfall	Likely	80%	60%
% Effective Rainfall	Likely	80%	100%
Water Holding Capacity (mm/m)	Likely	FAO Soil Map	50
Water Holding Capacity (mm/m)	Likely	FAO Soil Map	100
Water Holding Capacity (mm/m)	Unlikely	FAO Soil Map	150
Excess Rainfall Threshold (mm)	Unlikely	100	50
Excess Rainfall Threshold (mm)	Unlikely	100	150
WRSI Reduction on Excess	Likely	3	0
WRSI Reduction on Excess	Unlikely	3	6
Polygon Size	Likely	Admin 2	Admin 1
Polygon Size	Likely	Admin 2	Pool 1
Benchmark	Unlikely	10-Yr Mean	1-Yr Mean
Benchmark	Likely	10-Yr Mean	5-Yr Mean
Benchmark	Likely	10-Yr Mean	15-Yr Mean
Drought Det Pt (from 1st Cal Pt)	Likely	5%	0%
Drought Det Pt (from 1st Cal Pt)	Likely	5%	10%
Response Cost	Unlikely	$60	50% Increase
Response Cost	Unlikely	$60	50% Decrease

MAURITANIA

Parameter	Likelihood	Default Value	Adjusted Value
Rainfall	Likely	RFE2	ARC2
Rainfall	Unlikely	RFE2	TAMSAT
Drought Index	Unlikely	WRSI	NDVI
Pot EVT	Unlikely	FAO Normal	NOAA Real-Time PET
Planting Start Window (dekad)	Likely	18–22	19
Planting Start Window (dekad)	Unlikely	18–22	20
Planting End Window (dekad)	Unlikely	27–28	28 for all country
Planting End Window (dekad)	Likely	27–28	29 for all country
Cycle Length (dekads)	Likely	3	4
Cycle Length (dekads)	Unlikely	3	5
Pre-Season Kc	Unlikely	0.25	0.1
Pre-Season Kc	Unlikely	0.25	0.5
% Effective Rainfall	Unlikely	100%	60%
% Effective Rainfall	Unlikely	100%	70%
% Effective Rainfall	Unlikely	100%	80%
% Effective Rainfall	Likely	100%	90%
Water Holding Capacity (mm/m)	Unlikely	FAO Soil Map	50
Water Holding Capacity (mm/m)	Unlikely	FAO Soil Map	150
Excess Rainfall Threshold (mm)	Unlikely	60	100
WRSI Reduction on Excess	Unlikely	0	3
Polygon Size	Likely	Wilaya	Livelihood Zone
Polygon Size	Likely	Wilaya	Admin 2
Benchmark	Unlikely	5-Yr Mean	1-Yr Mean
Benchmark	Likely	5-Yr Mean	10-Yr Mean
Benchmark	Unlikely	5-Yr Mean	15-Yr Mean
Drought Detect Pt (from 1st Cal Pt)	Likely	10%	15%
Drought Detect Pt (from 1st Cal Pt)	Unlikely	10%	20%
Response Cost	Unlikely	$100	50% Increase
Response Cost	Likely	$100	50% Decrease

Annex 2: List of Robustness Combinations

MALAWI/MAIZE		LGP	WHC	Start Win	Plant Opp	Agg Method	Polygon Size	% Rainfall	PET	End Win	Benchmark	DDP	Likelihood	Description
Parameter	**Category**	**Default**	**50**	**32**	**20-0-0**	**Maximum**	**Admin 2**	**95**	**FAOPET**	**Default**	**5**	**0% (10%)**		**Default (Pool 2 Original Customisation)**
1	Season Start	9	50	28	20-0-0	First	Admin 2	95	FAOPET	Default	5	Default	Likely	9, first, early start window, 20-0-0
2	Season Start	9	50	28	20-0-0	First	Admin 2	95	FAOPET	Default	10	Default	Likely	9, first, early start window, 20-0-0 with Benchmark
3	Season Start	9	50	34	20-5-5	First	Admin 2	95	FAOPET	Default	5	Default	Likely	9, first, late start window, 20-5-5
4	Season Start	9	50	28	20-5-5	Maximum	Admin 2	95	FAOPET	Default	5	Default	Likely	9, max, early start window, 20-5-5
5	Season Start	9	50	34	20-0-0	Maximum	Admin 2	95	FAOPET	Default	5	Default	Unlikely	9, max, late start window, 20-0-0
6	Season Start	14	50	28	20-5-5	First	Admin 2	95	FAOPET	Default	5	Default	Unlikely	14, first, early start window, 20-5-5
7	Season Start	14	50	34	20-5-5	First	Admin 2	95	FAOPET	Default	5	Default	Unlikely	14, first, late start window, 20-5-5
8	Season Start	14	50	28	20-0-0	Maximum	Admin 2	95	FAOPET	Default	5	Default	Unlikely	14, max, early start window, 20-0-0
9	Season Start	14	50	34	20-5-5	Maximum	Admin 2	95	FAOPET	Default	5	Default	Unlikely	14, max, late start window, 20-5-5
10	Season Start	14	50	34	20-5-5	Maximum	Admin 2	95	FAOPET	Default	10	Default	Unlikely	14, max, late start window, 20-5-5 with Benchmark
11	Water Stress	9	50	32	20-0-0	Maximum	Admin 2	75	RTPET	Default	5	Default	Likely	9, RTPET, low-WHC, Low %Rainfall
12	Water Stress	9	50	32	20-0-0	Maximum	Admin 2	75	RTPET	Default	10	Default	Likely	9, RTPET, low-WHC, Low %Rainfall with Benchmark
13	Water Stress	9	100	32	20-0-0	Maximum	Admin 2	95	RTPET	Default	5	Default	Likely	9, RTPET, High-WHC, High %Rainfall
14	Water Stress	9	100	32	20-0-0	Maximum	Admin 2	75	FAOPET	Default	5	Default	Likely	9, FAOPET, high-WHC, Low %Rainfall
15	Water Stress	14	50	32	20-0-0	Maximum	Admin 2	95	RTPET	Default	5	Default	Unlikely	14, PTPET, Low WHC, High %Rainfall

16	Water Stress	14	100	32	20-0-0	Maximum	Admin 2	75	RTPET	Default	5	Default	Unlikely	14, PTPET, High WHC, Low %Rainfall
17	Water Stress	14	50	32	20-0-0	Maximum	Admin 2	75	FAOPET	Default	5	Default	Unlikely	14, FAOPET, Low WHC, Low %Rainfall
18	Water Stress	14	100	32	20-0-0	Maximum	Admin 2	95	FAOPET	Default	5	Default	Unlikely	14, FAOPET, High WHC, High %Rainfall
19	Water Stress	14	100	32	20-0-0	Maximum	Admin 2	95	FAOPET	Default	10	Default	Unlikely	14, FAOPET, High WHC, High %Rainfall with Benchmark
20	Digital Jumps	Default	50	32	20-5-5	Maximum	Admin 2	95	FAOPET	36	5	Default	Likely (with 9)	Admin 2, Short Window, 20-5-5
21	Digital Jumps	Default	50	32	20-5-5	Maximum	Admin 2	95	FAOPET	36	10	Default	Likely (with 9)	Admin 2, Short Window, 20-5-5 with Benchmark
22	Digital Jumps	Default	50	28	20-0-0	Maximum	Admin 2	95	FAOPET	4	5	Default	Likely (with 9)	Admin 2, Long Window, 20-0-0
23	Digital Jumps	Default	50	32	20-0-0	Maximum	Admin 1	95	FAOPET	36	5	Default	Unlikely	Admin 1, Short Window, 20-0-0
24	Digital Jumps	Default	50	28	20-5-5	Maximum	Admin 1	95	FAOPET	4	5	Default	Unlikely	Admin 1, Long Window, 20-5-5
25	Digital Jumps	Default	50	28	20-0-0	Maximum	Admin 1	95	FAOPET	4	5	Default	Unlikely	Admin 1, Long Window, 20-0-0
26	Digital Jumps	Default	50	28	20-0-0	Maximum	Admin 1	95	FAOPET	4	10	Default	Unlikely	Admin 1, Long Window, 20-0-0 with Benchmark
27	Digital Jumps Extra	Default	Default	Default	Default	Default	Admin 1	Default	Default	Default	Default	0%	Unlikely	Admin 1, no DDP (i.e., steep VP)
28	Digital Jumps Extra	Default	Default	Default	Default	Default	Admin 1	Default	Default	Default	Default	5%	Unlikely	Admin 1, large DDP (i.e., gradual initial step in VP)
29	Digital Jumps Extra	Default	Default	Default	Default	Default	Admin 2	Default	Default	Default	Default	0%	Likely (with 9)	Admin 2, no DDP
30	Digital Jumps Extra	Default	Default	Default	Default	Default	Admin 2	Default	Default	Default	Default	15%	Likely (with 9)	Admin 2, large DDP
31	Season Start + Water Stress	9	50	28	20-0-0	First	Admin 2	75	RTPET	Default	5	Default	Likely	9, first, early start window, 20-0-0, RTPET, low-WHC, Low %Rainfall
32	Season Start + Water Stress	9	100	28	20-0-0	First	Admin 2	95	FAOPET	Default	5	Default	Likely	9, first, early start window, 20-0-0, FAOPET, High WHC, High %Rainfall
33	Season Start + Water Stress	14	50	32	20-5-5	Maximum	Admin 2	75	RTPET	Default	5	Default	Unlikely	14, max, late sowing window, 20-5-5, RTPET, low-WHC, Low %Rainfall

(continued)

MALAWI/MAIZE		LGP	WHC	Start Win	Plant Opp	Agg Method	Polygon Size	% Rainfall	PET	End Win	Benchmark	DDP	Likelihood	Description
Parameter	Category	Default	50	32	20-0-0	Maximum	Admin 2	95	FAOPET	Default	5	0% (10%)		Default (Pool 2 Original Customisation)
34	Season Start + Water Stress	14	100	32	20-5-5	Maximum	Admin 2	95	FAOPET	Default	5	Default	Unlikely	14, max, late sowing window, 20-5-5, FAOPET, High-WHC, High
35	Season Start + Digital Jump	9	50	28	20-0-0	First	Admin 2	95	FAOPET	Default	5	Default	Likely	9, first, early start window, 20-0-0, Admin 2
36	Season Start + Digital Jump	9	50	28	20-0-0	First	Admin 1	95	FAOPET	4	5	Default	Unlikely	9, first, early start window, 20-0-0, Admin 1, Long Sowing Window
37	Season Start + Digital Jump	14	50	32	20-5-5	Maximum	Admin 2	95	FAOPET	36	5	Default	Unlikely	14, max, late sowing window, 20-5-5, Admin 2, Short Window
38	Season Start + Digital Jump	14	50	32	20-5-5	Maximum	Admin 1	95	FAOPET	Default	5	Default	Unlikely	14, max, late sowing window, 20-5-5, Admin 1
39	Water Stress + Digital Jump	9	50	32	20-0-0	Maximum	Admin 2	75	RTPET	36	5	Default	Likely	9, RTPET, low-WHC, Low %Rainfall, Admin 2, Short Window
40	Water Stress + Digital Jump	9	50	28	20-0-0	Maximum	Admin 1	75	RTPET	4	5	Default	Likely	9, RTPET, low-WHC, Low %Rainfall, Admin 1, Long Sowing Window
41	Water Stress + Digital Jump	14	100	32	20-0-0	Maximum	Admin 2	95	FAOPET	36	5	Default	Unlikely	14, FAOPET, High WHC, High %Rainfall, Admin 2, Short Window
42	Water Stress + Digital Jump	14	100	28	20-0-0	Maximum	Admin 1	95	FAOPET	4	5	Default	Unlikely	14, FAOPET, High WHC, High %Rainfall, Admin 1, Long Sowing Window

NIGER/MILLET		LGP	WHC	Start Win	Plant Oppo	Agg Method	Polygon Size	% Rainfall	PET	End Win	Benchmark	DDP	Likelihood	Description
Combination	**Category**	**10**	**Default**	**13**	**15-0-0**	**Maximum**	**Pool 3**	**80**	**FAOPET**	**21**	**10**	**5%**		**Default (Pool 3 Original Customisation)**
1	Season Start	9	Default	10	15-0-0	First	Pool 3	80	FAOPET	21	10	Default	Likely	9, first, early start window, 15-0-0
2	Season Start	9	Default	10	15-0-0	First	Pool 3	80	FAOPET	21	5	Default	Likely	9, first, early start window, 15-0-0 with Benchmark 5
3	Season Start	9	Default	10	15-0-0	First	Pool 3	80	FAOPET	21	15	Default	Likely	9, first, early start window, 15-0-0 with Benchmark 15
4	Season Start	9	Default	16	20-5-5	First	Pool 3	80	FAOPET	21	10	Default	Likely	9, first, late start window, 20-5-5
5	Season Start	9	Default	10	20-5-5	Maximum	Pool 3	80	FAOPET	21	10	Default	Likely	9, max, early start window, 20-5-5
6	Season Start	14	Default	10	20-5-5	First	Pool 3	80	FAOPET	21	10	Default	Unlikely	14, first, early start window, 20-5-5
7	Season Start	14	Default	16	15-0-0	First	Pool 3	80	FAOPET	21	10	Default	Unlikely	14, first, late start window, 15-0-0
8	Season Start	14	Default	10	15-0-0	Maximum	Pool 3	80	FAOPET	21	10	Default	Unlikely	14, max, early start window, 15-0-0
9	Season Start	14	Default	16	20-5-5	Maximum	Pool 3	80	FAOPET	21	10	Default	Unlikely	14, max, late sowing window, 20-5-5
10	Season Start	14	Default	16	20-5-5	Maximum	Pool 3	80	FAOPET	21	5	Default	Unlikely	14, max, late sowing window, 20-5-5 with Benchmark 5
11	Season Start	14	Default	16	20-5-5	Maximum	Pool 3	80	FAOPET	21	15	Default	Unlikely	14, max, late sowing window, 20-5-5 with Benchmark 15
12	Water Stress	9	100	13	15-0-0	Maximum	Pool 3	100	RTPET	21	10	Default	Likely	9, RTPET, low-WHC, High %Rainfall
13	Water Stress	9	100	13	15-0-0	Maximum	Pool 3	100	RTPET	21	5	Default	Likely	9, RTPET, low-WHC, High %Rainfall with Benchmark 5
14	Water Stress	9	100	13	15-0-0	Maximum	Pool 3	100	RTPET	21	15	Default	Likely	9, RTPET, low-WHC, High %Rainfall with Benchmark 15

(*continued*)

NIGER/MILLET		LGP	WHC	Start Win	Plant Oppo	Agg Method	Polygon Size	% Rainfall	PET	End Win	Benchmark	DDP	Likelihood	Description
Combination	Category	10	Default	13	15-0-0	Maximum	Pool 3	80	FAOPET	21	10	5%		Default (Pool 3 Original Customisation)
15	Water Stress	9	150	13	15-0-0	Maximum	Pool 3	60	RTPET	21	10	Default	Likely	9, RTPET, High-WHC, Low %Rainfall
16	Water Stress	9	100	13	15-0-0	Maximum	Pool 3	60	FAOPET	21	10	Default	Likely	9, FAOPET, low-WHC, Low %Rainfall
17	Water Stress	9	150	13	15-0-0	Maximum	Pool 3	100	FAOPET	21	10	Default	Likely	9, FAOPET, High-WHC, High %Rainfall
18	Water Stress	14	100	13	15-0-0	Maximum	Pool 3	60	RTPET	21	10	Default	Unlikely	14, RTPET, low-WHC, Low %Rainfall
19	Water Stress	14	150	13	15-0-0	Maximum	Pool 3	100	RTPET	21	10	Default	Unlikely	14, RTPET, High-WHC, High %Rainfall
20	Water Stress	14	100	13	15-0-0	Maximum	Pool 3	100	FAOPET	21	10	Default	Unlikely	14, FAOPET, low-WHC, High %Rainfall
21	Water Stress	14	150	13	15-0-0	Maximum	Pool 3	60	FAOPET	21	10	Default	Unlikely	14, FAOPET, High WHC, Low %Rainfall
22	Water Stress	14	150	13	15-0-0	Maximum	Pool 3	60	FAOPET	21	5	Default	Unlikely	14, FAOPET, High WHC, Low %Rainfall with Benchmark 5
23	Water Stress	14	150	13	15-0-0	Maximum	Pool 3	60	FAOPET	21	15	Default	Unlikely	14, FAOPET, High WHC, Low %Rainfall with Benchmark 15
24	Digital Jumps	10	Default	16	20-5-5	Maximum	Pool 3	80	FAOPET	18	10	Default	Likely	Pool 3, Short Window, 20-5-5
25	Digital Jumps	10	Default	16	20-5-5	Maximum	Pool 3	80	FAOPET	18	5	Default	Likely	Pool 3, Short Window, 20-5-5 with Benchmark 5
26	Digital Jumps	10	Default	16	20-5-5	Maximum	Pool 3	80	FAOPET	18	15	Default	Likely	Pool 3, Short Window, 20-5-5 with Benchmark 15
27	Digital Jumps	10	Default	10	15-0-0	Maximum	Pool 3	80	FAOPET	24	10	Default	Likely	Pool 3, Long Window, 15-0-0
28	Digital Jumps	10	Default	16	15-0-0	Maximum	Admin 1	80	FAOPET	18	10	Default	Likely	Admin 1, Short Window, 15-0-0
29	Digital Jumps	10	Default	10	20-5-5	Maximum	Admin 1	80	FAOPET	24	10	Default	Likely	Admin 1, Long Window, 20-5-5
30	Digital Jumps	10	Default	10	15-0-0	Maximum	Admin 1	80	FAOPET	24	10	Default	Likely	Admin 1, Long Window, 15-0-0
31	Digital Jumps	10	Default	10	15-0-0	Maximum	Admin 1	80	FAOPET	24	5	Default	Likely	Admin 1, Long Window, 15-0-0 with Benchmark 5
32	Digital Jumps	10	Default	10	15-0-0	Maximum	Admin 1	80	FAOPET	24	15	Default	Likely	Admin 1, Long Window, 15-0-0 with Benchmark 15
33	Digital Jumps Extra	Default	Default	Default	Default	Default	Admin 1	Default	Default	Default	Default	0%	Likely	Admin 1, no DDP (i.e., steep VP)

34	Digital Jumps Extra	Default	Default	Default	Default	Default	Admin 1	Default	Default	Default	Default	10%	Likely	Admin 1, large DDP (i.e., gradual initial step in VP)
35	Digital Jumps Extra	Default	Default	Default	Default	Default	Pool 3	Default	Default	Default	Default	0%	Likely	Pool 3, no DDP
36	Digital Jumps Extra	Default	Default	Default	Default	Default	Pool 3	Default	Default	Default	Default	10%	Likely	Pool 3, large DDP
37	Season Start + Water Stress	9	100	10	15-0-0	First	Pool 3	100	RTPET	21	10	Default	Likely	9, first, early start window, 15-0-0, RTPET, low-WHC, High %Rainfall
38	Season Start + Water Stress	9	150	10	15-0-0	First	Pool 3	60	FAOPET	21	10	Default	Likely	9, first, early start window, 15-0-0, FAOPET, High WHC, Low %Rainfall
39	Season Start + Water Stress	14	100	16	20-5-5	Maximum	Pool 3	100	RTPET	21	10	Default	Unlikely	14, max, late sowing window, 20-5-5, RTPET, low-WHC, High %Rainfall
40	Season Start + Water Stress	14	150	16	20-5-5	Maximum	Pool 3	60	FAOPET	21	10	Default	Unlikely	14, max, late sowing window, 20-5-5, FAOPET, High WHC, Low %Rainfall
41	Season Start + Digital Jump	9	Default	10	15-0-0	First	Pool 3	80	FAOPET	21	10	Default	Likely	9, first, early start window, 15-0-0, Pool 3
42	Season Start + Digital Jump	9	Default	10	15-0-0	First	Admin 1	80	FAOPET	24	10	Default	Likely	9, first, early start window, 15-0-0, Admin 1, Long Sowing Window
43	Season Start + Digital Jump	14	Default	16	20-5-5	Maximum	Pool 3	80	FAOPET	18	10	Default	Unlikely	14, max, late sowing window, 20-5-5, Pool 3, Short Window
44	Season Start + Digital Jump	14	Default	16	20-5-5	Maximum	Admin 1	80	FAOPET	21	10	Default	Unlikely	14, max, late sowing window, 20-5-5, Admin 1
45	Water Stress + Digital Jump	9	100	16	20-5-5	Maximum	Pool 3	100	RTPET	18	10	Default	Likely	9, RTPET, low-WHC, High %Rainfall, Pool 3, Short Window, 20-5-5
46	Water Stress + Digital Jump	9	100	10	15-0-0	Maximum	Admin 1	100	RTPET	24	10	Default	Likely	9, RTPET, low-WHC, High %Rainfall, Admin 1, Long Sowing Window, 15-0-0
47	Water Stress + Digital Jump	14	150	16	20-5-5	Maximum	Pool 3	60	FAOPET	18	10	Default	Unlikely	14, FAOPET, High WHC, Low %Rainfall, Pool 3, Short Window, 20-5-5
48	Water Stress + Digital Jump	14	150	10	15-0-0	Maximum	Admin 1	60	FAOPET	24	10	Default	Unlikely	14, FAOPET, High WHC, Low %Rainfall, Admin 1, Long Sowing Window, 15-0-0

MAURITANIA/RANGELAND		Kc	WHC	Start Win	Index	Polygon Size	% Rainfall	PET	End Win	Benchmark	DDP	Likely?	Description
Combination	**Category**	**0.25**	**FAO (60-125)**	**18-22**	**WRSI**	**Pool 3**	**100**	**FAOPET**	**28**	**5**	**1% (10%)**		**Default (Pool 3 Original Customisation)**
1	Season Start	0.5	Default	18	WRSI	Pool 3	100	FAOPET	28	5	Default	Likely	Early start window, High Kc, Benchmark 5
2	Season Start	0.5	Default	18	WRSI	Pool 3	100	FAOPET	28	15	Default	Unlikely	Early start window, High Kc, Benchmark 15
3	Season Start	0.1	Default	18	WRSI	Pool 3	100	FAOPET	28	5	Default	Likely	Early start window, Low Kc, Benchmark 5
4	Season Start	0.1	Default	18	WRSI	Pool 3	100	FAOPET	28	15	Default	Unlikely	Early start window, Low Kc, Benchmark 15
5	Season Start	0.5	Default	22	WRSI	Pool 3	100	FAOPET	28	5	Default	Unlikely	Late start window, High Kc, Benchmark 5
6	Season Start	0.5	Default	22	WRSI	Pool 3	100	FAOPET	28	15	Default	Unlikely	Late start window, High Kc, Benchmark 15
7	Season Start	0.1	Default	22	WRSI	Pool 3	100	FAOPET	28	5	Default	Unlikely	Late start window, Low Kc, Benchmark 5
8	Season Start	0.1	Default	22	WRSI	Pool 3	100	FAOPET	28	15	Default	Unlikely	Late start window, Low Kc, Benchmark 15
9	Water Stress	0.5	50	Default	WRSI	Pool 3	60	RTPET	28	5	Default	Unlikely	RTPET, low-WHC, Low %Rainfall, High Kc
10	Water Stress	0.5	50	Default	WRSI	Pool 3	60	RTPET	28	15	Default	Unlikely	RTPET, low-WHC, Low %Rainfall, High Kc, Benchmark 15
11	Water Stress	0.1	50	Default	WRSI	Pool 3	100	RTPET	28	5	Default	Likely	RTPET, low-WHC, High %Rainfall, Low Kc
12	Water Stress	0.1	150	Default	WRSI	Pool 3	60	RTPET	28	5	Default	Unlikely	RTPET, High-WHC, Low %Rainfall, Low Kc
13	Water Stress	0.5	150	Default	WRSI	Pool 3	100	RTPET	28	5	Default	Unlikely	RTPET, High-WHC, High %Rainfall, High Kc
14	Water Stress	0.1	50	Default	WRSI	Pool 3	60	FAOPET	28	5	Default	Unlikely	FAOPET, low-WHC, Low %Rainfall, Low Kc
15	Water Stress	0.5	50	Default	WRSI	Pool 3	100	FAOPET	28	5	Default	Likely	FAOPET, low-WHC, High %Rainfall, High Kc
16	Water Stress	0.5	150	Default	WRSI	Pool 3	60	FAOPET	28	5	Default	Unlikely	FAOPET, High-WHC, Low %Rainfall, High Kc
17	Water Stress	0.1	150	Default	WRSI	Pool 3	100	FAOPET	28	5	Default	Unlikely	FAOPET, High WHC, High %Rainfall, Low Kc
18	Water Stress	0.1	150	Default	WRSI	Pool 3	100	FAOPET	28	15	Default	Unlikely	FAOPET, High WHC, High %Rainfall, Low Kc with Benchmark 15
19	Digital Jumps	0.25	Default	22	WRSI	Admin 2	100	FAOPET	27	5	Default	Unlikely	Admin 2, Short Window, Benchmark 5
20	Digital Jumps	0.25	Default	22	WRSI	Admin 2	100	FAOPET	27	15	Default	Unlikely	Admin 2, Short Window, Benchmark 15
21	Digital Jumps	0.25	Default	18	WRSI	Admin 2	100	FAOPET	29	5	Default	Likely	Admin 2, Long Window, Benchmark 5
22	Digital Jumps	0.25	Default	18	WRSI	Admin 2	100	FAOPET	29	15	Default	Unlikely	Admin 2, Long Window, Benchmark 15
23	Digital Jumps	0.25	Default	22	WRSI	Pool 3	100	FAOPET	27	5	Default	Unlikely	Pool 3, Short Window, Benchmark 5
24	Digital Jumps	0.25	Default	22	WRSI	Pool 3	100	FAOPET	27	15	Default	Unlikely	Pool 3, Short Window, Benchmark 15
25	Digital Jumps	0.25	Default	18	WRSI	Pool 3	100	FAOPET	29	5	Default	Likely	Pool 3, Long Window, Benchmark 5
26	Digital Jumps	0.25	Default	18	WRSI	Pool 3	100	FAOPET	29	15	Default	Unlikely	Pool 3, Long Window, Benchmark 15
DDP1	Digital Jumps Extra	Default	Default	Default	WRSI	Admin 2	Default	Default	Default	Default	0%	Likely	Admin 2, no DDP (i.e., steep VP)

DDP2	Digital Jumps Extra	Default	Default	Default	WRSI	Admin 2	Default	Default	Default	Default	20%	Unlikely	Admin 2, large DDP (i.e., gradual initial step in VP)
DDP3	Digital Jumps Extra	Default	Default	Default	WRSI	Pool 3	Default	Default	Default	Default	0%	Likely	Pool 3, no DDP
DDP4	Digital Jumps Extra	Default	Default	Default	WRSI	Pool 3	Default	Default	Default	Default	20%	Unlikely	Pool 3, large DDP
27	Season Start + Water Stress	0.5	50	18	WRSI	Pool 3	60	RTPET	28	5	Default	Unlikely	Early start window, High Kc, Benchmark 5, RTPET, low-WHC, Low %Rainfall
28	Season Start + Water Stress	0.5	150	18	WRSI	Pool 3	100	FAOPET	28	5	Default	Unlikely	Early start window, High Kc, Benchmark 5, FAOPET, High WHC, High %Rainfall
29	Season Start + Water Stress	0.1	50	22	WRSI	Pool 3	60	RTPET	28	15	Default	Unlikely	Late start window, Low Kc, Benchmark 15, RTPET, low-WHC, Low %Rainfall
30	Season Start + Water Stress	0.1	150	22	WRSI	Pool 3	100	FAOPET	28	15	Default	Unlikely	Late start window, Low Kc, Benchmark 15, FAOPET, High WHC, High %Rainfall
31	Season Start + Digital Jump	0.5	Default	18	WRSI	Admin 2	100	FAOPET	28	5	Default	Likely	Early start window, High Kc, Benchmark 5, Admin 2
32	Season Start + Digital Jump	0.5	Default	18	WRSI	Pool 3	100	FAOPET	29	5	Default	Likely	Early start window, High Kc, Benchmark 5, Pool 3, Long Sowing Window
33	Season Start + Digital Jump	0.1	Default	22	WRSI	Admin 2	100	FAOPET	27	15	Default	Unlikely	Late start window, Low Kc, Benchmark 15, Admin 2, Short Window
34	Season Start + Digital Jump	0.1	Default	22	WRSI	Pool 3	100	FAOPET	28	15	Default	Unlikely	Late start window, Low Kc, Benchmark 15, Pool 3
35	Water Stress + Digital Jump	0.5	50	22	WRSI	Admin 2	60	RTPET	27	5	Default	Unlikely	RTPET, low-WHC, Low %Rainfall, High Kc, Admin 2, Short Window, Benchmark 5
36	Water Stress + Digital Jump	0.5	50	18	WRSI	Pool 3	60	RTPET	29	15	Default	Unlikely	RTPET, low-WHC, Low %Rainfall, High Kc, Pool 3, Long Sowing Window, Benchmark 15
37	Water Stress + Digital Jump	0.1	150	22	WRSI	Admin 2	100	FAOPET	27	5	Default	Unlikely	FAOPET, High WHC, High %Rainfall, Low Kc, Admin 2, Short Window, Benchmark 5
38	Water Stress + Digital Jump	0.1	150	18	WRSI	Pool 3	100	FAOPET	29	15	Default	Unlikely	FAOPET, High WHC, High %Rainfall, Low Kc, Pool 3, Long Sowing Window, Benchmark 15
39	Index	N/A	N/A	18	NDVI	Pool 3	N/A	N/A	29	5	Default	Likely	NDVI, Long Sowing Window, Benchmark 5
40	Index	N/A	N/A	18	NDVI	Pool 3	N/A	N/A	29	15	Default	Unlikely	NDVI, Long Sowing Window, Benchmark 15
41	Index	N/A	N/A	22	NDVI	Pool 3	N/A	N/A	27	5	Default	Unlikely	NDVI, Short Sowing Window, Benchmark 5
42	Index	N/A	N/A	22	NDVI	Pool 3	N/A	N/A	27	15	Default	Unlikely	NDVI, Short Sowing Window, Benchmark 15

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