KNOWLEDGE AND EXPERIENCE SHARING SYMPOSIUM

Towards Highly Rewarding and Inclusive Flood-based Livelihoods

Modelling Risk and Uncertainty in Flood-based farming systems.

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VOI WILDLIFE LODGE, TAITA TAVETA COUNTY, KENTA

Introduction

DEFINITION OF FLOOD-BASED FARMING SYSTEMS

PROBLEM STATEMENT

EXPECTATIONS

METHODOLOGICAL CONCEPTS

Definition of Flood-based Farming Systems

Properties of Flood-based farming systems (FBFS):

- Nor rainfed neither irrigated (Mehari Haile, 2007; van Steenbergen et al., 2010; Puertas et al., 2011).
- Additional irrigation from various type of floods (Puertas et al., 2011).
- These flood are unpredictable, of short duration, of low annual frequency (van Steenbergen et al., 2010).
- "Flood" in FBFS is to be flood pulse (Junk et al.,1989), or Crue/Décrue (Harlan & Pasquereau, 1969).
- Mostly found in relatively lowlands areas with gentile topography where water supply to crops is governed by complex socio-institutional arrangements.

- **van Steenbergen, F., Lawrence, P., Mehari, A., Salman, M., & Faurès, J.-M. (2010).** *Guidelines on spate irrigation*. *Vasa*. Aden.
- **Mehari Haile, A. (2007).** A Tradition in Transition, Water Management Reforms and Indigenous Spate Irrigation Systems in Eritrea. London: CRC Press
- **Junk, W., Bayley, P., & Sparks, R. (1989).** The Flood Pulse Concept in River - Floodplain Systems. In D. P. Dodge (Ed.), *Proceedings of the International Large River Symposium* (pp. 110–127). Honey Harbour, Ontario, Canada: Can. Spec. Publ.
- **Puertas, D. G.-L., Steenbergen, F. van, Haile, A. M., Kool, M., & Embaye, T. G. (2011).** Flood based farming systems in Africa (Overview paper No. 5). The netherland.
- **Harlan, J. R., & Pasquereau, J. (1969).** Décrue Agriculture in Mali. *Economic Botany*, *23*(1), 70–74.

Problem statement

- FBFS convey the noble idea of managing scarce water resources, hence alleviating the challenges of drought and dry spells in dryland areas (Mehari Haile, 2007; van Steenbergen et al., 2010; Puertas et al., 2011).
- They are also risky in nature and the lack of data make their subject highly uncertain.
- There is a need for crop models specific for FBFS because current models do not suit them.

Expectations

Data input for such a model MUST :

- Tolerate imperfect information.
- Be able to describe processes/functions with an acceptable degree of complexity.
- Be capable of handling qualitative (e.g. socio-institutional arrangements, type of water diversion) as well as quantitative (e.g. yield) information.
- Be participative and cross-cut across domain specifics expertise.

Expectations

Model output are expected to (Luedeling et al., 2017)**:**

- Assess various crop yields in both grains and biomass and other useful yield metrics (e.g. yield gap).
- Transparently consider uncertainty in estimates.
- Provide ways for comparative analysis of different risk scenario.
- Provide possibility to prescribe pre-season / in-season management options.
- Permit customisation and assessment of real world problems.

Expectations

Model output are expected to (Luedeling et al., 2017):

- Provide results that are scalable to the needs of a range stakeholders (e.g. farmers, government institutions, donors etc.).
- Support further research (hypothesis specifications and testing).
- Transparent enough to be reproduced by peers.

- **Luedeling, E., Whitney, C., Rosenstock, T., & Shepherd, K. (2017)**. "Future Agriculture : Socio-ecological transitions and bio-cultural shifts." In *Modelling Agricultural Realities to Support Development Decisions* (p. 53113). Bonn, Germany: Tropentag.

Methodological concepts

Such a model can be achieved using the Decision Theory which convey the following principals (Luedeling & Shepherd, 2016):

- Consider all factors deemed important.
- Integrate domain-specific knowledge (e.g. water engineers, agronomists, sociologists, farmers, policies makers, etc.) with all other available information (e.g. published and unpublished works, online databases, etc.).
- Rely on the actual state of knowledge, not on assumptions.
- Fully consider and arising uncertainty.

This presentation will demonstrate how such a model can developed and use for various purposes.

- **Luedeling, E., & Shepherd, K. (2016)**. Decision analysis principles can guide the modelling of complex agroforestry systems. In F. Ewert, K. J. Boote, R. P. Rötter, P. Thorburn, & C. Nendel (Eds.), *International Crop Modelling Symposium* (pp. 308–309). Berlin, Germany: iCROPM2016.

Methodology

STUDY AREAS

CONCEPTUAL FRAMEWORK

DATA ACQUISITION

DATA PROCESSING

Study areas

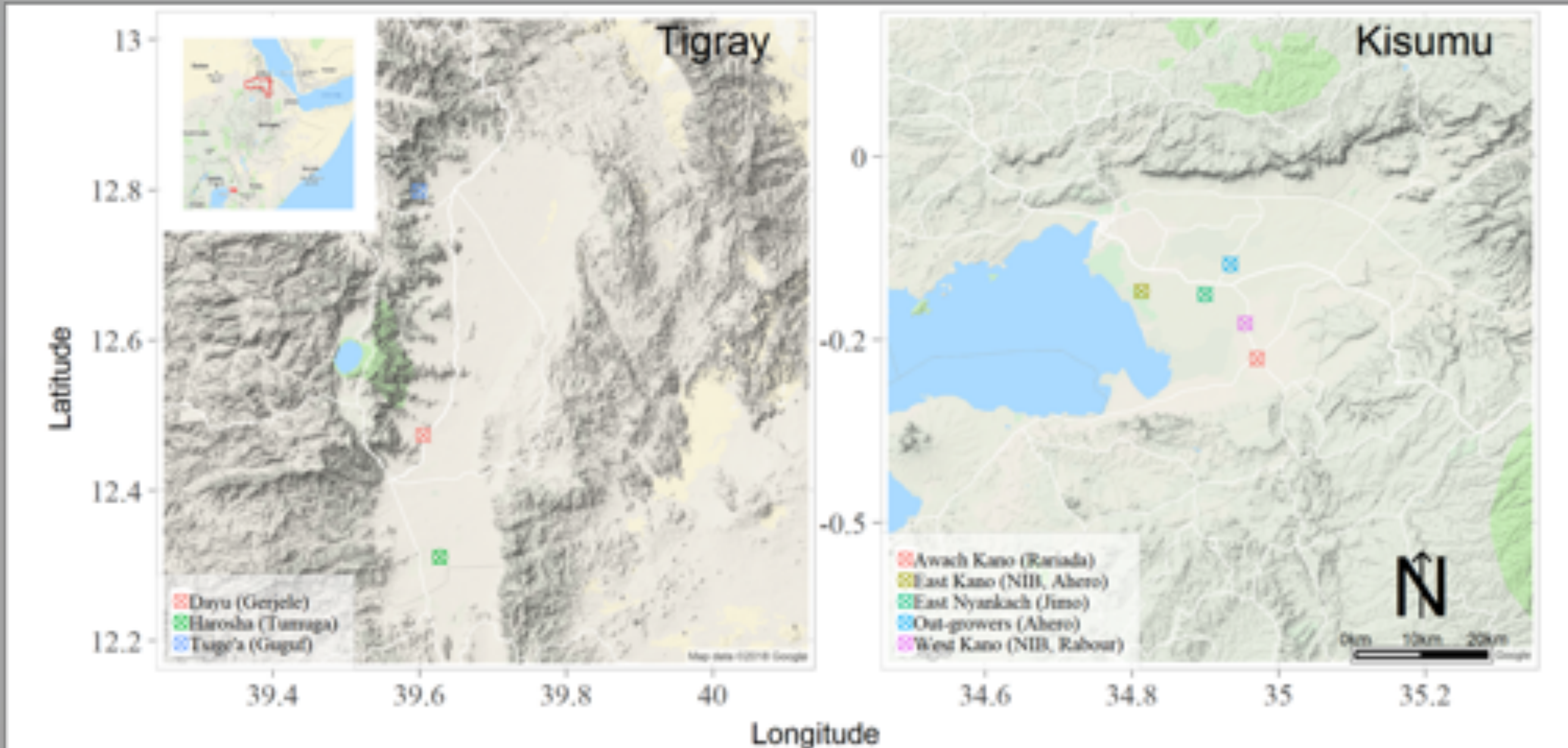

Figure 1. Topographical maps outlining the locations of the study areas and nearby water bodies / waterways in Kisumu County in Kenya and Tigray region in Ethiopia.

Completely different settings

Conceptual framework

- Farming systems can be described in terms of biotic and abiotic factors
- Farmyard quality can be defined by the quality of agricultural management
- Yield has history and this history inform on the quality of agricultural management

- Bayesian Networks mainly used to describe qualitative variables.
- Monte Carlo Model dedicated to quantitative variables.
- Sampling from the posterior distribution of the Bayesian network to feed the Monte Carlo model.

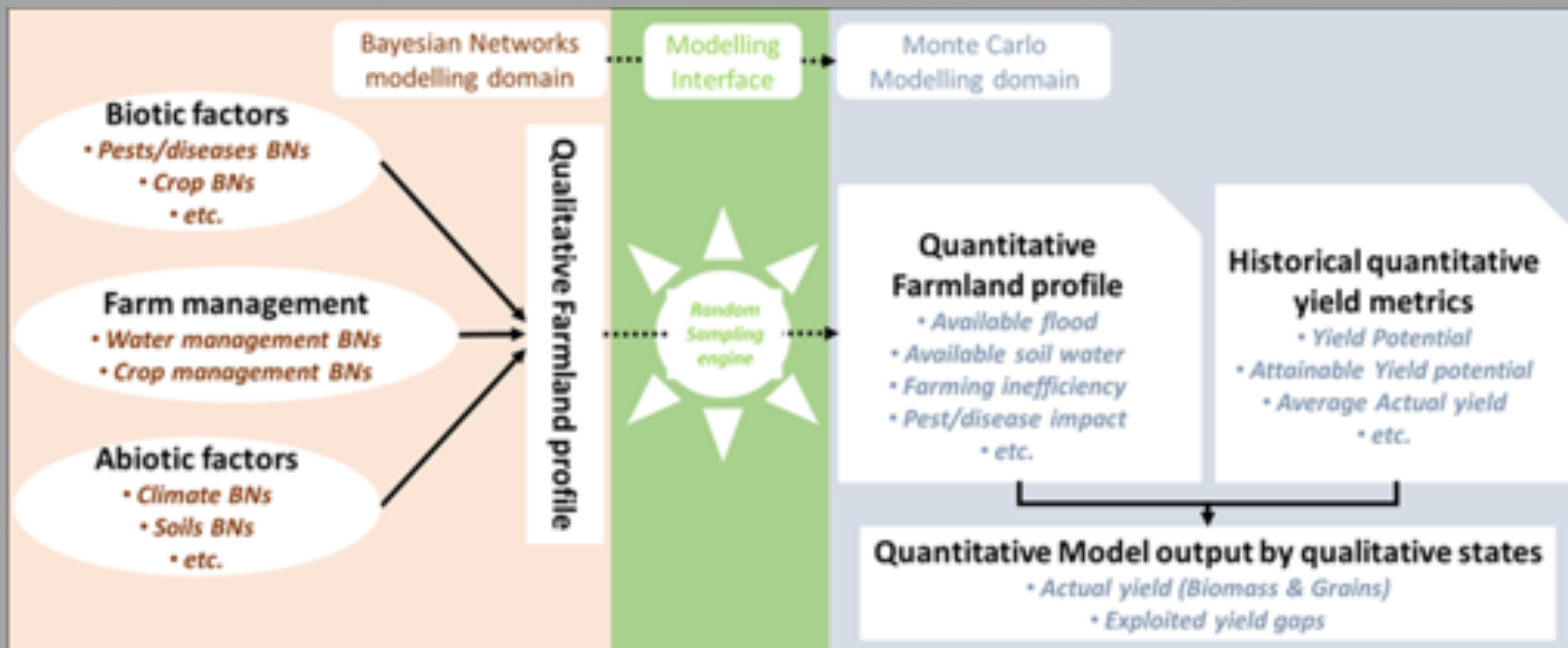

Figure 2. Conceptual framework of important processes to include in the development of a mixed model describing FBFS in Kenya and Ethiopia.

Data acquisition

- Data acquired in 5 sequential steps (Fig. 2)
- Concept based on the current state of knowledge through the literature.
- Primary experts were identified upon the literature review.

Awach, Kenya

Ahero, Kenya

Alamata, Ethiopia

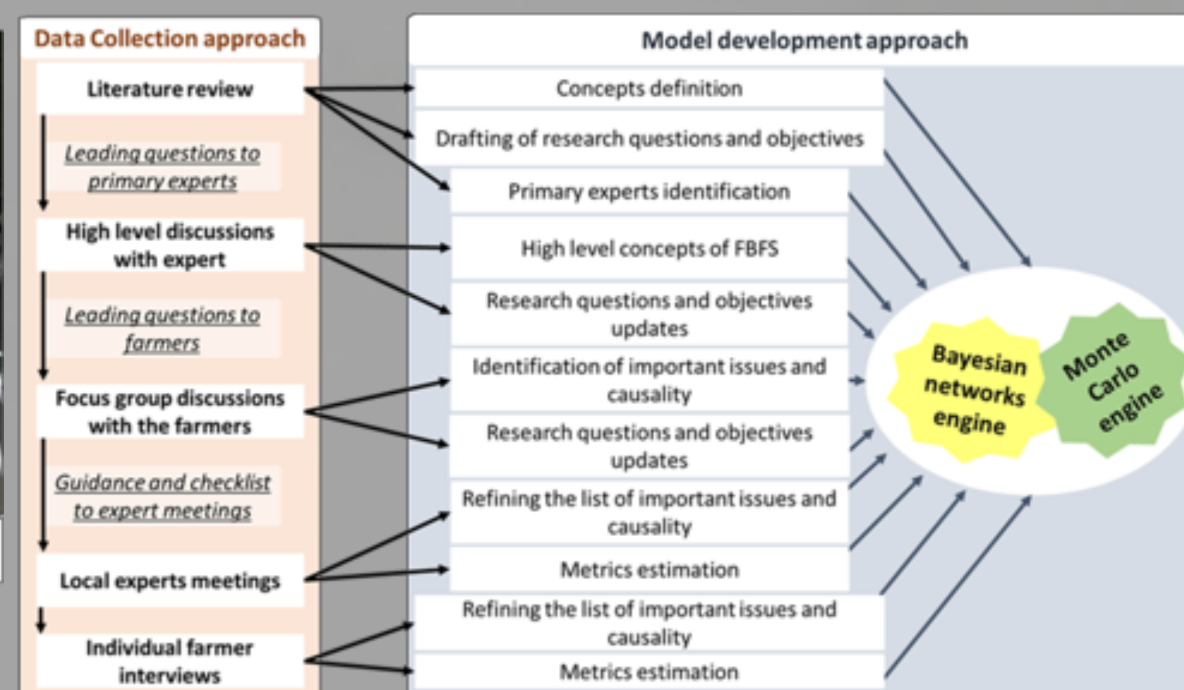

Figure 3. Overview of the approach as part of a mixed model used for FBFS model development in Kenya and Ethiopia.

- Concepts are clearly refined by experts themselves.
- Data collected across domain-specific expertise
- Causality were given a special slot

Data processing

Making of Conditional Probability tables (CPTs)

- Experts need simply to provide some prior estimates and the make_CTP function take care of the rest (Hansson & Sjökvist, 2013; Luedeling & Goehring, 2018).
- Interfacing the make_CPT () with the cptable () function from the gRain package (Højsgaard, 2012) to formalise the BNs following the experts' causal reasoning.

Compiling the CPTs into fully specified Bayesian Networks

- **Hansson, F., & Sjökvist, S. (2013)**. Modelling Expert Judgement into a Bayesian Belief Network -A Method for Consistent and Robust Determination of Conditional Probability Tables.
- **Luedeling, E., & Goehring, L. (2018)**. decisionSupport: Quantitative Support of 1.103.7., Making under Uncertainty. R package version 1.103.7.
- **Højsgaard, S. (2012)**. Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1–26.

Data processing

Bayesian Networks models at the modelling interface

- BNs were then used as synthetic inputs for MC simulations.
- Sampling from the posterior distribution of a target node (Farming constraint).
- Compute estimate as defined in decisonSupport package for mcSimulation () function of the same package (Luedeling & Goehring, 2018).

Monte Carlo models

- Bayesian Networks' nodes along with other quantitative nodes supplied to monte similation using mcSimulation ().

Results and Discussions

OVERVIEW OF THE CONCEPTUAL MODEL

BAYESIAN NETWORKS MODELS

MONTE CARLO MODELS

CASE STUDIES

Overview of the Conceptual Model

- Crops grow under specified cropping decided by the farmers at planting time.
- These crops development under various farming constraint.
- The degree at which these crops will be affected by these farming constraints are defined by resource allocation and others natural constraints.
- These resources are allocated by the farmer.

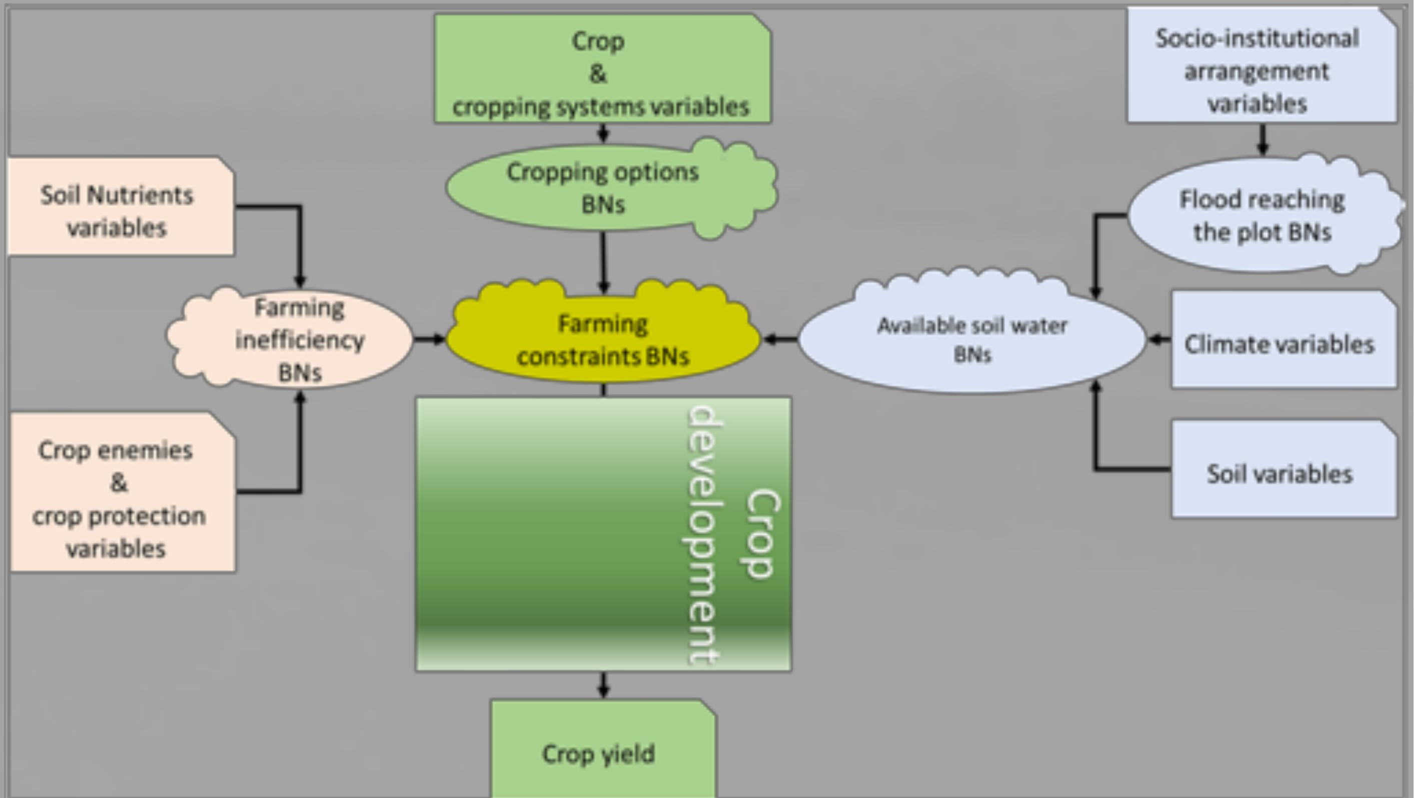

Figure 4. Conceptual model used to integrate the local Bayesian Networks as part of a mixed model describing input allocation and agricultural management in FBFS in Kenya and Ethiopia.

...Then the farmer is key !!!

Bayesian Networks Models

Farming Constraints at farming plot level

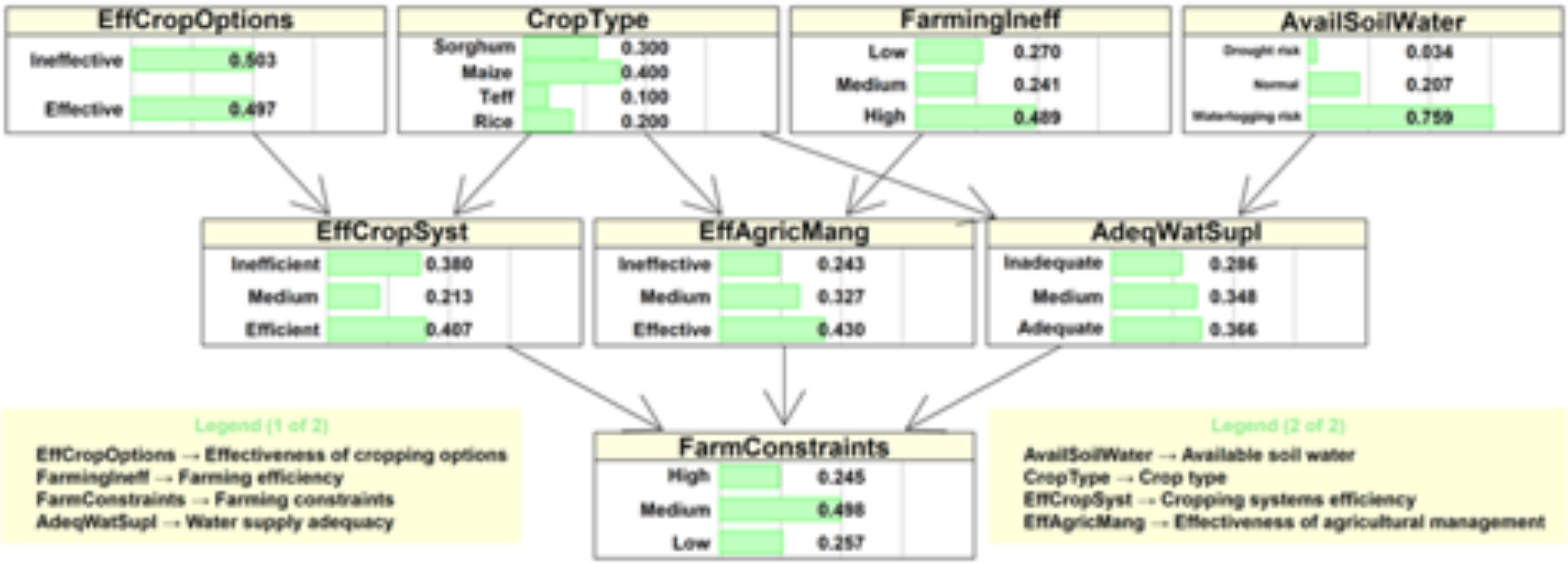

Figure 5. Bayesian network describing important variables as part of a mixed model describing the farming constraints in FBFS in Kenya and Ethiopia.

Bayesian Networks Models

Amount of flood at the farming plot level

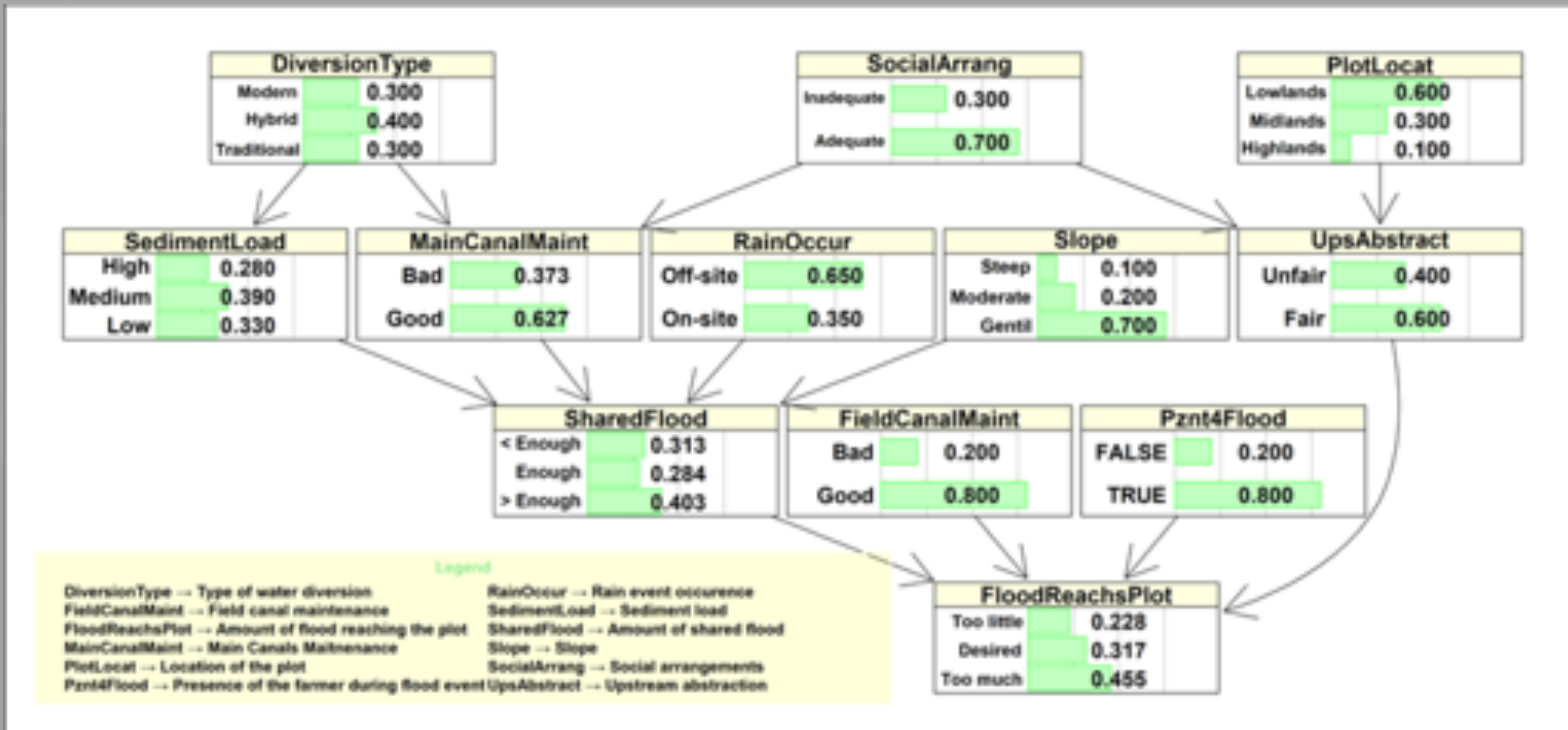

Figure 6. Bayesian network describing important variables as part of a mixed model describing the amount of flood at the farming plot level in FBFS in Kenya and Ethiopia.

Bayesian Networks Models

Available soil water

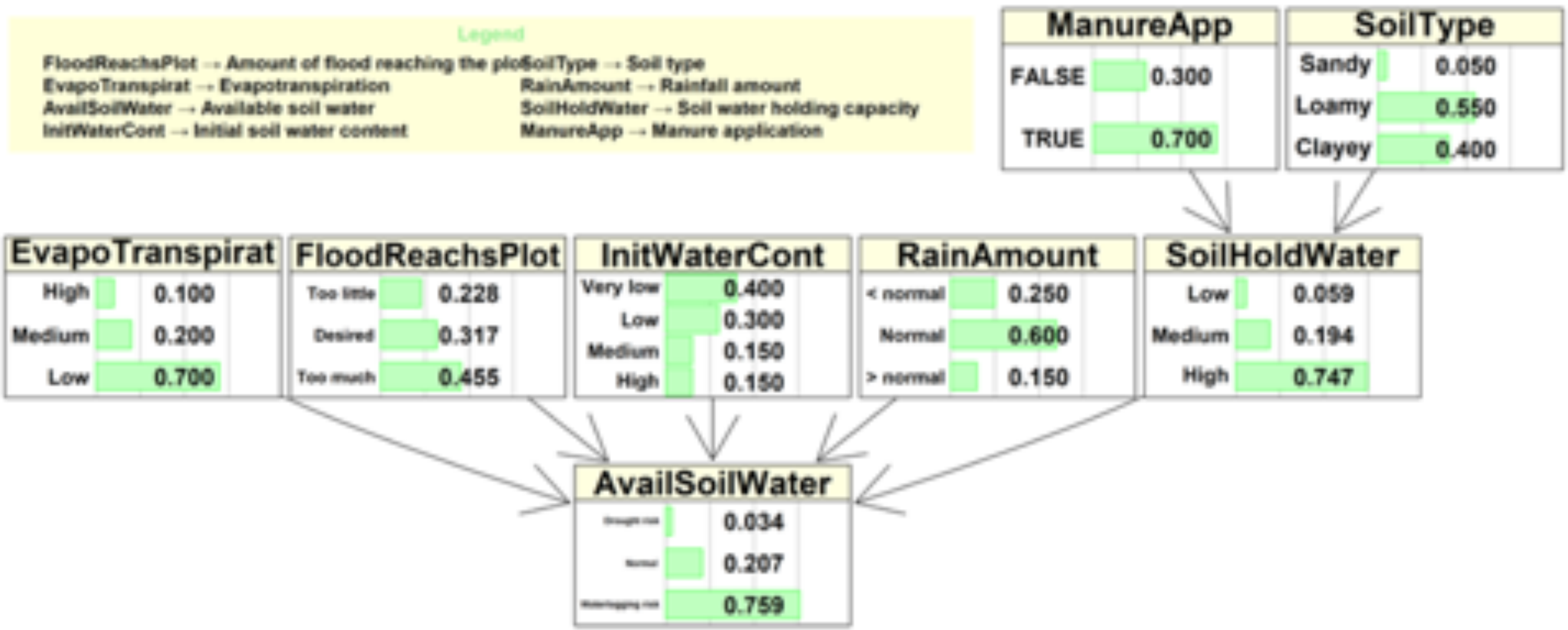

Figure 7. Bayesian network describing important variables as part of a mixed model describing the available soil water content in FBFS in Kenya and Ethiopia.

Bayesian Networks Models

Available soil Nutrients

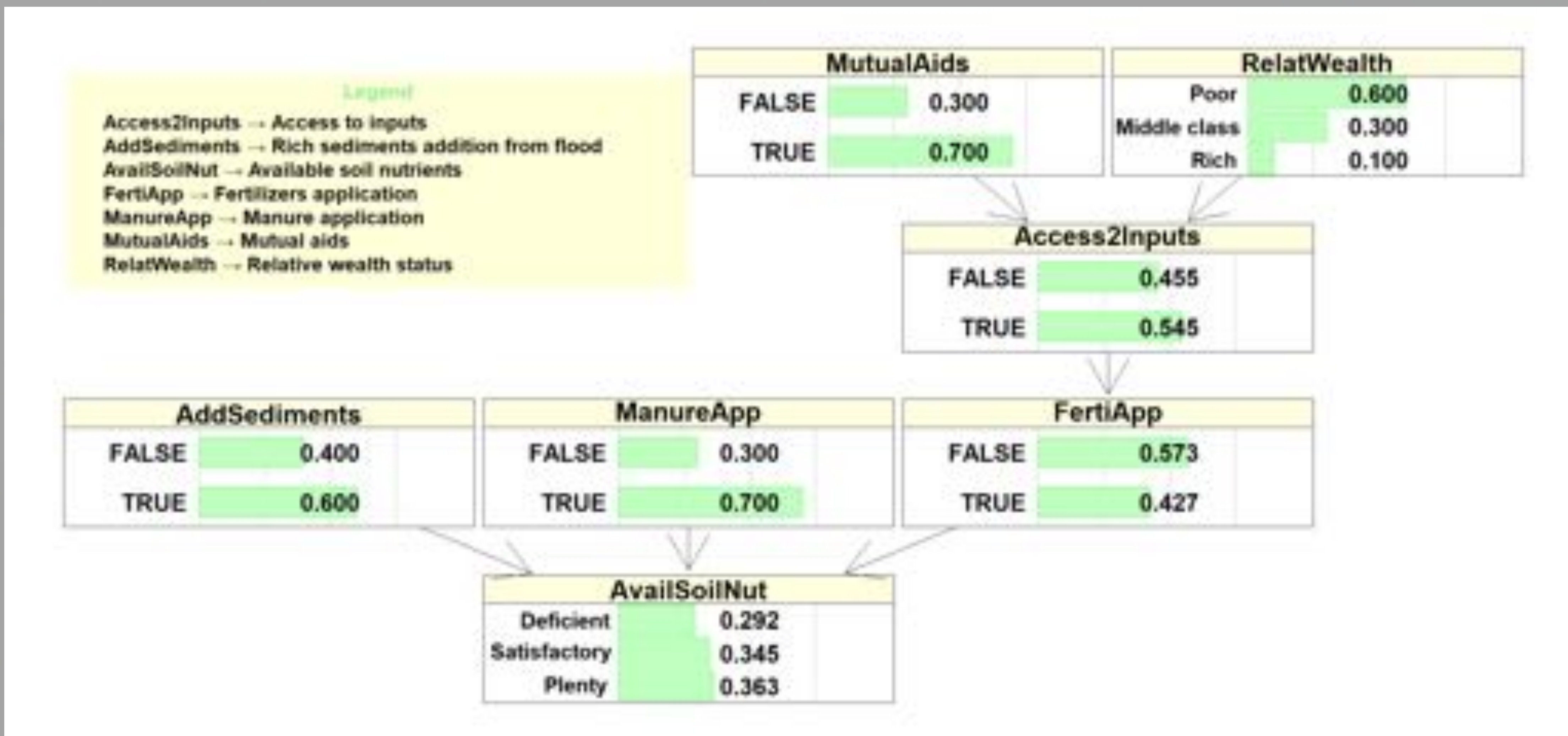

Figure 8. Bayesian network describing important variables as part of a mixed model describing the available nutrients in FBFS in Kenya and Ethiopia.

Bayesian Networks Models
Agricultural management efficiency

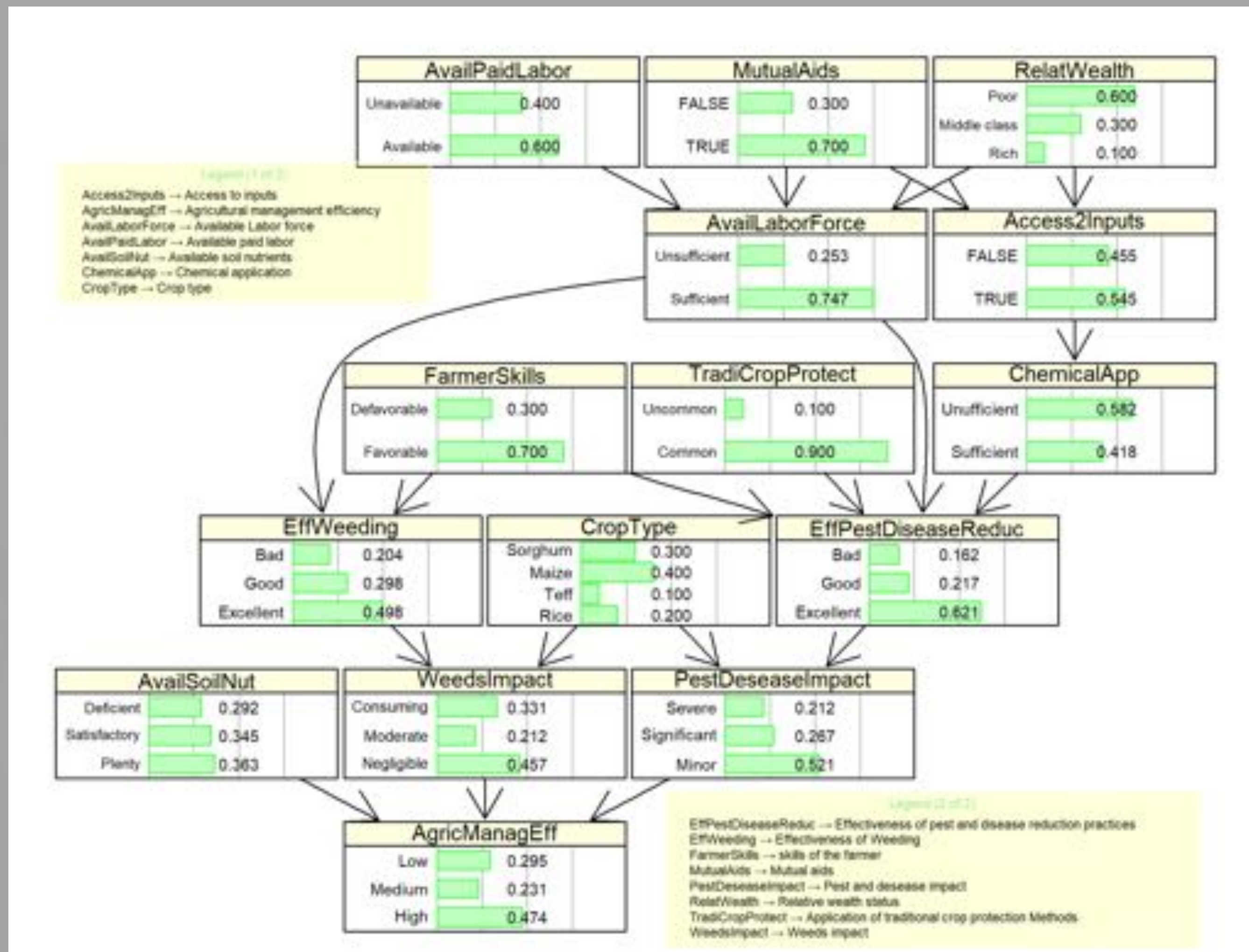

Figure 9. Bayesian network describing important variables as part of a mixed model describing agricultural management efficiency in FBFS in Kenya and Ethiopia.

Bayesian Networks Models

Effectiveness of cropping options

Figure 10. Bayesian network describing important variables as part of a mixed model describing the effectiveness of cropping options in FBFS in Kenya and Ethiopia.

Bayesian Networks Models

Quantitative assessment of Farming Constraints

- Beta distribution can be OK, particularly given the nature of the data.

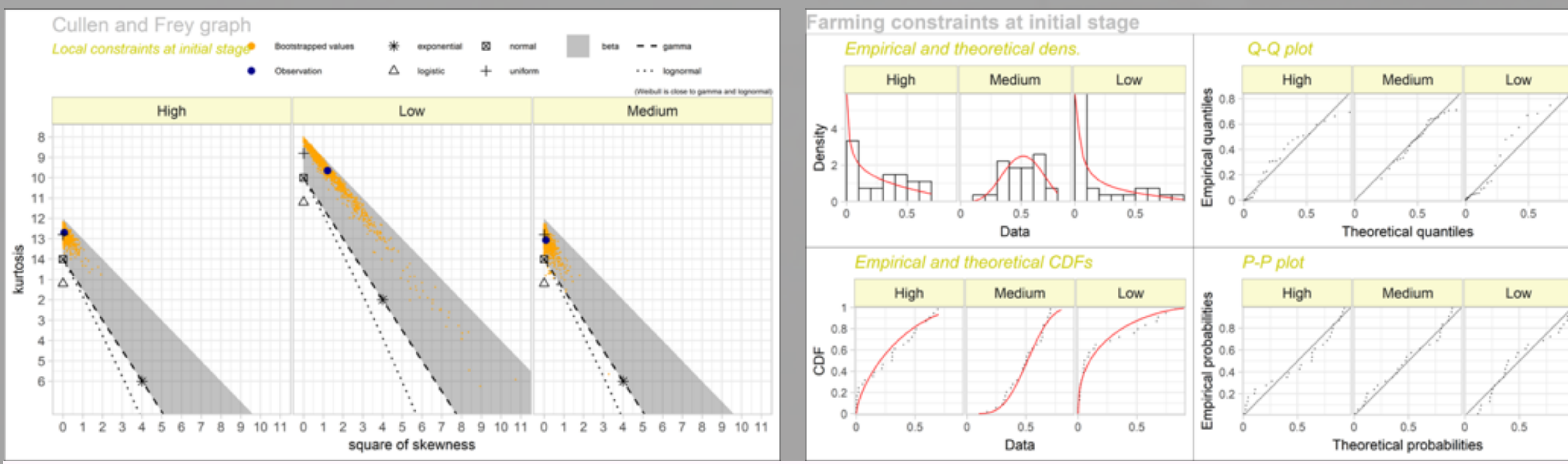

Figure 11. Target distribution based posterior distribution of the fully specified Bayesian networks sub-model (initial stage)

Monte Carlo Models

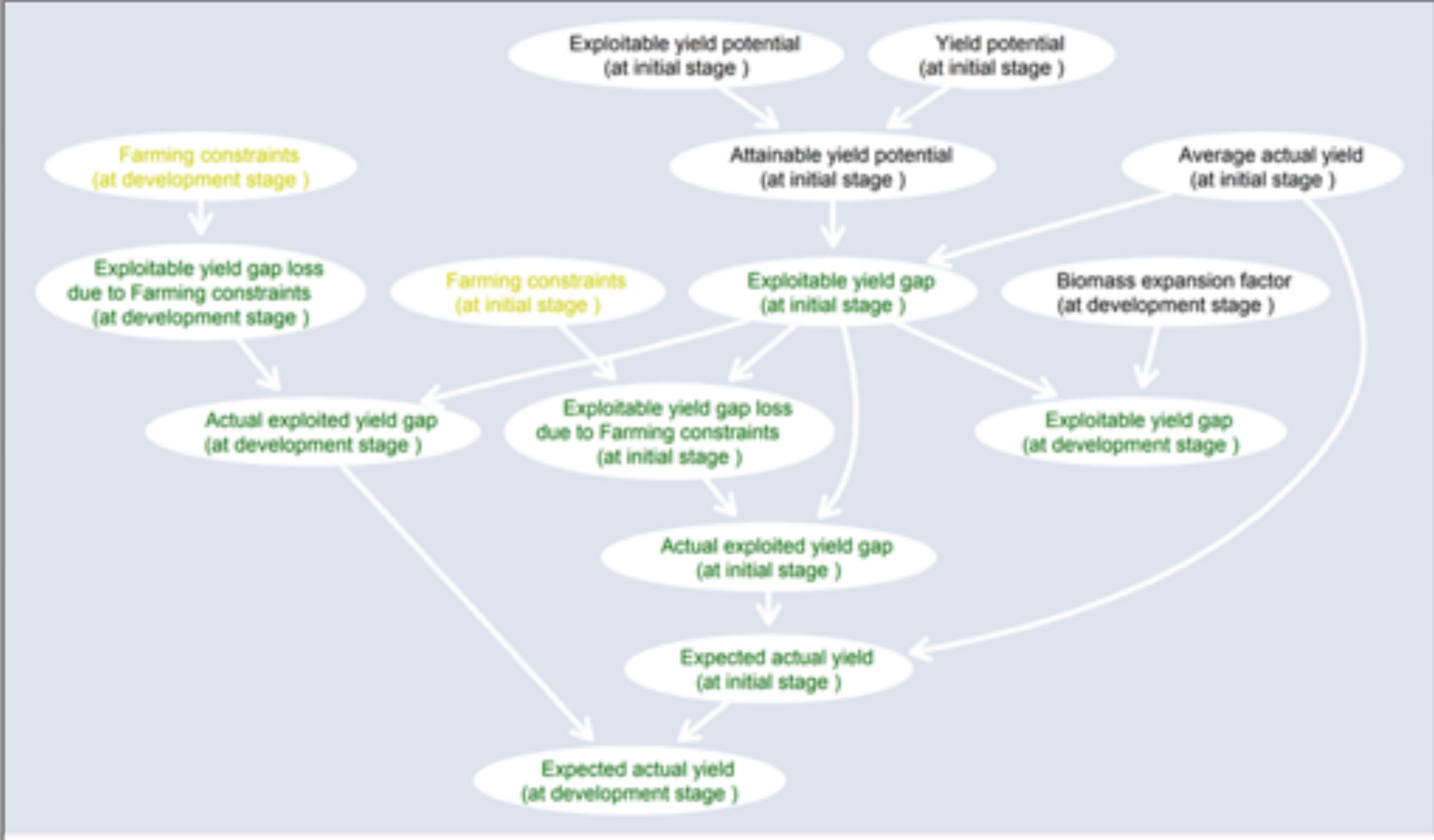

Figure 12. Monte Carlo model describing important variables as part of a mixed model describing the expected crop yield at different stages of crop development in FBFS in Kenya and Ethiopia.

Case Studies

This is gonna be sweet !!!

Case study 1

Qualitative Soil Water Assessment under different Management Decisions in Flood-based livelihood systems.

Rational and Methods

- Even though FBFS are solution to drought, drylands Farmers MUST manage the flood water in way that it is neither too little, nor too much.
- This requires maximizing water storage in soils (run-on, rainfall, etc.) while limiting waterlogging of soils and water loss (evapotranspiration, run-off, percolation, etc.).

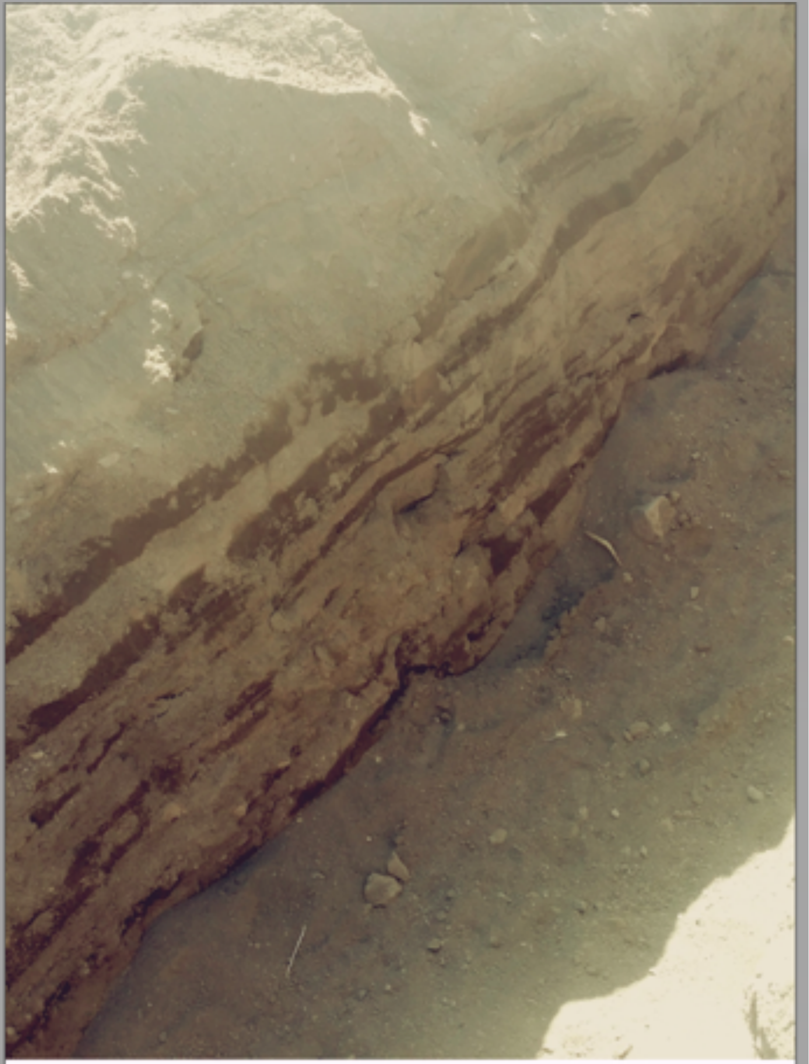

Figure 13: Soil profile showing soil moisture presence during dry season

Rational and Methods

A 3 x 3 x 2 Split Split-plot experiment to study the factors of available soil water content at initial stage:

- main plot: 3 levels of soil type as.
- subplot: 3 different amounts of diverted flood.
- sub-subplot: 2 levels of manure application.

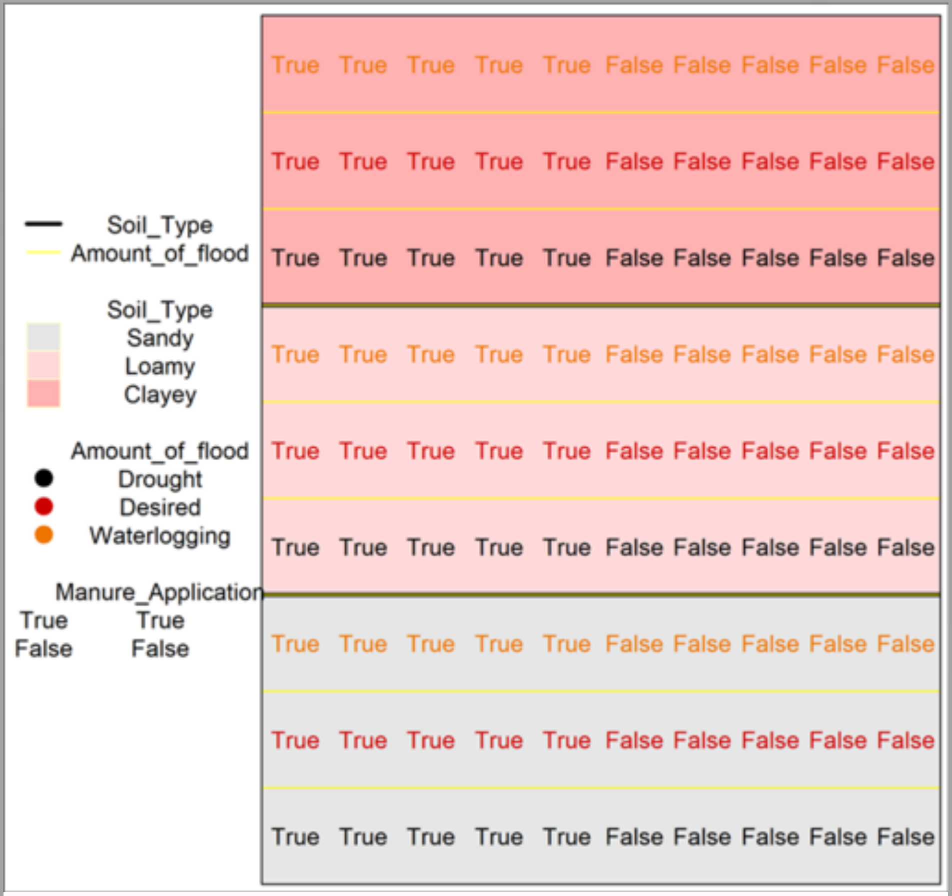

Figure 14: Layout of a 3 x 3 x 2 Split Split-plot experiment for studying the available soil water content at initial stage of crop development in FBFS in Kenya and Ethiopia.

Results

- Even without manure addition and little amount of flood, drought is unlikely to occur under clayey soils.
- A similar situation is observed under sandy soils when it comes to waterlogging.
- relatively high change of waterlogging particularly .under clayey soils.
- Drought, but also normal conditions are rather rare (mostly probabilities below 0.5).

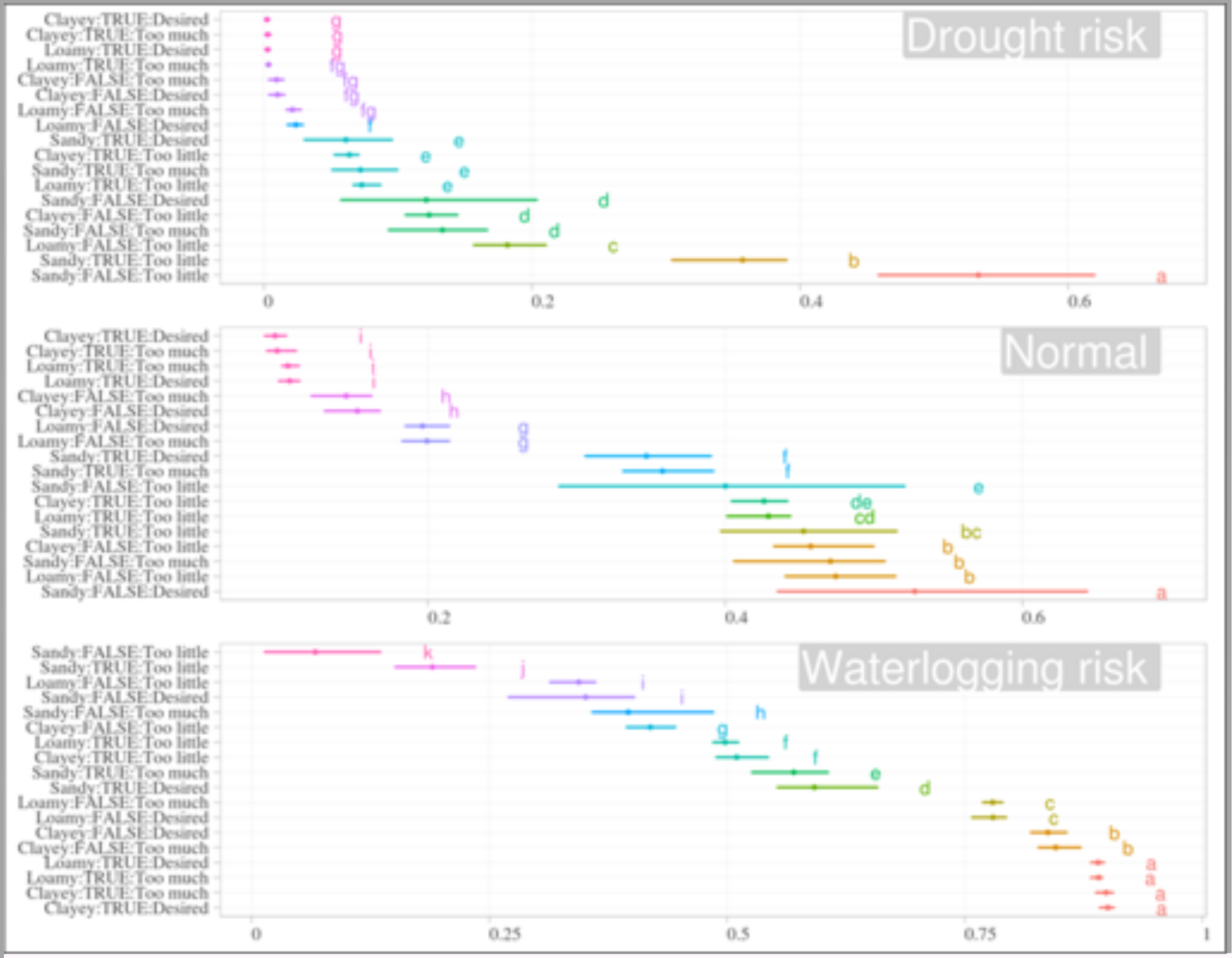

Figure 15. Tukey's HSD test of a Split Split-plot experiment with 3 levels of soil type as main plot, 3 different amounts of diverted flood as subplot, and 2 levels of manure application as sub-subplot for studying the available soil water content at initial stage.

Case study 2

Probabilistic Assessment of Biomass Accumulation in Major Crops grown under FBFS in Kisumu, Kenya and Tigray, Ethiopia.

Rational and Methods

- Apart from their contribution to food production, FBFS are also use for fodder / grassing areas for livestock.
- But biomass production is often overlooked in favour of grain production.
- This study provide a probabilistic assessment of biomass and biomass accumulation over time in FBFS.

Figure 16. FBFS as grazing areas in Awach basin, Kisumu, Kenya.

Rational and Methods

- The generic model was without any evidence specification to provide a lumped assessment.
- Biomass yields were simulated for only initial and late stage of crop development.
- Only few results will be presented.

Results

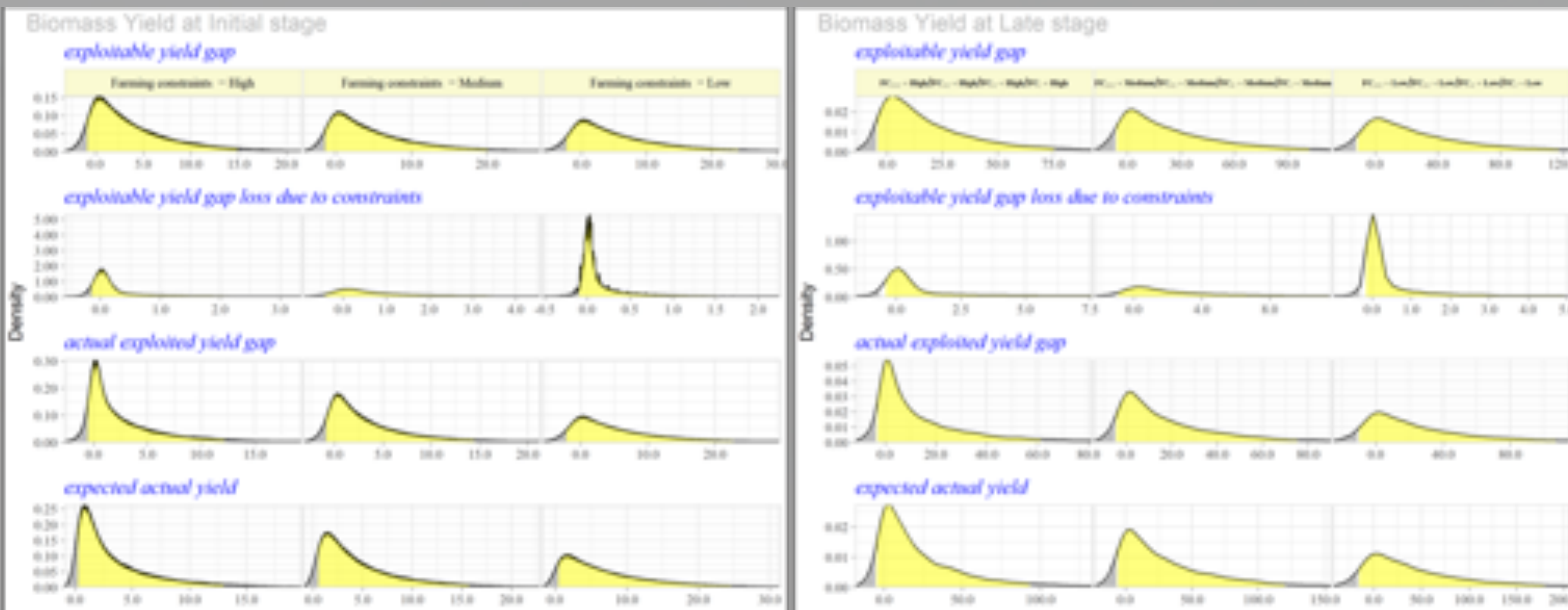

Figure 17. Probabilistic assessment of biomass yield and other related metrics

Case Studies 3

Quantitative grain yield variability and relative performance of Rice and Sorghum under different scenario for water and crop enemies at mid-stage of crop development in flood-based Agriculture.

Rational and Methods

- Risk factors such as pest and diseases, weeds etc. are of concern to farmers
- However, it is rare to see them in many crop models.
- Factors such as pest and disease or weeds becomes even more important in FBFS due to their hydrology.

Figure 18. Weeds in Rice and Sorghum

Rational and Methods

A 2 x 2 x 2 x 2 factorial experiment with 4 treatments in a completely randomized block design to study Rice and sorghum yield as function of:

- different level of weeds,
- different level of pest and diseases, and
- Different level of available soil water.
- scenario are considered at mid stage of crop development.

Drought, Sorghum, Consuming, Severe	Drought, Sorghum, Consuming, Severe	Waterlogging, Sorghum, Negligible, Severe	Waterlogging, Rice, Negligible, Severe
Waterlogging, Sorghum, Consuming, Severe	Waterlogging, Rice, Negligible, Minor	Waterlogging, Sorghum, Consuming, Severe	Waterlogging, Rice, Consuming, Minor
Waterlogging, Sorghum, Consuming, Minor	Waterlogging, Rice, Consuming, Minor	Drought, Rice, Negligible, Minor	Waterlogging, Rice, Negligible, Minor
Drought, Rice, Negligible, Severe	Drought, Sorghum, Negligible, Severe	Drought, Sorghum, Consuming, Minor	Waterlogging, Sorghum, Negligible, Minor
Drought, Rice, Consuming, Severe	Waterlogging, Sorghum, Consuming, Minor	Waterlogging, Sorghum, Consuming, Minor	Drought, Rice, Consuming, Severe
Waterlogging, Sorghum, Negligible, Severe	Waterlogging, Sorghum, Consuming, Severe	Drought, Rice, Negligible, Minor	Drought, Rice, Consuming, Minor
Waterlogging, Rice, Negligible, Minor	Drought, Rice, Consuming, Minor	Drought, Sorghum, Negligible, Minor	Drought, Sorghum, Negligible, Minor
Waterlogging, Rice, Negligible, Minor	Waterlogging, Rice, Negligible, Severe	Waterlogging, Sorghum, Negligible, Severe	Waterlogging, Sorghum, Negligible, Minor
Drought, Rice, Negligible, Minor	Drought, Sorghum, Negligible, Severe	Drought, Sorghum, Negligible, Severe	Drought, Sorghum, Consuming, Minor
Waterlogging, Sorghum, Negligible, Severe	Drought, Sorghum, Consuming, Minor	Drought, Rice, Negligible, Minor	Waterlogging, Rice, Consuming, Severe
Drought, Sorghum, Consuming, Minor	Drought, Sorghum, Consuming, Severe	Drought, Rice, Consuming, Minor	Waterlogging, Rice, Consuming, Minor
Drought, Rice, Consuming, Severe	Waterlogging, Sorghum, Consuming, Minor	Waterlogging, Sorghum, Negligible, Minor	Drought, Sorghum, Negligible, Severe
Waterlogging, Rice, Negligible, Severe	Waterlogging, Rice, Consuming, Minor	Waterlogging, Sorghum, Negligible, Minor	Drought, Rice, Negligible, Severe
Waterlogging, Rice, Negligible, Severe	Drought, Sorghum, Negligible, Minor	Drought, Sorghum, Consuming, Severe	Drought, Rice, Consuming, Severe
Drought, Rice, Negligible, Severe	Waterlogging, Rice, Consuming, Severe	Waterlogging, Rice, Consuming, Severe	Waterlogging, Sorghum, Consuming, Severe
Drought, Rice, Negligible, Severe	Drought, Sorghum, Negligible, Minor	Waterlogging, Rice, Consuming, Severe	Drought, Rice, Consuming, Minor

Figure 19. Layout of a 2 x 2 x 2 x 2 factorial experiment for studying the effects of different level of weeds, pest and diseases and available soil water at mid stage of crop development on grain yield of Sorghum and Rice in FBFS in Kenya and Ethiopia.

Results

	Grain yield groups	
Minor:Negligible:Rice:Drought risk	166.0966	a
Minor:Negligible:Rice:Waterlogging risk	133.2508	b
Severe:Negligible:Sorghum:Waterlogging risk	131.6462	b
Minor:Negligible:Sorghum:Drought risk	119.7207	bc
Minor:Consuming:Sorghum:Waterlogging risk	119.1722	bc
Severe:Consuming:Sorghum:Waterlogging risk	110.5669	cd
Minor:Consuming:Rice:Drought risk	108.2687	cd
Severe:Consuming:Rice:Drought risk	108.1058	cd
Severe:Consuming:Rice:Waterlogging risk	103.1724	cd
Severe:Consuming:Sorghum:Drought risk	97.06859	de
Severe:Negligible:Rice:Drought risk	83.95261	ef
Minor:Consuming:Rice:Waterlogging risk	83.3691	ef
Minor:Consuming:Sorghum:Drought risk	76.90688	f
Severe:Negligible:Sorghum:Drought risk	76.51145	f
Minor:Negligible:Sorghum:Waterlogging risk	74.0806	f
Severe:Negligible:Rice:Waterlogging risk	73.56149	f

Table 1. Comparative analysis of joint effects of different treatments levels on grain yield of Rice and Sorghum in FBFS in Kenya and Ethiopia.

Recommendations, Model limitations, and future works

Recommendations

Model limitations

future works

Recommendations

- Recommend such a model for each scheme: stakeholders should come together and address real world problem of agriculture, and build a tool towards understanding deep functions and processes with regards to their systems.
- Calibration training to farmers, and other experts for more accurate estimates.
- Variables should be measured as much as possible. FBLN should keep records of raw data across countries for crop modelling.

Limitations

- Distribution fitting can be improved by using more formal statistical procedure.
- Pest and disease can be separated and more detailed.
- More crops should be included.
- Customization is good, but also time consuming at require some level of programming skill.

Future works

- FBFS Type-specific Modules
- Detailed Modules / description of Pests, diseases, and Weeds.
- Upscaling / agronomic trials in different countries
- Towards a graphical user interface.

Thank you!!!