1-2 Proposal for a multi-goal integrated farm management model to enhance smallholder decision-making in sub-Saharan Africa

Junji Koide*

Japan International Research Center for Agricultural Sciences

** Corresponding author; E-mail: koidej0187@jircas.go.jp*

Abstract

Agricultural decision-support models based on mathematical programming are frequently employed to determine the economically optimal allocation of available resources to achieve desired farm objectives. However, efforts to develop a realistic, comprehensive, and easily applicable model that fully integrates the farm management strategies of African smallholders have been limited. This paper first reviews the major modeling approaches prevalent in the literature and subsequently proposes a comprehensive farm management model designed to more effectively support African smallholders in achieving their food security and livelihood goals. The proposed model's features include the capability to manage diverse cropping systems, encompassing not only monocropping but also mixed cropping and intercropping with various crop combinations—practices commonly adopted by African smallholders as a key risk management strategy in the face of fluctuating climate and market conditions. The model also ensures the fulfillment of food production demands aligned with household dietary preferences and derives optimal solutions to enhance overall income through efficient labor allocation, both within agricultural activities and between agricultural and non-agricultural pursuits. Furthermore, this paper discusses several applications of the proposed model with specific technological components to identify optimal technology choices and adoption strategies for smallholder farmers.

1. Introduction

Significant efforts are being made to establish and promote sustainable agricultural innovation to mitigate the persistent threats of food insecurity and poverty in sub-Saharan Africa (SSA). However, there remains a gap between developing and applying methods specifically designed to effectively assist farmers in making informed decisions, including the judicious adoption of these agricultural innovations. For such decision support to be practical, the expected benefits must be substantial enough to incentivize farmers, necessitating efficient use of farm resources to realize those benefits. Inefficiency in resource use, often resulting from suboptimal resource management decisions, has historically compromised agricultural performance in SSA (Mesike et al., 2009). Consequently, there is a pressing need for robust farm decision-support tools to enhance resource use efficiency; however, their development and application remain limited in SSA. Greater efforts should be directed toward promoting decision-support mechanisms for African farmers to efficiently utilize available resources.

Mathematical programming is one of the most promising techniques for addressing resource use inefficiency in agriculture. It can identify alternative solutions that fully exploit economies of scope and maximize whole-farm profits. This technique has long been recognized as pivotal in elaborating and applying operations research across civilian sectors. Computer-aided decision-support systems have been developed and employed for a range of optimization purposes, including transportation scheduling, land allocation, and production planning. Compared to heuristic decision trees—another informative tool often used in decision-making research—mathematical model-based optimization techniques offer several advantages. These include accommodating multiple input and output decisions, conducting sensitivity and tradeoff analyses, and providing clear policy recommendations that identify sources of economic inefficiencies (Schreinemachers and Berger, 2006). Leveraging these advantages, numerous studies have applied mathematical programming to address the inefficiencies of conventional farm resource use practices and compute optimal alternatives (Mellaku and Sebsibe, 2022). However, as discussed below, existing modeling frameworks are often inadequate to provide effective and beneficial decision support for smallholder farmers in SSA. This inadequacy stems from the limited integration of their highly diversified cropping systems and food production requirements, the timely allocation of labor resources between farm and non-farm activities, and the impact of these factors on livelihood outcomes. All these elements are essential for establishing a realistic and comprehensive decision-support model that fully incorporates the livelihood strategies of smallholder farmers.

This paper first reviews the significant opportunities and challenges of mathematical programming model-based farm decision supports in developing regions, including SSA. Based on the review findings and the whole-farm modeling implications identified in Chapters 1-1, a basic structure for an alternative farm management model is then proposed, designed to efficiently assist smallholders in achieving their goals, including food security and income enhancement. Finally, this paper outlines exemplary applications and extensions of the proposed model to identify optimal technology adoption under varying contexts of technical promotion.

2. Mathematical programming model-based farm decision supports in developing regions

Most mathematical programming models used to optimize agricultural resource allocation in developing countries fall into single-objective linear programming (LP) models, multi-objective goal programming (GP) models, fuzzy goal programming (FGP) models, or GIS-based mathematical models (Mellaku and Sebsibe, 2022). Regardless of the model type, studies highlight the advantage of model-based agricultural resource use decisions in achieving optimal results compared to conventional agricultural resource decision-making practices.

Numerous studies employ LP decision-support models that aim to maximize the economic performance of cropping patterns, livestock systems, and land and water resource use. Compared to single-objective LP models, multi-objective GP models are less frequently used. However, they are well-suited to addressing different sustainability goals, including economic and environmental objectives, by assigning equal or desired weights to the objectives. Studies employing GP have demonstrated its potential role in significantly improving agricultural performance without compromising the sustainable use of natural resources (e.g., Leung and Lung, 2007; Hassan et al., 2012; Pastori et al., 2017). For instance, the multi-objective model analysis by Pastori et al. (2017) indicates that in most African countries, farmers can significantly increase their income while preserving the environment by adopting efficient soil nutrient and water management strategies. However, deterministic parameter estimation used in both LP and GP models is contested, given the precarious nature of agriculture, which is subject to climate and market fluctuations (Pal and Moitra, 2004). To reflect the uncertainty in model parameter estimation, FGP models were developed to allow flexibility by considering the risk level of each goal that may arise from imprecise climate and market information (Pal and Moitra, 2004; Sharma et al., 2007). Studies employing FGP models conclude that they may yield better results than conventional deterministic decision-making approaches (Sharma et al., 2007; Rezayi et al., 2017). Following the evolution of respective mathematical models, a current trend in mathematical model-based decision research in agriculture combines these models with geographic information systems (GIS) (Mellaku and Sebsibe 2022).

Although many studies employing mathematical programming—be it LP, GP, FGP, or their variants—report a positive influence on agricultural decision-making, there are practical concerns about how farmers benefit from these models (Collins et al., 2013). Notably, the mathematical decision-support models have varied levels of complexity, timescale, technical capability requirements, and data demands. While GP, FGP, and GIS-based models are more informative than LP models, their relatively high programming and computational costs of treating numerous objectives and parameters significantly limit their practical use. Moreover, the reliable data required for multi-objective models, particularly those incorporating environmental risk variables, are limited or costly to acquire. Data procurement is even more challenging when employing such models for dynamic decision analysis that requires reliable time series or panel data sources. Besides substantial data requirements, fuzzy logic and GIS-integrated models demand more extensive technical skill and expertise than others (Mellaku and Sebsibe 2022). The high cost of acquiring specialized software to run these models is another key constraint to extending their application, especially in low-income countries. On the other hand, simple LP models serve as relatively adaptable decision-support tools that might be used immediately to optimize single-time decision outcomes with limited technical skill, employing existing secondary or primary data.

LP models are common in agricultural decision-support studies in SSA, providing valuable insights into the economic inefficiencies of conventional resource allocation in agriculture and the potential for profitability enhancement through optimal solutions. Since a common problem most farmers encounter when aiming to maximize profit is crop mix selection, many decision-support studies have applied the LP model to identify profit-maximizing crop mixes (e.g., Mohamad and Said, 2011; Felix et al. 2013; Otoo et al. 2015; Buzuzi and Buzuzi, 2018). However, their findings are often unconvincing due to the insufficient consideration of cropping options, including mixed and intercropping systems, diverse food self-sufficiency requirements, the efficient allocation of labor between farm and non-farm sectors, and the subsequent impact on livelihood performance.

In many regions of SSA, smallholder farmers employ mixed and intercropping systems as essential strategies to mitigate the risks inherent in rainfed agriculture and to secure multiple sources of food and income. Yet, studies exploring optimal crop mixes typically optimize the selection of monocropping systems without incorporating farmers' mixed and intercropping options into the model (e.g., Mohamad and Said, 2011; Buzuzi and Buzuzi, 2018). Regarding the efficient allocation of labor between farm and non-farm activities and its impact on livelihood outcomes, no optimization studies, to the best of our knowledge, have accounted for these factors. Notably, non-farm activities are often overlooked but are crucial in household modeling (van Wijk et al., 2012). Furthermore, previous model-based optimization studies have rarely integrated alternative technology components into their models. Consequently, there is a lack of decision support that can inform farmers on which technologies to adopt and on what scale, and the expected benefits they would bring. Given the significant role that innovative technologies can play in enhancing smallholder farm productivity and profitability, it is imperative to identify resource use strategies that optimally leverage these technologies to achieve smallholders' food security and income objectives.

3. Basic structure of a farm management model to support African smallholder decision-making

As emphasized in the previous chapter (Chapter 1-1), African smallholders adopt farming systems designed to mitigate production and market risks by diversifying crop types and cropping patterns while simultaneously addressing household needs for food security and income. Moreover, they engage in livelihood strategies that enhance risk management and ensure the sustainable provision of food and income by securing a variety of non-agricultural livelihoods. The African Smallholder Farm Management Model (ASFAM) has been developed to integrate these strategies. As depicted in Figure 1, this model incorporates farming conditions (farm size, number of family labor, and wages), farming indexes (cropping systems, technology, yields, prices, costs, and labor hours), subsistence conditions (types and quantities of subsistence crops), and non-agricultural activities (water fetching, firewood collection, hunting/gathering, and off-farm employment). The ASFAM is designed to ensure (1) securing food production areas based on household dietary preferences, (2) incorporating risk mitigation strategies such as mixed/intercropping, and (3) maximizing income through optimal labor allocation between agricultural and non-agricultural activities. It enables identifying optimal cropping systems that enhance overall household income and offer farm improvement strategies tailored to smallholder farmers' dietary needs, risk management, and non-farm activity requirements (Koide et al., 2019).

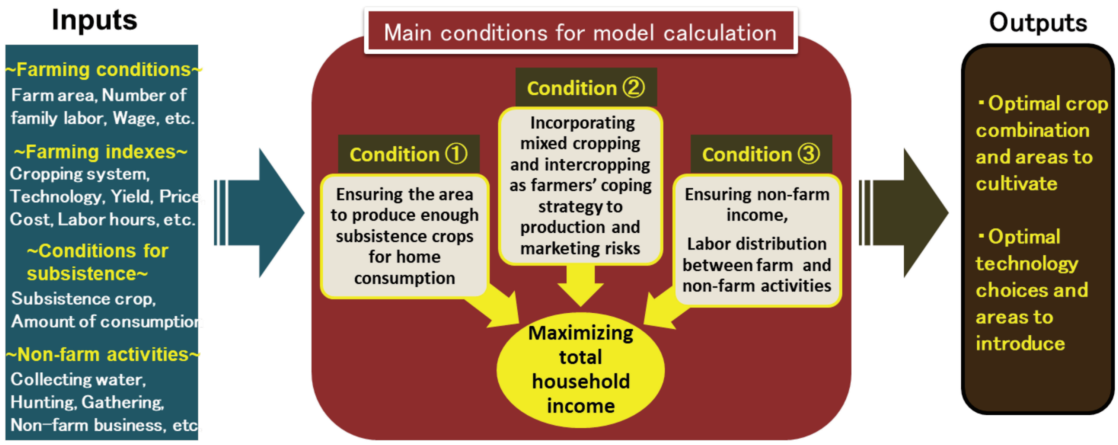

Figure 1. Schematic diagram of the basic structure of ASFAM

Following the above modeling framework, the basic structure of ASFAM is defined by the following single-objective linear programming, which simultaneously determines the optimal allocation of multiple farm resources to maximize the profitability of the entire cropping system while meeting household food self-sufficiency requirements.

$$\max Z = \sum_{i=1}^{m} c_i x_i$$

s.t.

$$\sum_{i=1}^{m} a_{ki} x_i \leq b_k, \qquad for\ all\ k$$

$$\sum_{i=1}^{m} d_{il} x_i \geq e_l, \qquad for\ all\ l$$

$$x_i \geq 0, \qquad for\ all\ i$$

where c_i is the net income of activity i, x_j is the area of activity i, a_{ki} is the technical coefficient that captures the level of use of resource k for activity i, b_k is available resource k, d_{il} is the yield of crop l from activity i, e_l is the household self-sufficiency requirement of crop l. i covers both farm and non-farm activities. k covers all types of farm resources to be considered, including farmland, which may be divided into several land categories (e.g., upland crops, lowland rice, and vegetable plots) and labor, reflecting the seasonality of family and hired labor inputs. In irrigation farming, water resources are included in k. Financial resource constraints may also be considered when the data are available. Crop l covers all edible crops used in each household, with e_l determined by the annual consumption of each crop.

The ASFAM has several unique features not found in traditional farm management models. One of these is the optimization of diverse cropping systems, including mixed and intercropping, contrasting with other models that focus on monocropping optimization. Additionally, the ASFAM addresses the efficient allocation of available labor between agricultural and non-agricultural activities and the consequent improvement of total household income. Despite the increasing importance of non-farm activities in household economies in SSA, this aspect has not been explicitly considered in current farm management models (van Wijk et al., 2012). While some studies have incorporated crop-specific subsistence requirements (e.g., Adesina and Ouattara, 2000; Igwe et al., 2013), they primarily focus on food self-sufficiency based on monocrop yields. The ASFAM, however, enables optimal calculations that meet farmers' food production demands based on the yields of each crop within mixed/intercropping systems, aligning more closely with the actual practices of smallholder farmers in SSA. Moreover, the ASFAM's structure is simple enough to be implemented in mathematical programming software that does not require specialized knowledge (or cost), making it accessible to non-researchers such as local agricultural extension agents. This enhances the model's applicability by facilitating technical guidance and decision support for potential local users (see Chapter 5-2).

The ASFAM is designed to simultaneously determine the optimal allocation of multiple resources, including land and labor (and other resources when available), to maximize household income—a primary livelihood objective for smallholders and a key indicator for practical decision support. Other economic metrics commonly used in mathematical programming-based farm management models, such as profit calculated by accounting for imputed costs (e.g., owned land and family labor costs) or utility measured by integrating various functions, are often challenging for smallholder farmers in SSA to comprehend and interpret. These metrics also demand relatively high data inputs and costs. Consequently, such measures are avoided in ASFAM to facilitate smoother model application and decision support for farmers. However, adjusting ASFAM to optimize resource allocation based on these metrics could be valuable for alternative purposes such as academic research. Furthermore, extending ASFAM into a stochastic simulation model that accounts for variations in crop yields and prices may be advantageous, aiming to maximize expected value or minimize the volatility of household income, profit, or utility.

4. Integration of technological components into the model

The ASFAM is fundamentally designed to identify the optimal configuration of multiple cropping options feasible for smallholders, the optimal adoption area for each cropping option, and the aggregate income derived from them. Additionally, if specific technologies are employed within these cropping options, the ASFAM can determine the adoption feasibility and the optimal adoption area for these technologies. For instance, consider the scenario where smallholder farmers in SSA gain access to chemical fertilizers—still limited in use—through governmental subsidies or technical guidance on fertilizer application. Development practitioners and local agricultural extension agents might want to know whether the target farmers should adopt cropping options involving chemical fertilizers to maximize overall profitability based on available resources and food requirements, and if so, to what extent. By incorporating the farm management indicators (yield, cost, and labor hours) of alternative cropping options involving the use of chemical fertilizers into the ASFAM, by either replacing or adding to those of conventional cropping options, it can determine the feasibility and optimal adoption area of such fertilized cropping options. An example of this model application will be presented in Chapter 2-2. Similarly, if there is an interest in guiding smallholder farmers in adopting a specific technology package—such as improved varieties or sowing methods coupled with chemical fertilizers—the ASFAM can identify the feasibility and optimal adoption area for such a package through similar data input and calculation processes.

The ASFAM can also be utilized to assess the feasibility and optimal adoption of technologies achievable by utilizing additional natural resources beyond the preexisting ones used in conventional agriculture. This involves extending the model constraints. For example, consider irrigation technologies. Agriculture in SSA largely relies on rainfed systems and is vulnerable to climate variability. Therefore, the development of irrigation technologies utilizing existing water resources like reservoirs has gained renewed attention for stabilizing crop productivity and profitability (Fox et al., 2005; Xie et al., 2014). However, even though SSA has substantial potential for irrigation, conventional irrigated agriculture practices are underdeveloped and often lack technical and input use efficiency (Nigussie et al., 2020). Therefore, it is imperative to provide decision support to farmers to efficiently utilize recommended irrigation technologies. Optimizing irrigation technology utilization necessitates explicitly incorporating the availability of water resources into the model alongside the resources of land and labor possessed by irrigation farmers. The availability of water resources, especially when sourced from reservoirs, is determined by hydrological conditions such as storage capacity and water balance. Furthermore, since reservoirs are often community-owned assets in SSA, the actual availability and allocation of water are practically regulated by social conditions, including customary rules, gender roles, and arrangements of local organizations, particularly water user associations. Thus, integrating these hydrological and social conditions into the modeling framework is crucial to appropriately analyze the feasibility and optimal adoption of irrigation technologies (Figure 2). Moreover, extending this integrated model into a stochastic simulation model, considering interannual variability in crop yields, production costs, and sale prices, allows evaluation of the stabilizing effects of irrigation technologies on the productivity and profitability of the entire cropping systems, thereby assessing their risk mitigation benefits. Chapter 3-2 will provide an example of such optimization of irrigation technology adoption considering risks.

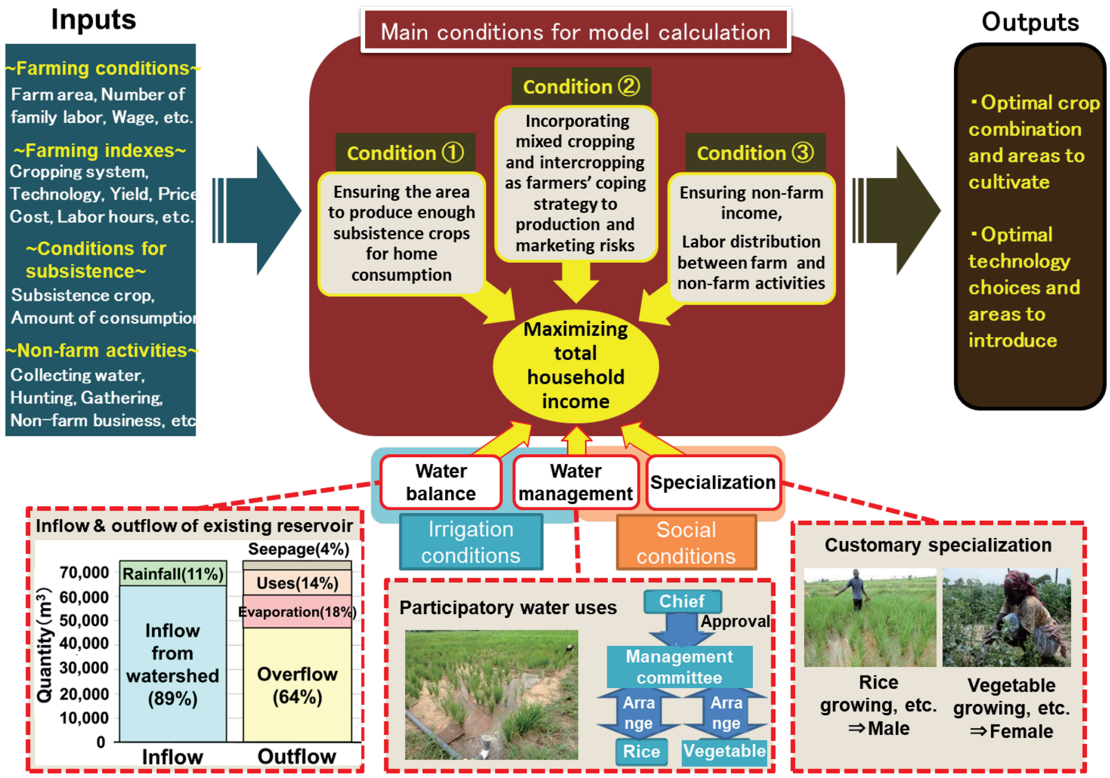

Figure 2. Schematic diagram of the extended ASFAM that integrates irrigation components

One might seek to enhance the ASFAM by incorporating new production sectors and determining the efficient resource allocation between these and the existing production sectors. In many cases, agriculture practiced by smallholders in SSA heavily relies on crop production. However, there is increasing emphasis on diversifying food, nutrition, and income sources, such as by promoting the introduction of valuable livestock like dairy cows. Moreover, in crop-livestock farming systems, the adoption of integration technologies—such as using crop residues as livestock feed or applying manure containing livestock excreta to crop fields—is essential for efficiently utilizing available farm resources and achieving desired outcomes, such as stable food and feed supply and income enhancement. The ASFAM can be expanded and applied to simultaneously optimize farm resource allocation between crop and livestock enterprises to maximize overall outcomes.

For example, Figure 3 presents a schematic diagram of a crop-livestock integrated management model that is an extension designed to derive optimal farm resource utilization for both cropping and dairy enterprises. The key optimization conditions added to this model include the animal composition and the feed supply-demand balance, both of which are necessary to sustain livestock production. The former condition is based on the composition ratio of animals at each growth stage that enables livestock reproduction, derived from factors such as calving intervals, accident rates, and rearing and production periods. The latter condition specifies the composition and quantity of feed and the nutrients required to achieve a certain level of livestock production. Among these feed compositions, the nutrient supply from self-produced feed is determined by the production of crop residues and forage. Consequently, the optimal cropping system can vary significantly depending on the relative productivity and profitability performance of different crop options, the nutrient supply required for the chosen livestock options, and their associated profitability. Additionally, among the optimal cropping area and livestock numbers simultaneously determined by the integrated farm management model, the latter must be an integer. Therefore, the model calculations rely on mixed-integer programming, in contrast to the linear programming used in models that solely optimize cropping systems. Chapter 4-2 presents an example of optimizing integrated farm management based on crop-dairy interactions using the ASFAM-based mixed-integer programming model.

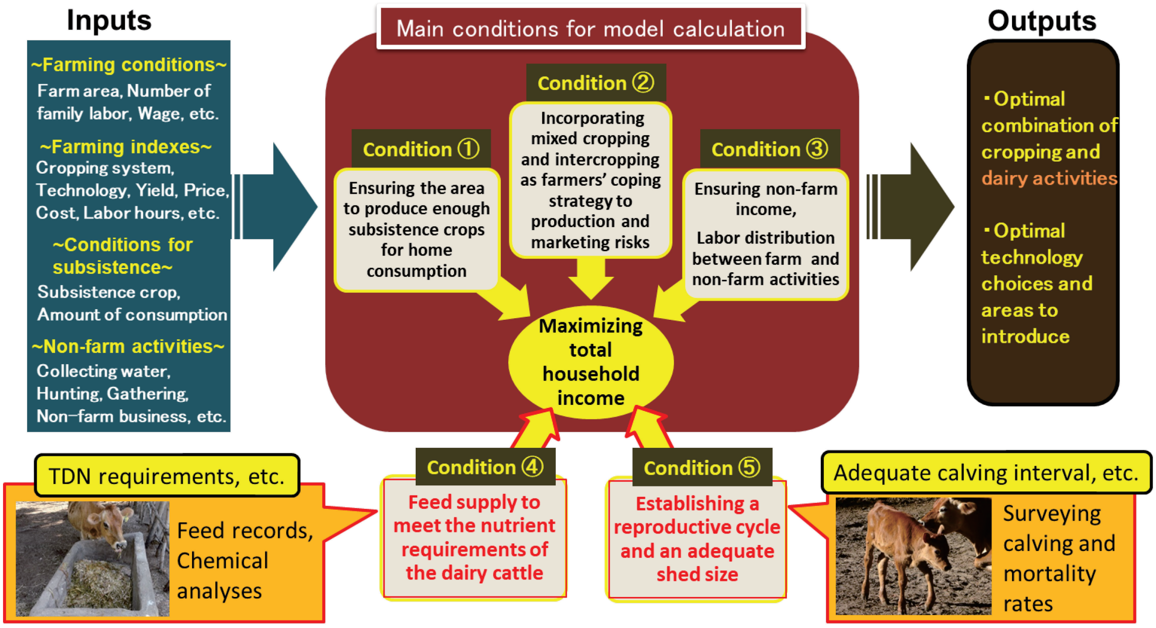

Figure 3. Schematic diagram of the extended ASFAM that integrates livestock components

5. Concluding remarks

This paper presents the development of a basic farm management model designed to support food security and income improvement among smallholder farmers in SSA. By applying ASFAM, it is possible to identify the optimal cropping solutions and their income-enhancing effects, which may effectively satisfy the needs of smallholder farmers. Moreover, by comparing these model outputs across multiple regions with differing agroecological environments and/or among various categories of farming households with distinct socioeconomic attributes (such as total farm size), it becomes feasible to pinpoint specific farm management issues that need to be addressed and to recommend tailored decision support for each region or household category. An example of such analyses is provided in the following chapter (Chapter 1-3).

This chapter discussed several examples of the application and extension of ASFAM aimed at identifying optimal technology adoption. From Chapter 2 to Chapter 4, research findings from various parts of SSA, obtained by applying models that incorporate additional technological components such as fertilization, irrigation, and crop-livestock integration, are presented. However, it is also possible to integrate other technological components into ASFAM and analyze optimal technology adoption and its effects on whole-farm benefits. The key strength of the proposed model lies in its fundamental and straightforward structure, which allows for easy extension and application in the development of optimal farming plans utilizing various technology options.

The farm management model proposed in this chapter is designed to efficiently address the multiple livelihood strategies currently employed by smallholder farmers in SSA. However, since these strategies may evolve, it is essential to apply the model in a way that allows for flexible adjustments to parameters and the types and weights of objectives considered within the model rather than constraining them in a deterministic manner. For instance, if the penetration of market economies in SSA leads to an increase in farmers pursuing more commercial-oriented agriculture, it will be crucial to recalibrate optimal farm management by carefully adjusting the weightings of updated food security and income objectives. The application of such adaptive modeling has not been thoroughly explored in this chapter and should be addressed in future research.

References

Adesina, A. A. & Ouattara, A. D. (2000). Risk and agricultural systems in Northern Côte d'Ivoire. *Agricultural Systems*, 66, 17–32. https://doi.org/10.1016/s0308-521x(00)00033-0.

Buzuzi, G. & Buzuzi, A. N. (2018). A mathematical programming technique to crop mix problem on a farm in Mutasa, Manicaland Province, Zimbabwe. *International Journal of Economic Management Studies*, 5(11), 6–10.

Chagunda, M. G., Mwangwela, A., Mumba, C., Dos Anjos, F., Kawonga, B. S., Hopkins, R., & Chiwona-Kartun, L. (2016). Assessing and managing intensification in smallholder dairy systems for food and nutrition security in sub-Saharan Africa. *Regional Environmental Change*, 16(8), 2257–2267.

Collins, A. J., Vegesana, K. B., Seiler, M. J., O'Shea, P., Hettiarachchi, P., & McKenzie, F. (2013). Simulation and mathematical programming decision-making support for smallholder farming. *Environment Systems and Decisions*, 33, 427–439.

Duncan, A. J., Tarawali, S. A., Thorne, P. J., Valbuena, D., Descheemaeker, K., & Tui, S. H. K. (2013). Integrated crop-livestock systems: A key to sustainable intensification in Africa. *Tropical*

Grasslands, 1(2), 202-206. https://doi.org/10.17138/tgft(1)202-206.

Felix, M., Judith, M., Jonathan, M., & Munashe, S. (2013). Modeling a small farm livelihood system using linear programming in Bindura, Zimbabwe. *Research Journal of Management Sciences*, 2(5), 20–23.

Fox, P., Rockström, J., & Barron, J. (2005). Risk analysis and economic viability of water harvesting for supplemental irrigation in semi-arid Burkina Faso and Kenya. *Agricultural Systems*, 83, 231–250. https://doi.org/10.1016/j.agsy.2004.04.002.

Hassan, N., Safiai, S., Raduan, N. H. M., & Ayop, Z. (2012). Goal programming formulation in nutrient management for chilli plantation in Sungai Buloh, Malaysia. *Advances in Environmental Biology*, 4008–4013.

Igwe, K. C. & Onyenweaku, C. E. (2013). A linear programming approach to food crops and livestock enterprises planning in Aba agricultural zone of Abia State, Nigeria. *American Journal of Experimental Agriculture*, 3(2), 412–431.

Kafle, K., Winter-Nelson, A., & Goldsmith, P. (2016). Does 25 cents more per day make a difference? The impact of livestock transfer and development in rural Zambia. *Food Policy*, 63, 62–72.

Kidoido, M. & Korir, L. (2015). Do low-income households in Tanzania derive income and nutrition benefits from dairy innovation and dairy production? *Food Security*, 7(3), 681–692.

Leung, S. C. & Ng, W. L. (2007). A goal programming model for production planning of perishable products with postponement. *Computers & Industrial Engineering*, 53(3), 531–541.

Mellaku, M. T. & Sebsibe, A. S. (2022). Potential of mathematical model-based decision making to promote sustainable performance of agriculture in developing countries: A review article. *Heliyon*, 8(2).

Mesike, C. S., Owie, O. E. D., & Okoh, R. N. (2009). Resource-use efficiency and return to scale in smallholders rubber farming system in Edo State, Nigeria. *Journal of Human Ecology*, 28(3), 183–186.

Mohamad, N. H. & Said, F. (2011). A mathematical programming approach to crop mix problem. *African Journal of Agricultural Research*, 6(1), 191–197.

Nigussie, E., Olwal, T., Musumba, G., Tegegne, T., Lemma, A., & Mekuria, F. (2020). IoT-based irrigation management for smallholder farmers in rural sub-Saharan Africa. *Procedia Computer Science*, 177, 86–93.

Otoo, J., Ofori, J. K., & Amoah, F. (2015). Optimal selection of crops: A case study of small scale farms in Fanteakwa district, Ghana. *International Journal of Scientific and Technology Research*, 4, 142–146.

Pal, B. B. & Moitra, B. N. (2004). Using fuzzy goal programming for long range production planning in agricultural systems. *Indian Journal of Agricultural Economics*, 59(1).

Pastori, M., Udías, A., Bouraoui, F., & Bidoglio, G. (2017). A multi-objective approach to evaluate the economic and environmental impacts of alternative water and nutrient management strategies in Africa. *Journal of Environmental Informatics*, 29(1), 193–201.

Rezayi, A. & Mardani, M. (2017). Using fuzzy goal programming technique in optimal cropping pattern. *International Journal of Applied Operational Research*, 7(1), 63–75.

Schreinemachers, P. & Berger, T. (2006). Land use decisions in developing countries and their representation in multi-agent systems. *Journal of Land Use Science*, 1(1), 29–44.

Sharma, D. K. (2016). Fuzzy goal programming for agricultural land allocation problems. *Yugoslav Journal of Operations Research*, 17(1).

Sumberg, J. (2003). Toward a dis-aggregated view of crop-livestock integration in Western Africa. *Land Use Policy*, 20(3), 253–264. https://doi.org/10.1016/S0264-8377(03)00021-8.

Van Wijk, M. T., Rufino, M. C., Enahoro, D., Parsons, D., Silvestri, S., Valdivia, R. O., & Herrero, M. (2012). A review on farm household modelling with a focus on climate change adaptation and mitigation. *Working Paper No. 20*. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Copenhagen, Denmark.

Xie, H., You, L., Wielgosz, B., & Ringler, C. (2014). Estimating the potential for expanding smallholder irrigation in sub-Saharan Africa. *Agricultural Water Management*, 131, 183–193. https://doi.org/10.1016/j.agwat.2013.08.011.