Mautam famines in Mizoram:
An exploratory system dynamics approach

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Abstract

Mizoram, a state in the Northeast of India, is affected every half-century by cycles of crop damages and famines. These events - locally known as Mautam - have been hypothesized to follow the periodic flowering of bamboo forests and subsequent rodent outbreaks. As such, the 1958-1960 Mautam resulted in a significant loss of lives; more recently, a 2007-2008 outbreak caused heavy damages to crops. However, the dynamics of the bamboo and rodent ecosystems remain poorly understood, as are their interrelationships with Mizoram's agriculture. This draft paper therefore presents an exploratory System Dynamics model of Mizoram's Mautam phenomenon, focusing on the application of a systematic framework for uncertainty analysis. Furthermore, a representative set of policies was tested under deep uncertainty to evaluate possible outcomes. Preliminary results indicate that although the model is highly sensitive to the properties of the human and rodent population subsystems, emphasizing market connectivity to facilitate food imports may be a promising and robust policy.

1. INTRODUCTION

Mizoram, a state in the Northeast of India, is affected every half-century by cycles of crop damages and famines. These events have been hypothesized to follow the periodic flowering of bamboo forests and subsequent rodent outbreaks. The state is inhabited by approximately 1 million people, and ranges across 21,000 km^2 of heavily forested mountainous terrain between Bangladesh and Myanmar; notably, Mizoram's vegetation is dominated by a bamboo forest which covers 26,000 km^2 of the north-eastern Indian states (Aplin & Lalsiamliana, 2010). The most common bamboo species is *Melocanna baccifera,* which flowers almost fully synchronically every 48 years. A few months after flowering, this species produces huge quantities of fruit - up to 80 tons/hectare - and dies off. The black rats that are endemic to the region benefit from this increase in food supply and quickly reproduce, dramatically increasing their population and eventually turning to human food supplies. Although rats may typically cause losses of 5% of the crop harvest in a given year, this figure can increase by an order of magnitude after the bamboo flowering (Aplin & Lalsiamliana, 2010). The combination of all these processes is called *Mautam* and causes the cyclical famines. The 1958-1960 Mautam was associated with the death of approximately 5% of the population (Nag, 1999), and led to significant political disturbances; although the most recent 2007-2008 event was better controlled, it nonetheless yielded significant crop losses.

Due to the dynamic complexity of the system and its variety of feedback loops, System Dynamics modelling can be used to explore the system. Furthermore, due to the uncertainty that surrounds these problems, Exploratory Modelling and Analysis can help in developing a deeper understanding of the possible system behaviours. The goals of this research are thus to model the dynamic behaviour of the system under deep uncertainty, applying the framework of Exploratory System Dynamics Modelling and Analysis (ESDMA) to identify particularly critical variables and relationships (Pruyt, Kwakkel & Hamarat, 2013). Various policies have been developed by the Indian government to reduce the impact of the Mautam; a simplified representation of these policies will be tested to evaluate their effectiveness and advise on further actions.

Section 2 follows this introduction and explains the research framework. Section 3 quickly describes the model outline and assumptions, after which section 4 applies the research framework to the given case. Section 5 draws conclusions and provides directions for further research.

2. RESEARCH FRAMEWORK

As described by Aplin & Lalsiamliana (2010), the basic drivers of the Mautam phenomenon are a clear example of a "pulsed resource", which, in terms of outbreak ecology, essentially yields predictable aggregate outcomes. However, the authors note the variability of small-scale impacts across geographical locations, and a lack of knowledge regarding several causal relationships between the tightly coupled systems of rat ecology, bamboo growth, and human agriculture.

As such, system dynamics is an appropriate modeling method to represent the dynamic complexity of the Mautam phenomenon, as well as its strongly time-dependent behavior. However, the system is subject to deep uncertainty (Kwakkel, Walker & Marchau, 2010; Lempert, Popper & Bankes, 2003): a multitude of potential, plausible outcomes can be enumerated at a lower scale of aggregation, yet their likelihood under local conditions is difficult to assess - as are the exact underlying causal drivers. This uncertainty can be traced to the natural variability of the processes involved, and to the epistemic uncertainty (Walker et al., 2003) caused by a lack of empirical research data.

In this context, Pruyt, Kwakkel & Hamarat (2013) present Exploratory System Dynamics Modeling and Analysis (ESDMA) as a useful tool for systematically exploring the outcomes of a model under deep uncertainty. This paper therefore applies a basic analysis framework based on ESDMA, structured as follows (Logtens & Pruyt, 2012):

- Open exploration of the model's uncertainties in a baseline scenario, and visualization of key outcomes using envelope graphs and a kernel density estimator;
- Classification of the data set over key performance indicators, and application of machine learning algorithms to identify the individual contribution of different uncertainty ranges to this classification;
- Identification of uncertainty subspaces which yield undesirable (or favorable) dynamics for key performance indicators through a given combination of uncertain parameters;
- Activation of a set of static policies within the model, and iterated open exploration in order to evaluate policy interventions under uncertainty.

Given the preliminary nature of the model, the analysis is limited to a simple application of the ESDMA methodology. Further steps could apply optimization techniques to evaluate policy performance and tradeoffs under uncertainty, as well as techniques for adaptive policy design.

3. MODEL OUTLINE AND ASSUMPTIONS

The model created consists of 4 subsystems: the human population, agriculture, bamboo area and rat population. These structures are coupled through various feedbacks, which are summarized in the causal loop diagram below:

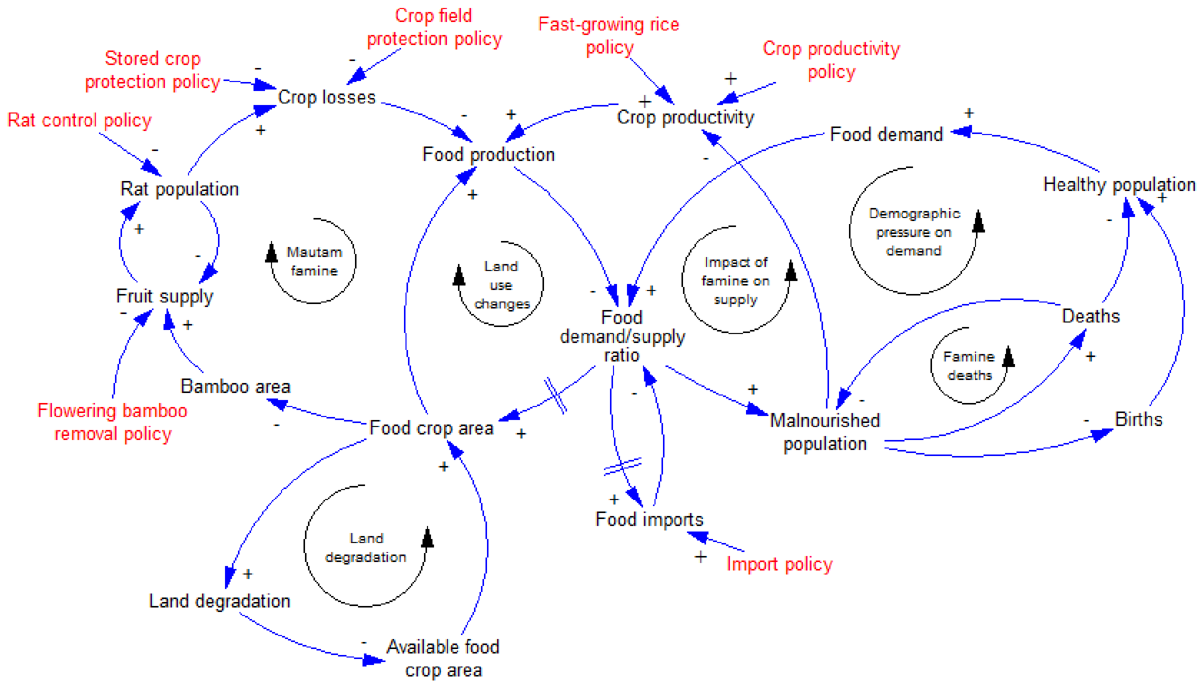


Figure 1: Aggregated causal loop diagram with policies

The human population consists of healthy and malnourished subpopulations, with “normal” birth and death rates being modelled according to current demographic patterns (which show a growing, but relatively stable, population). Malnourished people are assumed to die at a higher rate, and people flow between the healthy and the malnourished subpopulations based on food availability.

Food availability is determined by the in-state food production and imports. Low supply increases imports and, over time, yields an increase in land cultivation. However, after a few cycles of *jhum* cultivation, the land is assumed to lose its fertility and new cultivation area has to be developed from the bamboo forest. The low-fertile land eventually recovers and returns to bamboo forest. Crops are planted on cultivated land in spring and harvested in autumn, after which it is stored. This structure causes seasonality in the food availability, food being abundant just after harvest and become scarcer over the year. Both the growing crops and stored crops are affected by a base loss rate, and additional losses which are a function of the rat population. Food shortages may be overcome by increasing imports of food from neighboring areas, but due to the poor infrastructure and rugged terrain, imports may not cover the full shortage.

The rat population is highly dependent on fruit available from the bamboo forest. The fruit availability during Mautam drives up birth rates and decreases death rates, generating a sharp increase in rat population. After eating the easily available bamboo fruit, the rats turn to the human food stocks. The fruit is produced during well-defined cycles of approximately 48 years in the bamboo forest that largely covers Mizoram. Flowering starts in autumn, after which fruit is produced during spring. The plants die after producing fruit, making way for new stands.

These seasonal patterns are key to the underlying dynamics of the Mautam-driven famine. The figure below graphically summarizes a hypothesis which may explain different outcomes of the Mautam, as observed in two localities (Aplin & Lalsiamliana, 2010); although the timing of crop planting and harvest were essentially similar, the observed rat population and crop damages were significantly higher in the village of Tlangkhang. The authors explain these results by focusing on the timing of bamboo fruit production, which was advanced by at least six weeks around the region of Tlangkhang. This indicates that a detailed representation of seasonal dynamics may be crucial to evaluate potential outcomes and policy interventions.

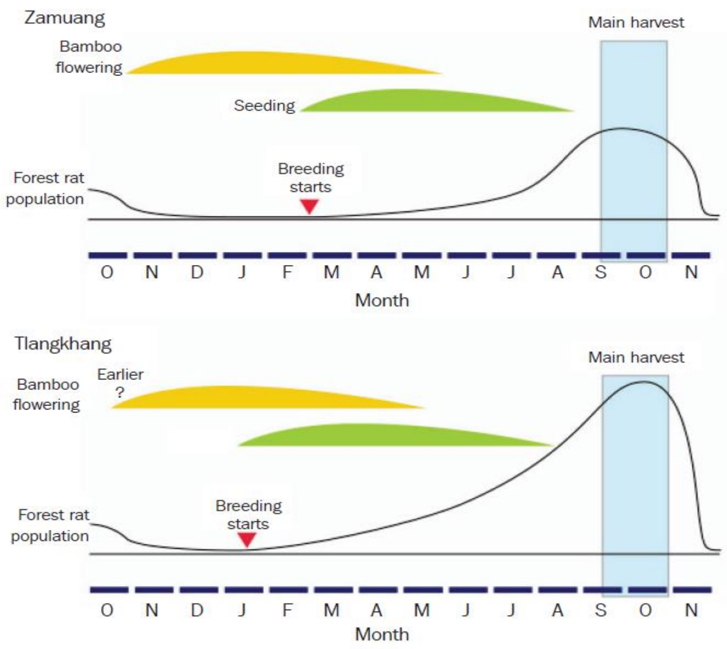


Figure 2: Hypothesized seasonal drivers of the Mautam famine (Aplin & Lalsiamliana, 2010)

In order to follow the run-up period and aftermath of a Mautam, twenty years of model time are investigated, with the Mautam starting in year 2.

4. APPLICATION OF FRAMEWORK

This section will summarize the results obtained by investigating a stock-flow model of the Mizoram case, using a set of Python scripts interfaced with Vensim Professional through the EMA Workbench*.

4.1 Open exploration

As a first approach to uncertainty analysis, a baseline case without exogenous policies was defined with the following parametric ranges:

Table 1: Uncertainty ranges for the base scenario

Variable	Min	Max	Unit
Base consumption rate	4.38	6.57	Kg/rat/Year
Base crop consumption per capita	140	180	Kg/person/Year
Base food crop loss rate	0.04	0.06	1/Year
Base fruit supply	9.44E+06	1.42E+07	Kg
Base rat death rate	0.8	1.2	1/Year
Base rat population	1.20E+06	1.80E+06	Rats
Base stored crop loss rate	0.04	0.06	1/Year
Cyclical flowering fraction	0.48	1	-
Decomposition delay	0.3	0.7	Year
Deforestation rate	0	0.02	1/Year
Flowering cycle length	0.1	0.14	Year
Fraction of young rats vs adults	0.6	1	-

* Available from http://simulation.tbm.tudelft.nl/

Variable	Min	Max	Unit
Base fruit production	30,000	70,000	Kg/Ha/Year
Initial malnourished population	45,000	105,000	Person
Initial stored food crops	1.80E+08	4.20E+08	Kg
Litter size	5	8	Rats
Litters per year	1.5	3	1/Year
Malnourishment death rate	0.06	0.14	1/Year
Malnourishment time	0.3	1.4	Year
Offcycle flowering fraction	0.0015	0.0035	-
Recovery time	0.2	0.9	Year
Regrowth delay	3	7	Year
Time for land use conversion	1.5	2.5	Year
Time to sexual activity	0.25	0.35	Year
Young rat consumption rate	1.64	3.83	Kg/rat/Year
Cycle length	2.4	5.6	Year
Land recovery time	6	14	Year
Planting time of year	0.15	0.35	Year
Crop growth time	0.24	0.56	Year
Short growth time rice	0.15	0.35	Year
Base growing crop fraction accessible	0.6	1	-
Base stored food fraction accessible	0.3	1	-
Death delay after fruit growth	0.09	0.21	Year
Fruit growth time	0.18	0.42	Year
Variation in fruit growth time	0.04	0.06	Year
Impact of healthy fraction on productivity	0	1	Interpolated lookup
Non-linear lookup for rat births	0	1	Interpolated lookup
Non-linear lookup for rat deaths	0	1	Interpolated lookup

As a first approximation, the uncertainties typically correspond to a range of +/- 20%; several variables for which empirical data was readily available (i.e. the current population, or the bamboo area) were excluded from the uncertainty analysis.

Considering the objectives of the model, the key performance indicators used for the analysis largely concern the population model: as such, the main parameters are the *Healthy fraction* (i.e. the ratio between the healthy and malnourished populations) and the total *Deaths from malnourishment*, which are closely related due to the structure of the model. For clarity, the latter is further detailed through *Relative deaths from malnourishment*, which corresponds to the ratio of deaths under a given run under uncertainty, relative to a baseline run using the initial assumptions for the model's parameters.

To support the analysis of causal relationships between the submodels for agricultural production and bamboo/rat ecology, the other selected outcomes were the *Bamboo fruit production*, the *Food crop area*, and the *Rat population*. Based on this setup, a sample of 2000 cases was then defined using Latin Hypercube sampling. The figures below first present a set of line graphs for the base ensemble, including the Gaussian kernel density estimator at the end state of the simulation:

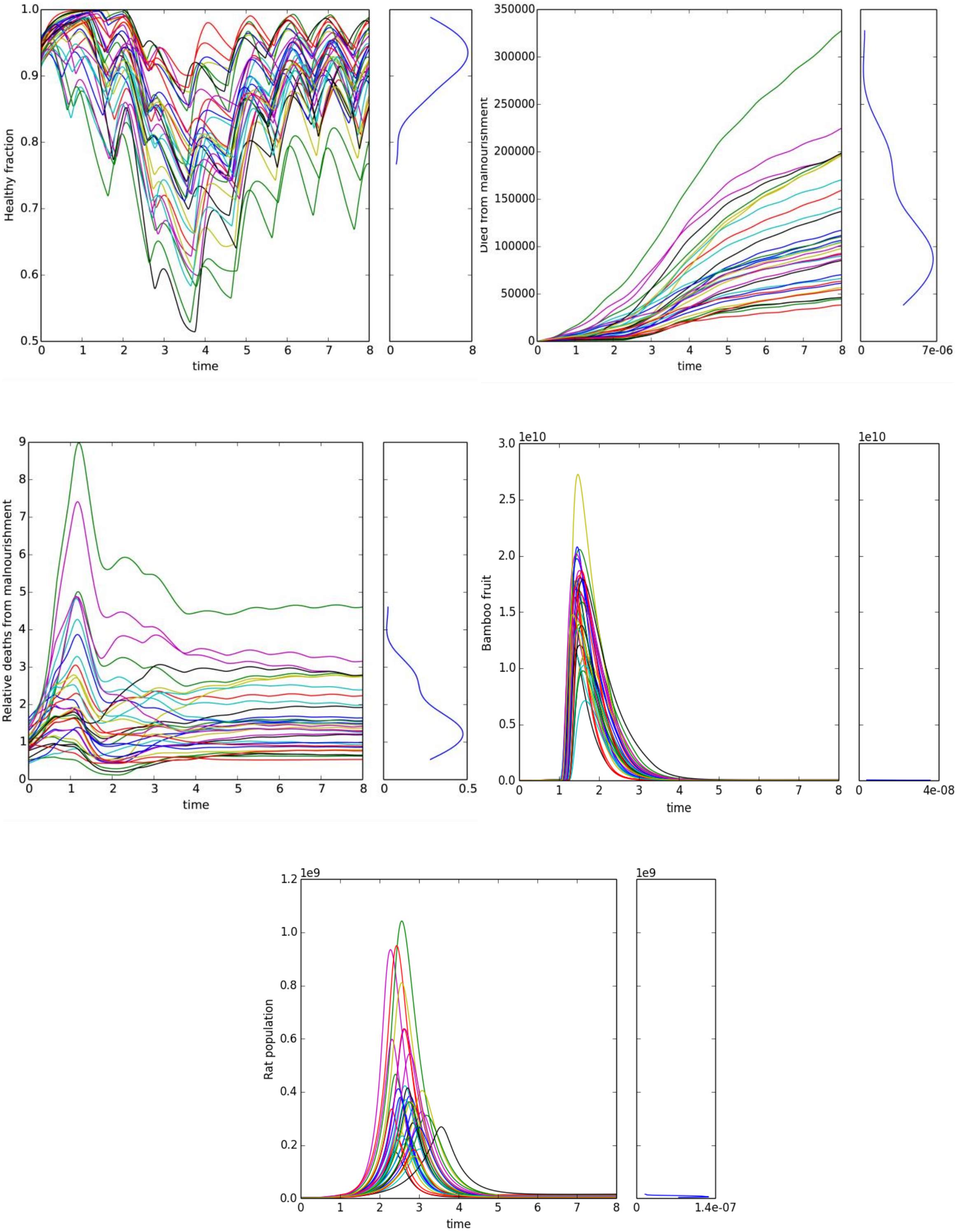


Figure 3: Line graphs for 2000 runs of the base scenario

The indicator for *Healthy fraction* shows a strong and consistent cyclical component, due to the seasonal planting and harvest patterns: the malnourished population consistently increases in late summer prior to the harvest, as stocked crops tend to be depleted.

It can be noted that the *Rat population* indicator yields some significant and unrealistic outliers, with a population exceeding a billion rats in some cases. The uncertainty ranges within the rat submodel should thus be refined. Nonetheless, the relationships between the bamboo flowering (which typically peaks at 1.8 years), the increase in rat population (which reaches a maximum roughly half a year later), and the impacts on the human population (which are most apparent in the summer following the Mautam), are a clear indicator of the dynamics reported in the literature.

The outcomes for the *Healthy fraction* and total *Deaths from malnutrition* can be examined in more detail by plotting the evolution of the kernel density estimator over time:

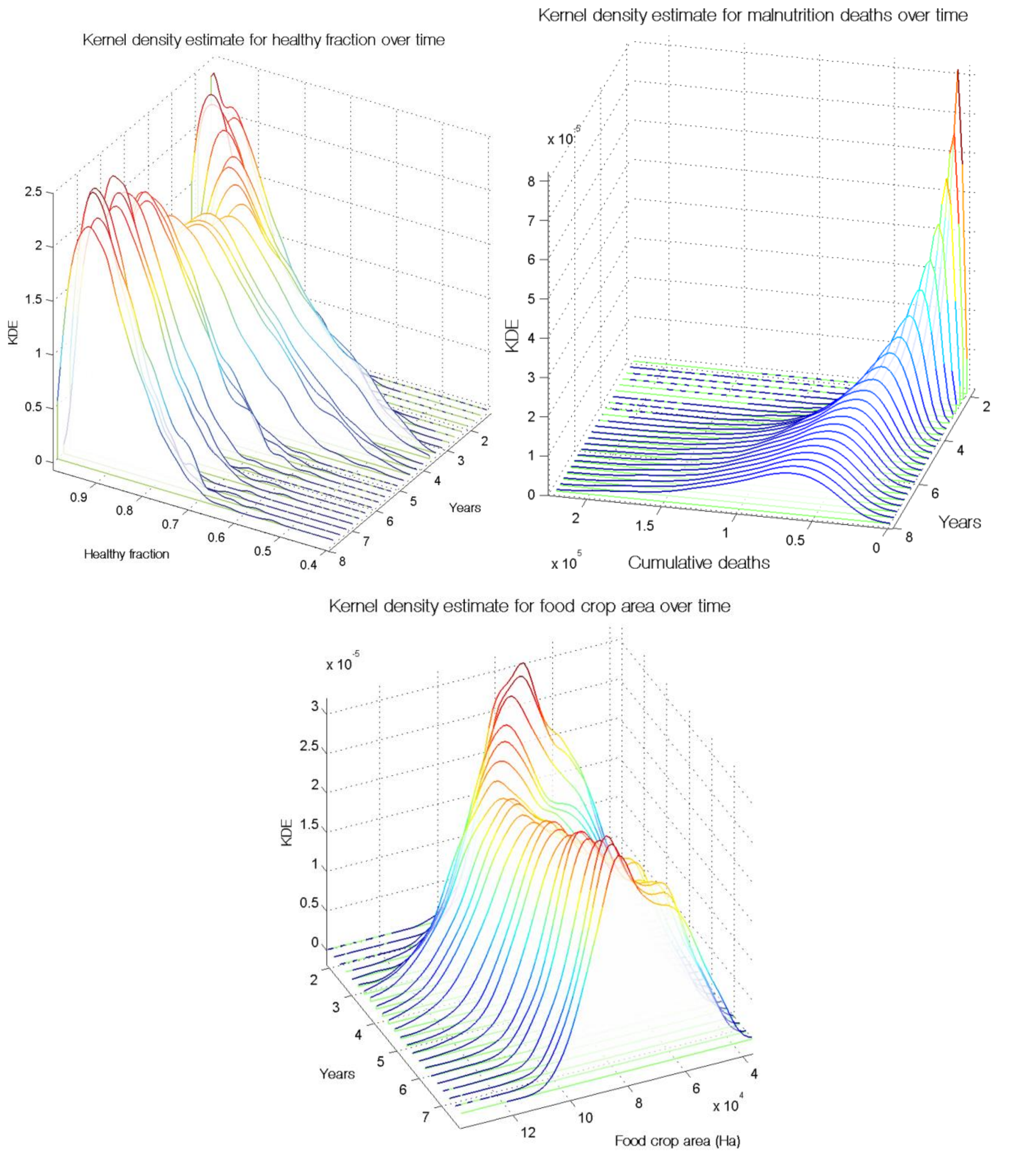


Figure 4: Kernel density estimator over time for key outcomes

The incidence of the Mautam thus has a clear impact on the *Healthy fraction*, which is approximately centered around 85% at the peak of the famine. Although estimates of the total population affected in the last Mautam are variable, this is generally consistent with values reported in the literature (Aplin, K., & Lalsiamliana, J., 2010).

The graph for *Food crop area* over time illustrates the delayed feedback which is driven by the Mautam-related reduction in the supply/demand ratio for crops: the cultivated area typically peaks three years after the Mautam, in response to the perceived need for an increase in food production, after which some of the newly created *jhum* areas are abandoned or degraded as the food supply stabilizes.

4.2 Random forest and feature selection for individual uncertainties

The previous section presented results for the full range of uncertainties, disregarding their individual contribution for total outcomes. However, sampling the complete set of parametric ranges introduces significant (and potentially unneeded) constraints on computation time and model analysis. Classification algorithms can therefore provide a useful tool to rank the importance of given uncertainties and exclude a subset of less relevant parameters from the analysis.

The tables below present the results obtained with the Random Forest and Feature Selection algorithms, as implemented in the EMA Workbench through the Orange library. The parameters are thus ranked for each algorithm, according to their contribution to a classification for the *Total cumulative deaths from malnourishment*, and limited to the top 20 variables:

Table 2: Scores for random forest and feature selection algorithms

Total deaths from malnourishment

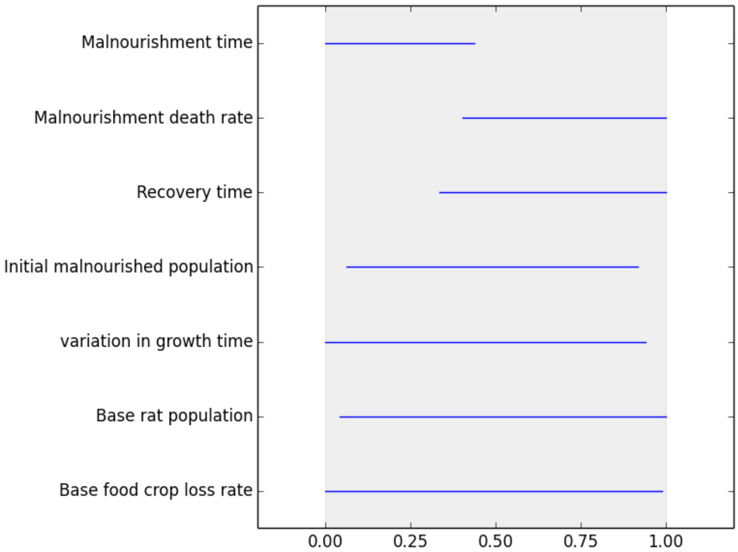
Random Forest	Score	Feature Selection	Score	Average rank
Malnourishment time	7.2994002	Malnourishment time	0.1255935	1
Recovery time	6.6498487	Recovery time	0.1127755	2
Malnourishment death rate	3.2025601	Malnourishment death rate	0.0474782	3
Base fruit production	0.2957467	Crop growth time	0.0424255	-
Short growth time rice	0.1679983	Base rat death rate	0.0249826	-
Initial stored food crops	0.1652558	Planting time of year	0.0204092	8
Variation in growth time	0.1340293	Base fruit production	0.0195389	5.5
Fruit growth time	0.1218364	Initial malnourished population	0.0167951	13.5
Base food consumption per capita	0.1166219	Fruit growth time	0.0162214	8.5
Planting time of year	0.1159143	Decomposition delay	0.0161385	-
Cycle length	0.1131857	Cycle length	0.0159402	11
Impact of healthy fraction on productivity lookup	0.0978446	Time for land use conversion	0.0151901	13.5
Non-linear lookup for rat deaths	0.0891394	Base food crop loss rate	0.0150589	-
Base stored food fraction accessible	0.0458213	Regrowth delay	0.0141972	-
Time for land use conversion	0.0409815	Base growing crop fraction accessible	0.0140676	-
Base rat population	0.0407493	Non-linear lookup for rat deaths	0.012568	14.5
Young rat consumption rate	0.0297463	Non-linear lookup for rat births	0.0115752	-
Base stored crop loss rate	0.0264189	Flowering cycle length	0.0108436	-
Initial malnourished population	0.0190676	Base fruit production	0.0096614	11.5
Litter size	0.0185185	Base consumption rate	0.0091081	-

Given the structure of the model, the parameters which directly affect the stock for the malnourished population (*Malnourishment time*, *Recovery time* and *Malnourishment death rate*) are logically the most influential. However, it is interesting to note that parameters in the submodels for bamboo and rat ecology (highlighted respectively in green and orange) remain fairly significant. This further illustrates the close couplings between the subsystems.

4.3 PRIM and classification tree for combinations of uncertainty

Given these interrelationships between the subsystems, the uncertainty analysis should be extended to cover combinations of uncertainties which yield outcomes of interest. As such, the Patient Rule Induction Method (PRIM) is applied for the key outcomes of *Deaths from malnourishment* and *Healthy fraction*, in order to identify subsets of uncertainties which lead to particularly undesirable results after the Mautam. Using a classifier threshold to identify cases with a final end state of over 150,000 cumulative deaths, the following results are first obtained (with the graphs showing normalized uncertainty bandwidths for each variable):

Table 3 : PRIM results for *Deaths from malnourishment*



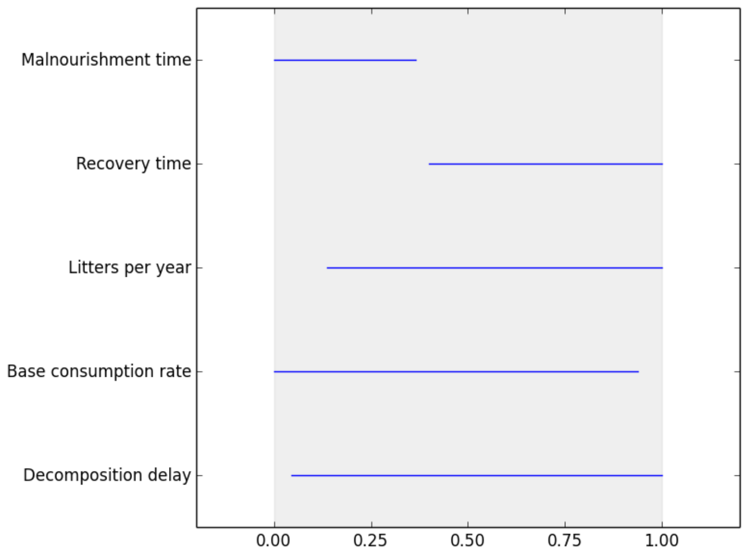
Total deaths from malnourishment

Box	Mean	Mass	Coverage	Density	Restr. dimensions
1	1	0.13	0.32	1	7
Rest	0.33	0.87	0.68	0.33	0

Uncertainty ranges	Box 1		Rest	
	Min	Max	Min	Max
Malnourishment time	0.3	0.78	0.3	1.4
Malnourishment death rate	0.09	0.14	0.06	0.14
Recovery time	0.43	0.9	0.2	0.9
Initial malnourished population	48633	99985	45037	104983
Variation in growth time	0.04	0.06	0.04	0.06
Base rat population	1225191	1799724	1200381	1799724
Base food crop loss rate	0.04	0.06	0.03	0.06

The algorithm appears to perform reasonably well, identifying 32% of the outcomes of interest with logically consistent results: most of the cases yielding high cumulative deaths involve a combination of low *malnourishment time* (which corresponds to the delay before people transition to the malnourished population), a high *death rate* for the malnourished population, and a high *recovery time* from malnourishment. However, the uncertainty ranges for the other parameters do not significantly contribute to the combined outcome. Similarly, the following results are obtained by targeting outcomes with a minimal *Healthy fraction* below 0.75 over the time of the simulation :

Table 4: PRIM results for *Healthy fraction*



Healthy fraction

Box	Mean	Mass	Coverage	Density	Restr. dimensions
1	1	0.17	0.45	1	5
Rest	0.25	0.83	0.55	0.25	0

Uncertainty ranges	Box 1		Rest	
	Min	Max	Min	Max
Malnourishment time	0.3	0.7	0.3	1.4
Recovery time	0.49	0.9	0.2	0.9
Litters per year	1.75	4	1.5	4
Base consumption rate	4.38	6.43	4.38	6.57
Decomposition delay	0.32	0.7	0.3	0.7

Although the first two variables remain the same, it is interesting to note that the parameter for *Rat litters per year*, which was not part of the 20 most significant individual uncertainties, contributes to negative outcomes for the *Healthy fraction* due to its contribution in increasing the rat population (and thus crop losses). Furthermore, this parameter was not identified by the PRIM algorithm for the cumulative deaths indicator; this can perhaps be explained by the arbitrary classification thresholds, as well as the different behavioural pattern of the two time series.

4.4 Base policy testing

The government of Mizoram set out a package of policies to decrease the impact of the last Mautam. They defined the following goals: “The ultimate objective of the scheme is to combat bamboo flowering and famine, including control of rodent population through proper means.” (Government of Mizoram, 2004). The scheme describes 8 sub-programmes:

I. Promotion of rodent control, including education about control measures and deployment of traps around crop fields.
II. Promotion of crop diversification into bamboo shoots; this policy aims at the use of bamboo sprouts as a food source decreasing overall malnourishment.
III. Promotion of early maturing rice; this rice can be harvested earlier in the year, before the rats arrive.
IV. Promotion of alternative crops, creating a more varied way of income.
V. Promotion of agriculture mechanisation, increasing productivity.
VI. Promotion of rain water harvesting ponds, increasing productivity.
VII. Promotion of market connectivity, making the area more easily accessible for imports.

Analysing the proposed policies results into the following policies that can be tested in the model: Policy I: crop protection; policy III, promotion of early maturing rice; policy V and VI, increasing productivity; and policy VII, increasing market connectivity. Next to these proposed policies, 3 other simple policies are tested: heavy rat control programs (decreasing the overall rat population, instead of simply protecting growing crops), increased protection of stored food, and clearing of flowered bamboo area before they are able to produce fruit. This leaves us with 7 policies that will be tested separately at this stage. Table 5 shows the practical implementation of the policies into the model. The small rates of 5% in the rat control and bamboo clearing policies are deliberately chosen because of the large quantities of effort that needs to be put in to achieve these rates. The rat control policy implies that a total of 30 million rats are caught within 2 years after the Mautam; the flowered bamboo clearing implies clearing 4000 hectares of land within half a year, which is highly unlikely as only 5% of the total area is easily accessible (Government of Mizoram, 2004).

Table 5: Policy implementation

Policy option	Effect on	Baseline value	Policy value
Crop protection	Growing crop fraction accessible	100%	50%
Short-growing rice	Rice growth time	5 months	3 months
Productivity	Food crop area productivity	1650 kg/(ha · year)	2475 kg/(ha · year)
Import policy	Import delay	5 months	1 month
Rat control policy	Rodent kill rate	0 % / (rat · year)	5 % / (rat · year)
Storage protection	Stored food fraction accessible	50%	20%
Bamboo clearing	Flowered bamboo clearing rate	0% / (ha · year)	5 % / (ha · year)

The impacts of the policies are measured using the KPI of people who have died from malnourishment. Figure 5 shows the effect of the 7 separate policies. The left side of the figure shows the effect on the total amount of people dying from malnourishment, and the right side of the figure shows the effect of the policies against normalised values. The largest decrease is caused by the import policy: shortening the import policy decreases food shortfalls. The productivity and short-growing rice policies decrease the total malnourished deaths during and directly after the Mautam; the effect is reduced in later years as the harvested food has to be stored for longer periods of time, increasing harvest losses. Despite the large efforts needed to apply the bamboo clearing and rat control policies, there is little effect on the death rate and hence these policies will not be further explored.

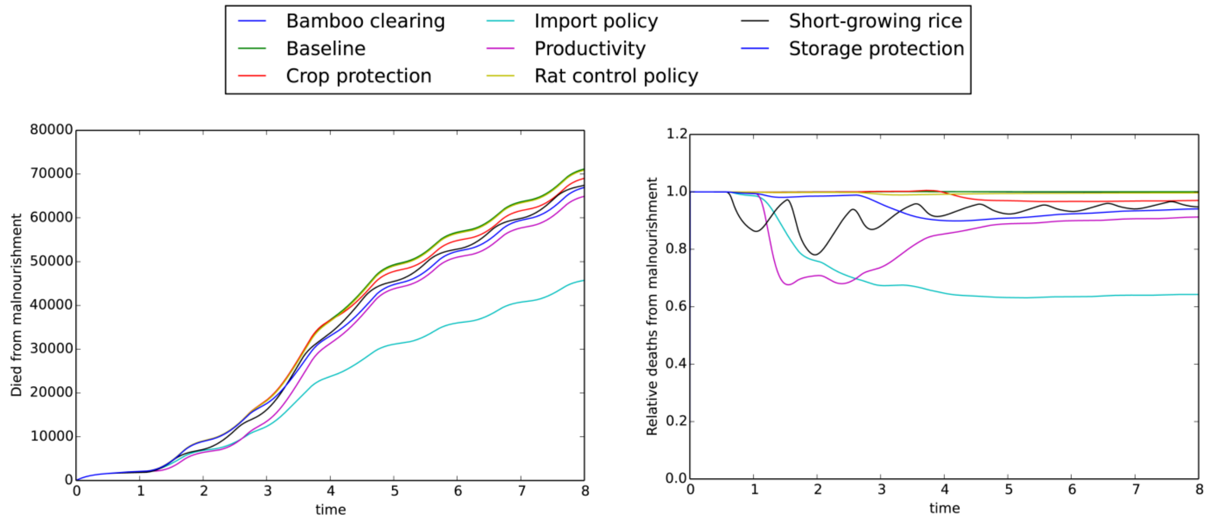


Figure 5: Effect of base policies on total deaths from malnourishment

In order to complement the analysis, the classification tree below shows a sample interpretation of the ensemble including categorical uncertainties for policy switches, in order to trace the parametric combinations which yield a final end-state of over 150,000 deaths from malnutrition:

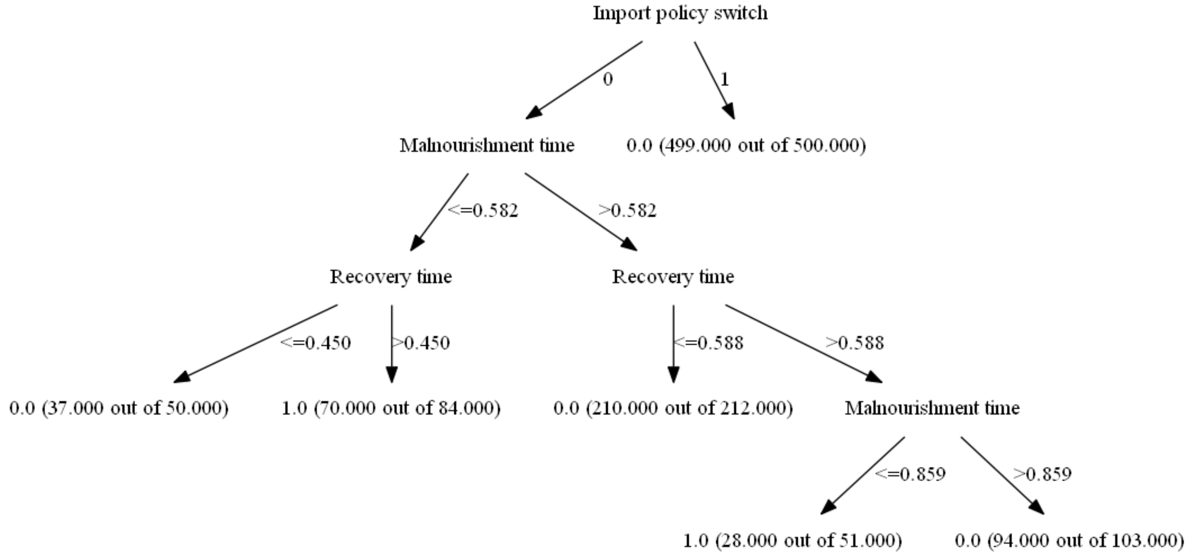


Figure 6 : Classification tree for total deaths from malnutrition, including policy switches

As described above, the import policy thus appears to play a significant role in reducing food shortfalls and dampening the famine, while the other contributing parameters were previously identified with the PRIM algorithm.

4.5 Combined policy testing

After this first single-policy exploration, the comparable policies are combined into policy packages to increase their effectiveness. The following 3 policy combinations are proposed: Increased food protection (protection of growing and stored crops), agricultural innovation (increase in productivity and use of early maturing rice) and increased import capacity (lower import delays). These policy packages are tested under uncertainty in order to capture their effectiveness on all plausible model outcomes.

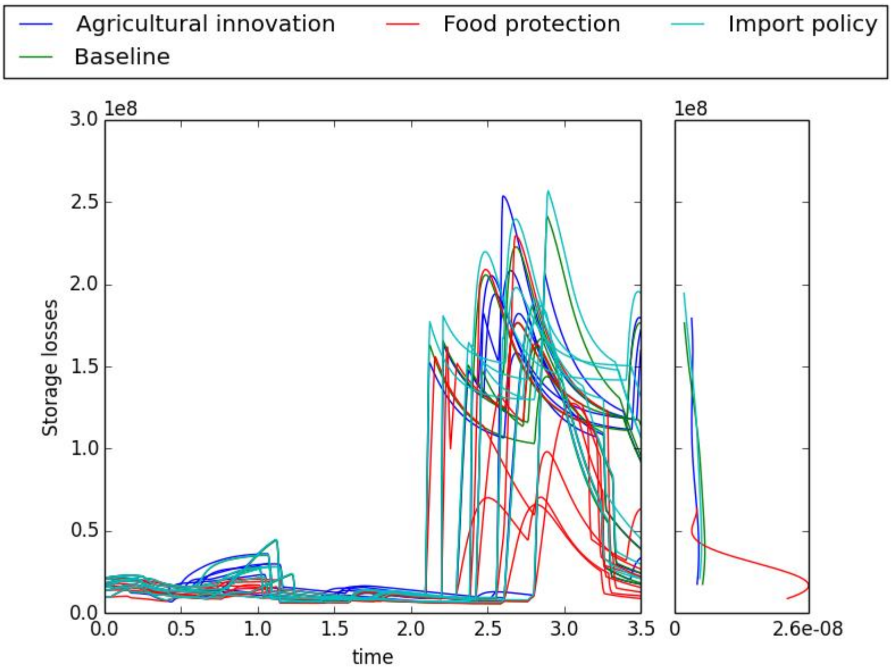


Figure 7: Effect of policy on storage losses

The different policy combinations influence different parts of the model. At first the effect of the policies on the effected parts are analysed, after which the effect of the policies is discussed in relation to the main KPIs: cumulative deaths from malnourishment, and the healthy fraction.

Figure 7 shows the storage losses during the Mautam. The food protection package (decreasing the accessibility of both stored and growing crops) has a large effect on the distribution of storage losses, as can be seen from the kernel density graph. The other policies do not seem to have any significant effect on the storage losses.

The policy package aimed at agricultural innovation decreases, as can be expected, the food crop area needed to provide the province with enough food. It shows from the kernel density graph (KDG) that protecting the food also decreases the necessary food crop area (most runs under the base case). This can be explained by the fact that rats eat less of the growing and stored crops, decreasing losses and therefore decreasing land needed for production. However, the KDG implies a larger spread of policy outcomes; this might be caused by computational limits that restricted executing more than 800 runs to test this particular policy. The import policy does not seem to decrease the amount of cultivated land, and therefore does not have a significant impact on the region's self-sustainability during times outside of the Mautam period.

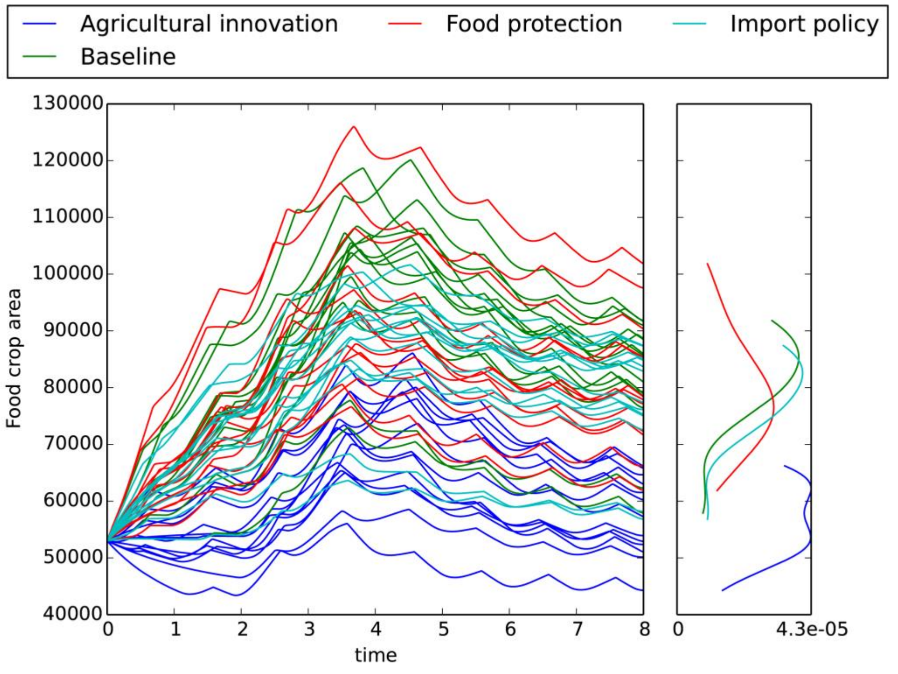


Figure 8: Effect of policy combinations on food crop area

The overall effectiveness of the policy combinations under uncertainty is measured using the healthy fraction and the cumulative deaths from malnourishment. The effects of the policy combinations on the healthy fraction (defined as the amount of healthy people over the total population) can be seen in Figure 6. The KDG shows the healthy fraction a few years after the Mautam; the effects of the policies remain visible even after the system has had some time to recover. At the end of the simulation, the most effective policy in terms of healthy fraction is the import policy. The increase in transport capabilities decreases the import delay, effectively increasing the import rate on the short term. This decreases the effect of the Mautam both during and after the Mautam. The KDG shows that agricultural innovation has no significant effect on the healthy fraction. This is caused by the fact that the agricultural innovation decreases the food crop area, for an equal food production. The food protection policy results show that although most runs end up with a higher healthy fraction, there is also more variability in the runs. A clear explanation for this result is not readily available; it might be caused by the fact that only 800 runs were explored using this policy.

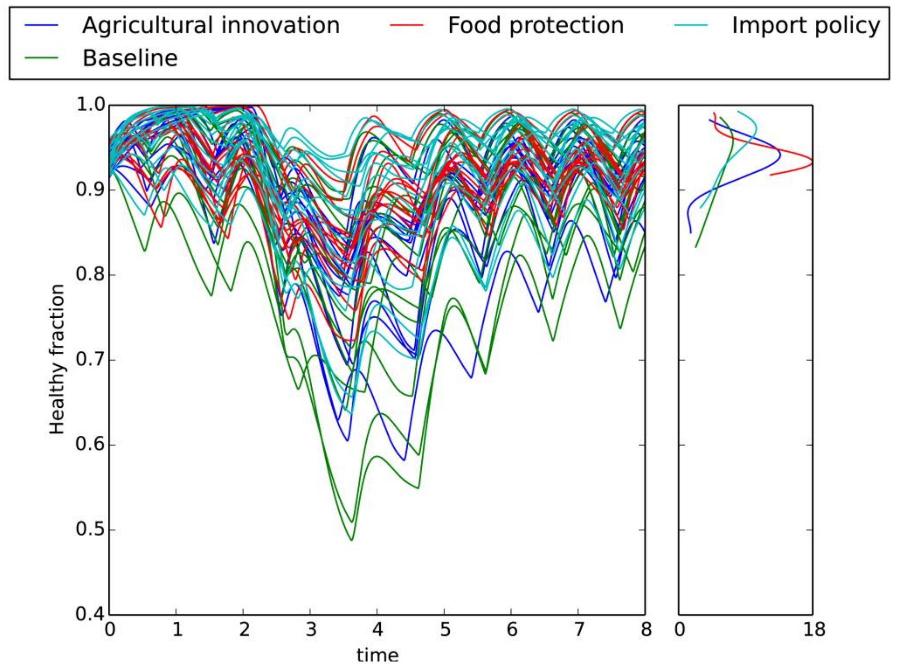


Figure 9: Effect of policy combinations on healthy fraction

Finally the effect of the policy packages on the total number of deaths from malnourishment is explored. The result of the 3 policy packages can be seen in Figure 10. On the left hand side the total deaths are shown, while the right hand side graph shows the normalised values. The normalised graph is in essence the same as the graph shown in Figure 5. As shown by the KDG the import policy is most effective. The peak of runs in the KDG for the food protection policy is almost at the same location as the import policy, but the spread is larger. The impact of agricultural innovation, increasing the use of short-growing rice and a higher productivity, shows little effect on the cumulative deaths.

Looking at the effectiveness of the combined policy packages under deep uncertainty we can conclude that the food import policy is most effective.

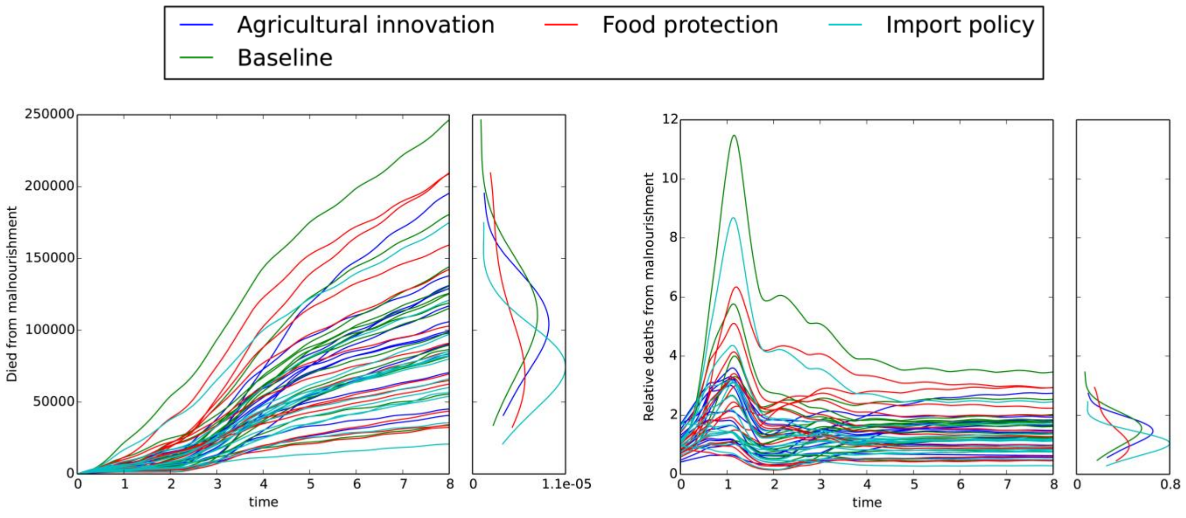


Figure 10: Effect of policy combinations on cumulative deaths from malnourishment

4.6 Adaptive and predictive policy exploration

Many complex dynamic systems can benefit from the use of adaptive policies (Hamarat, Pruyt & Loonen, 2013). Adaptive policies use information about the current state of the system to optimally time pre-specified actions. By only applying policies when the system shows that they are necessary, regret is minimized. Although adaptive policymaking is an elegant philosophy, it may be difficult to apply to the famines that have been hitting the province of Mizoram every 48 years: although the basic timing of the event is well-known, the state only has limited technical and financial resources at its disposal to react to local conditions. The main way to use adaptive policymaking therefore is to use the time since the last Mautam and the knowledge about the cyclical behaviour of 48 years. The next Mautam can be predicted with relatively high certainty, especially in comparison with the deep uncertainties that are used to model the system. Due to time and computational restrictions, a deep exploration of the possible adaptive policies was not possible within the scope of this research. Nonetheless, a first attempt at using the predictability of the Mautam for policymaking is presented below.

Intuitively, one could say that knowing that a Mautam is coming increases the desire to store more food: therefore, in the years before the Mautam, more food crop area is needed. This is modelled using a simple policy switch that turns on when the Mautam is less than two years away. During these 2 years the ‘desired area for food production’ is doubled, increasing the rate at which crop area is developed and therefore increasing production. The model results of this early exploration of adaptive policymaking are shown in Figure 11. As can be seen from the KDG the healthy fraction after the Mautam is generally higher due to the policy. The KDG for the cumulative deaths shows that the variation between the runs is lower than in the no-policy case.

This early exploration shows that adaptive (or predictive) policymaking gives promising results and therefore should be subject to more research.

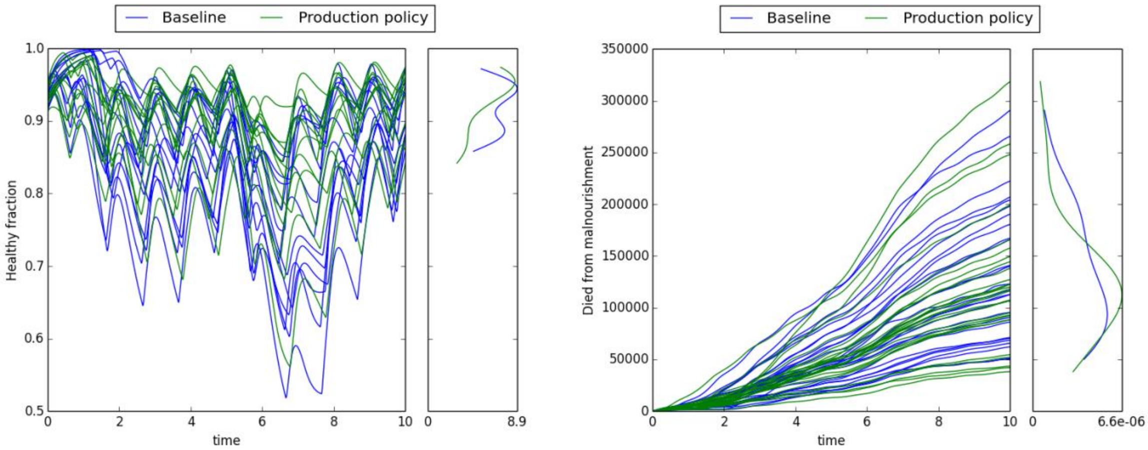


Figure 11: The effect of production policy on the healthy fraction and cumulative death rate

5. CONCLUSIONS

This paper set out to research the dynamic complexity of the rodent issues that plague the state of Mizoram, India using system dynamics modelling. The framework of Exploratory System Dynamics Modelling and Analysis has been used to research plausible system behaviors and identify particularly relevant uncertainties.

Five policies formulated by the Indian government as well as two other proposed policies were tested. Similar policy options were later combined into policy packages to test their combined impact on the famine under deep uncertainty. The most promising policy seems to be related to increasing the region's import capacity. During famines more food can be imported, decreasing the food shortage; the policy does not seem to have large effects on the internal food crop area and therefore does not affect the self-sustainability during non-famine periods. Besides this, the increase of food protection and better storage facilities also seems to decrease the effects of the Mautam. Efforts should likely not be directed at rodent control or bamboo area clearing, as this has no noticeable effect on the system.

The current open exploration results still need refinement, as some less-plausible outliers have been observed. Although significant ranges of uncertainty were already included within the analysis, other ways of improving the research include the addition of a multi-model analysis. As the name implies, multi-model analysis uses multiple plausible models to generate system behavior and embraces the fact that uncertainty is not only in the parameters of a model, but also can be found in the structures and feedbacks. Besides this, due to time limitations, the researchers only managed to shortly explore the realm of adaptive policymaking, which, as early applications have shown, can be highly beneficial for ecosystem policies (Holling, 1978; McLain and Lee, 1996 cited in Hamarat, Pruyt & Loonen). This leaves room for further research.

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