A Tool for Targeting and Scaling-Out Successful Agricultural Water Management Interventions

From field to basin scales, there are many appropriate interventions used to manage rainfall for agriculture efficiently and productively. Yet, successful targeting and scaling-out of these interventions remains a challenge. **Targeting AGwater Management Interventions (TAGMI)** is a decision support tool that addresses this challenge in the Limpopo and the Volta River Basins (available at www.seimapping.org/tagmi). TAGMI uses country-scale Bayesian network models to assess the likelihood of success of different Agricultural Water Management (AWM) technological interventions, to facilitate their targeting and scaling-out. The web-tool relies on data about a place's background context at the district-scale, i.e. key social, human, physical, financial and natural factors, to calculate the relative probability of success of an AWM intervention in the Limpopo and Volta River basins. TAGMI currently includes the following AWM technological interventions: Soil and water conservation (Volta Basin), Conservation Agriculture (Limpopo Basin), Small-Scale Irrigation and Small Reservoirs (both Basins). TAGMI is an output from the 3-year CGIAR Challenge Program on Food and Water (CPWF) Volta and Limpopo basin research-for-development projects.

What are AWM Interventions?

AWM interventions in rainfed systems aim to influence rainwater flows in order to maximize infiltration in the soil, retain run-off and minimize water losses (e.g., Douxchamps et al 2012). Interventions range from *in situ* technologies such as stone bunds or conservation agriculture to *ex situ* structures such as small reservoirs. By doing so, crops can access more water to improve yields and farmer benefits such as food, fodder and income. In small and large farming systems' soil and water management, these technologies have been used and promoted for decades (Figure 1).

The TAGMI tool supports decision making around three different AWM technological interventions in each Basin, which have been chosen to reflect a wide range of technologies, from the rainfed end of AWM technology spectrum, to full irrigation systems (Figure 2).

What are successful AWM interventions?

Expert consultations across the Limpopo and Volta Basins defined successful interventions as those cases where a technology has had a positive impact on farmers' well-being and where farmers adopted and continued to use the introduced AWM technology more than 2 years after the intervention ended. Consultation participants are aware of cases for most AWM technologies which were a success in some locations while a failure in others. AWM interventions have been an agricultural development priority in the Volta and Limpopo Basins for more than 40 years, leading to an intensification in agriculture and livestock production and its environmental impacts, but there is still scope for further improvement. To date little systematic evidence has been collected at country level of these changes (Morris and Barron, in review).

A number of factors influence the successful outcome of AWM interventions. For example, participants mentioned biophysical characteristics of an area, financial conditions of the targeted individual or community, and market connections. Consultations recognized that the most important factors for successful technology adoption relate to social and institutional factors. Project implementation factors are also critical to success: community ownership, the implementing organization has engaged with stakeholders throughout the process, and a clear demand for the proposed technology. Furthermore, the intervention must have clear objectives and offer an appropriately designed technology. AWM interventions have evolved in their approach over the last

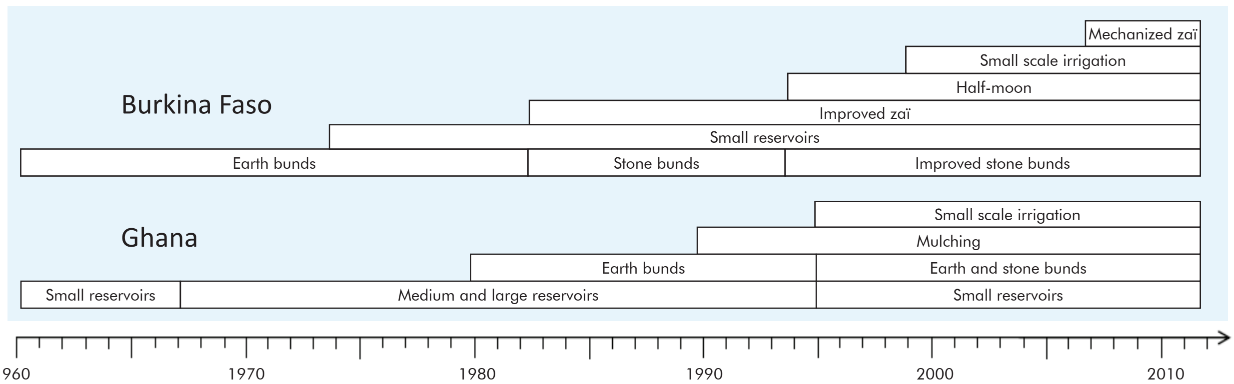

Figure 1: The types of technologies introduced over the past five decades in Burkina Faso and Ghana (after Douxchamps et al 2012).

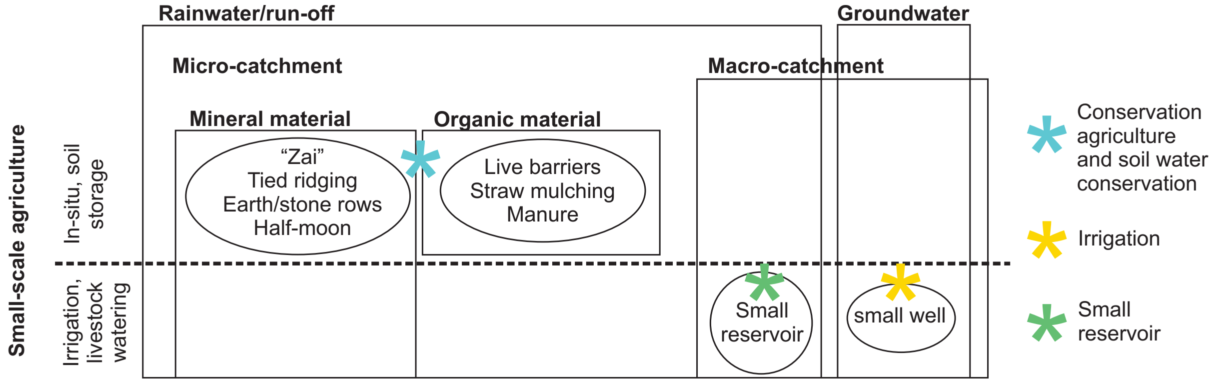

Figure 2: Classification of AWM technologies (modified after Johnston & McCartney 2010).

several decades; research and consultation discussions both reflect the increasing emphasis placed on aspects of implementation (see Figure 3 for timeline). Critical elements of implementation design like participation, gender inclusivity, and a more holistic approach to the farming system and landscape in which these technologies work have become mainstream. Unfortunately, the cases assessed during expert consultations show that despite this change in approach and rhetoric, some AWM intervention projects still fail, as success relies on the interaction and combination of numerous factors.

Stakeholder consultations: assessing the likelihood of success

TAGMI uses behind-the-scenes "Bayesian network models" to assess intervention success by estimating how different factors interact. The Bayesian models were built from participatory discussions and feedback received during in-country consultations with local researchers and experts. Participants were asked to describe how and to what extent various factors contribute to the success or failure of an AWM intervention. The models' calculation of likelihood of success uses probabilistic relationships drawn from that feedback.

A Bayesian network model exists for each technology within each Basin country. The model uses a range of country-specific socio-economic, biophysical, institutional and cultural factors. Other factors equally, if not more, important to the success of a technology are the 'Best practices of implementation' which are in the implementers' control. While these are not modelled directly, documentation available on the website provides further details about such practices.

Participants described how they often rely on a biophysical suitability analysis combined with an assessment of farmers' demands and needs to make decisions about targeting and scaling-out of different AWM technologies. TAGMI compliments the biophysical factors with socio-economic factors to enhance decision-making.

Advantages with a Bayesian Modelling Approach

The advantages of the Bayesian approach are that it

- combines multiple knowledge sources: tabular data, GIS layers, and key stakeholders' knowledge and expertise
- integrates quantitative and qualitative data about social, institutional and bio-physical aspects of a district and the people living there
- measures the certainty with which it has calculated the likelihood of success by assessing the 'strength of evidence', which reflects the quality of the knowledge and data underlying the calculated likelihood of success. The model's predictions are only as good as the data that goes in.

While those targeting and scaling-out an AWM intervention cannot have complete knowledge about famers' or communities' decisions to adopt a technology, a Bayesian model can communicate what is known about important factors for success. TAGMI currently offers a map-based visualization of the Bayesian country models' results, conveying the spatial differences in the likelihood that Soil and Water Conservation, Small-Scale Irrigation or Small Reservoirs can be successfully adopted across districts (Figure 6).

Further development of the tool

The tool is the result of a research-for-development project aimed to test a potential approach for looking into the likelihood of success of AWM interventions. It is therefore a product prototype exemplifying an online user interface to assist in targeting AWM interventions. It pilots the integration of different expertise and sources of knowledge. Currently, there is limited data available at district level while

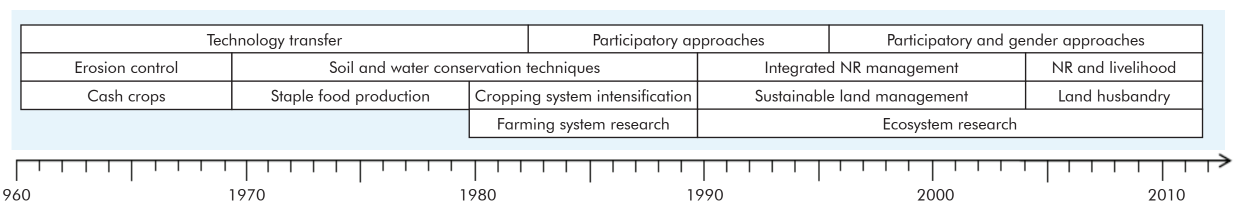

Figure 3: Evolution in the approach to implementing AWM interventions (after Douxchamps et al 2012).

Bayesian Network Model in Detail

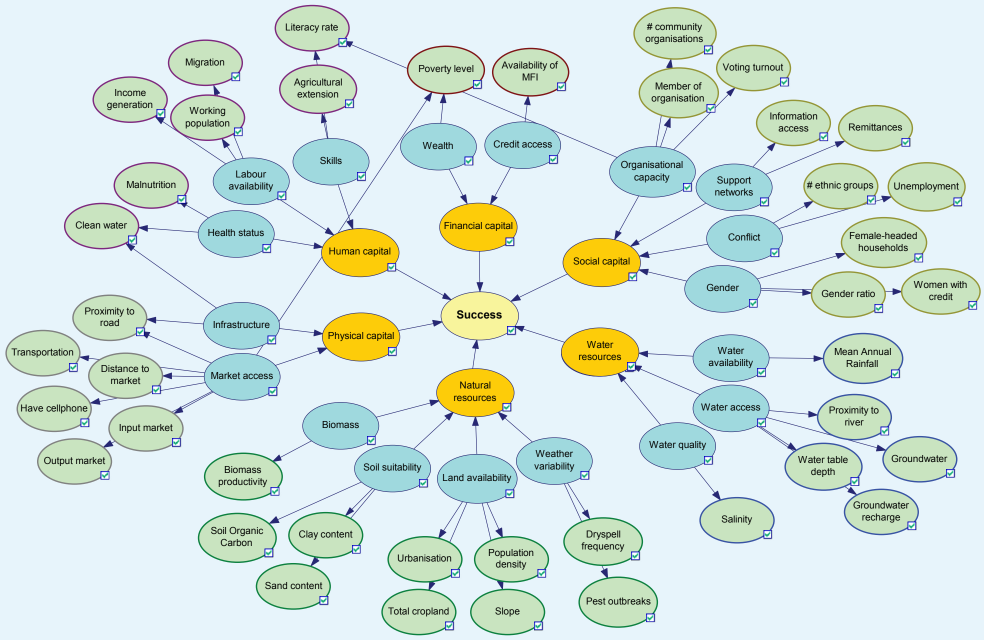

Figure 4: Bayes network for Soil and Water Conservation in the Volta Basin.

The Bayesian Model calculates a desired outcome, '**Success**', which is the likelihood that an AWM technology introduced in a target community will still be in use 2 years after the intervention project has ended (central node in Figure 4). Based on participants' discussions, and using the DFID Sustainable Livelihood Framework (DFID, 1999), 'Success' is conditional on adequate levels of 5 **capitals**: Human, Social, Financial, Physical and Natural. Water resources are included as a separate 6th capital given its centrality to AWM. Each **capital** comprises 2-4 key **factors** (e.g. Human capital is a combination of **Labour availability**, **Skills**, and **Health**). Each **factor** is described by 1-3 **data variables**, which are the foundation of the model (e.g. **Labour availability** is indicated by the relative size of the **working age population** and the **gender ratio** in the population). Figure 5 illustrates the tree structure of the model.

The **linking arrows** convey the conditional probabilities of how each node in the network influences the presence of the next node. The model calculates the probability that the **factor** is present given knowledge about the state of its **data variable** (high, medium or low), then the probability that the **capital** is present given the calculated state of its **factors**, then the probability that **success** is present given the calculated state of all **capitals**. A similar application of Bayesian network modelling to analyse the likelihood of water poverty is explained in detail in Kemp-Benedict et al. (2009).

Interpreting the result

The resulting '**likelihood of success**' is influenced by:

The data itself

- the data distribution is standardised: all data is classified into 3 categories (low-med-high) of equal numbers of districts
- results therefore show relative differences across districts
- the data quality may skew the distribution: where coarser data is allocated to the district-level, large blocks of districts with similar values are created

The importance of the data

- the conditional probability tables linking the data to the factors reflect both the *type* (positive or negative) and *strength* (very strong - strong -weak) of the relationship between the data and the factor
- a *very strong* relationship has more effect on the value of the factor, and therefore contributes more to the final result, than a *weak* relationship
- most of the data is set to a very strong relationship with the factor it represents, unless expert input indicated otherwise

The importance of the factors

- the calculated value of each factor also carries a weight that reflects how much it contributes to achieving the capital it belongs to - e.g., do **Health status**, **Labour availability** and **Skills** contribute equally to achieving **Human capital** or not?
- a factor with a high weight will have more effect on the value of the capital, and therefore contribute more to the final result, than a factor with a low weight

The importance of the capitals

- the calculated value of each capital also has a weight which reflects how necessary that capital is to achieving long-term success of the project:
  - if a capital that is *absolutely necessary* is absent, the likelihood of success will be significantly reduced
  - if the capital was only *somewhat important*, the likelihood of success will not be much affected

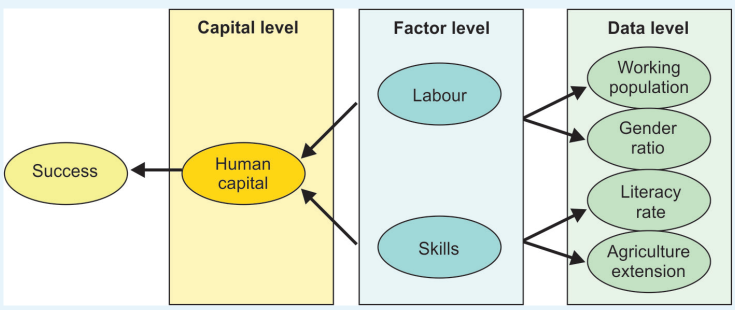

Figure 5: Example of the Bayes network structure.

at the same time covering the entire area of a country within the basin. The certainty with which the model predicts the likelihood of success of AWM interventions would be greatly improved if more data could be collected and made available.

Although the Bayesian models pilot the inclusion of social and institutional aspects of the districts, further work is needed to define appropriate data variables to represent these aspects and collect the relevant data for these variables. This would strengthen the holistic nature of the model and allow informed decisions about how to implement an intervention, for example if there is a need to focus on establishing a sense of community to allow the implementation to become a success.

The technologies used in the model are examples selected from a range of potential technologies. The TAGMI tool can be expanded by developing additional Bayesian network models tailored for other technologies .

The project team welcomes contributions or future collaborations on all these points: if you have better data, if you have suggestions for measurable or measured social and institutional variables, and if you would like to use the approach for other technologies, please let us know.

Partners

Volta Basin Research Partners: Institut National de l'Environnement et de Recherches Agricoles (INERA); Civil Engineering Dept. of the Kwame Nkrumah University of Science and Technology (KNUST); Savanna Agricultural Research Institute of the Council for Scientific and Industrial Research, Ghana (CSIR-SARI); Département de Géographie de l'Université de Ouagadougou

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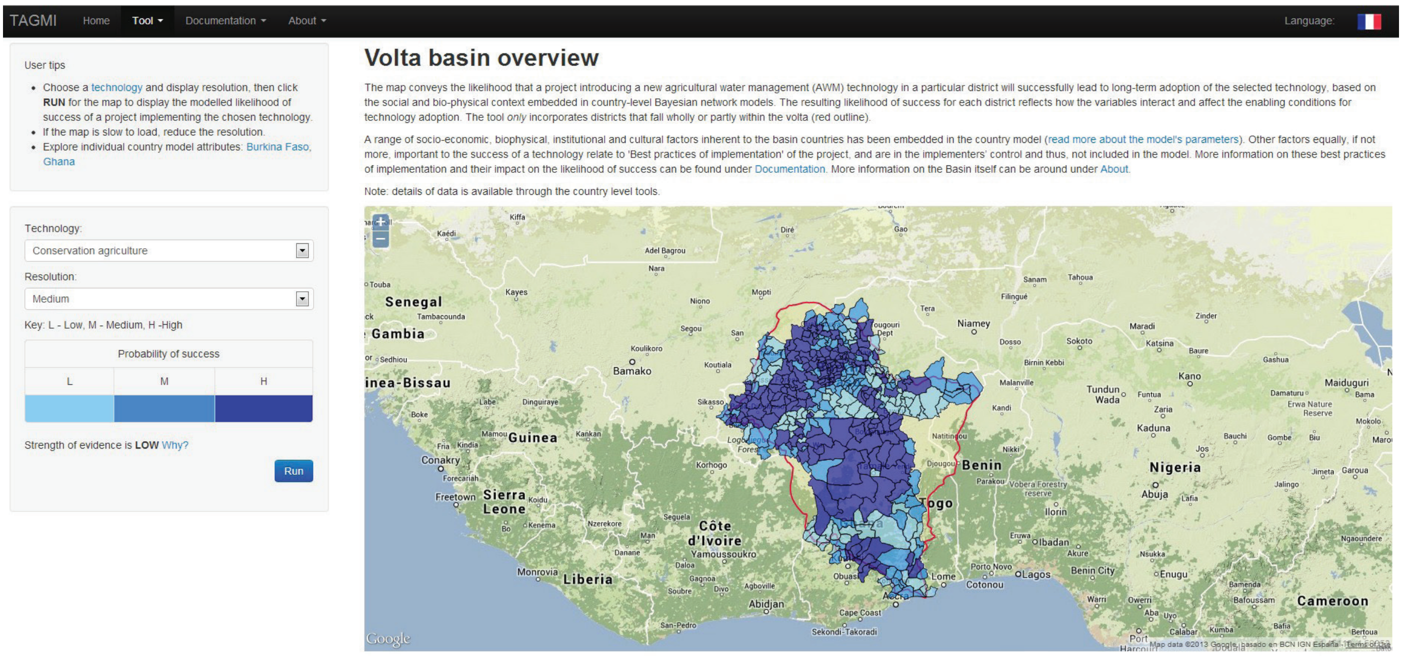

Figure 6: Screen shot of the TAGMI tool: Volta Basin.

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