Flagship 2, Project P265

Activity Report 2018

CSV Monitoring and Evaluation Plan

Deliverable D5256:
ICT based CSA-Calculator tool for farm level monitoring

By Nadine Andrieu and Osana Bonilla-Findji

March 2019

Activity report: CSV Monitoring and Evaluation Plan

2018 Deliverable (D5256): ICT based CSA-Calculator tool for farm level monitoring

Implementation period: January – December 2018

Summary description

This research activity focused on the development, calibration and piloting of one of the components of the CSV Monitoring plan currently been implemented across the CCAFS CSV network, and its integration into the ICT based App developed for data collection purposes.

The CSA calculator is a farm model tool allowing the prospective assessment of the trade-offs and synergies between the three pillars of CSA and between the CSA practices and other farming activities. A first version of this tool was developed and tested in Colombia (Osorio et al., 2019). During the implementing period, and in order to strengthen the quantitative assessment of CSA at farm level in the CSV monitoring, the tool was adjusted to allow a more generic assessment of farming systems (across sites) and to include it in the ICT-based CSV monitoring tool. Indeed the tool was adapted to take into account farming systems in 9 different countries in Latin America, West Africa, East Africa, South Asia and South East Asia. The associated data collection was carried in close collaboration with regional teams and flagship projects in 8 CSV sites: Cauca (Colombia), Santa Rita (Honduras), Tuma-La Dalia (Nicaragua), Olopa (Guatemala), Hoima (Uganda), Nawalparasi (Nepal), Barisal, Khulna (Bangladesh). It involved a strong capacity building component including the training of 14 Supervisors and 42 local enumerators.

The current report highlights the rationale and scope of this work, the challenges encounter along the calibration process, the analytical approach that will be applied to the data and perspectives of future work.

I. Scope and rationale: Presentation and justification of the initial version of the CSA calculator

The introduction of a new practice at the farm level implies specific reframing of existing production systems and activities (Andrieu et al., 2015). Whole-farm models are particularly relevant for analyzing such reframing since they can be used to represent the links between farm sub-systems and decisions taken by the farmer (Whitbread et al., 2010). Rodriguez et al. (2014) showed that whole-farm models are useful tools for ex-ante evaluations of options and identifying farming system characteristics that may increase resilience in the face of change and uncertainty. This scale of assessment is also the relevant one to assess synergies and trade-offs in portfolios of practices. Some whole farm models have been developed to analyze the effect at the farm level of different strategies to cope with climate change (Claessens et al, 2012; Rodriguez et al., 2014). Recently, Hammond et al. (2017) developed The Rural Household Multi-Indicator Survey (RHoMIS) for rapid characterization of households to inform climate smart agriculture interventions using quantitative indicators (income, emissions intensity, food availability) and qualitative indicators (poverty index, gender equity index, household dietary diversity).

For our assessment we used a tool developed in Colombia that aims to quantitatively assess the climate-smartness of a farm linking indicators associated to the three CSA pillars with farm resource (fodder, food, nutrient, water, cash) analysis (Osorio et al., 2019).

In the CSA literature, **productivity** is often assessed qualitatively (scores) or quantitatively in terms of yield, labor, income, and food security in some of its diverse dimensions (food access, availability, utilization, stability) (Richardson, 2010). In the CSA calculator we used three indicators: **caloric self-sufficiency** as a proxy for food utilization, **benefit/cost ratio of the farm** as a proxy of both food economic access and income, and **fodder ratio** to assess the balance between fodder production and fodder demand (Osorio et al., 2019).

Adaptation is probably the most challenging pillar generally assessed in terms of improved resilience, which itself includes various dimensions such as socioeconomic, ecological, or engineering resilience (Antwi et al. 2014). Acosta-Alba et al. (2019) proposed to assess ecological resilience using life cycle assessment. In the CSA calculator we focused on engineering resilience that is more specifically related to the reorganization capacity of farm production factors (e.g., soil, water, crops) and calculated the **water and nutrient self-sufficiencies** of the farm. We considered the partial supply of water (from rainfall and the water harvesting technologies tested) and nutrient (from mineral and organic fertilizers) for the different crops of the farm. Such indicators were used to detect imbalances between supply and demand in farm production factors that can lead to a depletion in environmental resources (Sempore et al. 2016, Van den Bosch et al. 1998). For nutrient self-sufficiency, we considered in Colombia only nitrogen supply and demand given that nitrogen was the main macronutrient found in mineral fertilizers applied by farmers. We also considered in this assessment of engineering resilience the planned **biodiversity** that is the biodiversity associated with the crops and livestock purposely included in the agroecosystem by the farmer, and which will vary depending on the management of inputs and crop spatial/temporal arrangements (Altieri 1999). We used the index proposed by Gobbi and Casasola (2003) that ranked this biodiversity between 0 and 1 according to the type of land use.

To assess the **mitigation potential** (carbon emissions and sequestration capacity), we used the CoolFarm Tool (version 2.0 Beta 3) (Hillier 2012) that despite presenting limitations associated to the uncertainty of the emission factors provides accessible approaches to estimate GHG impacts from agriculture, taking into account the whole farm source and sinks of emission (Richards et al. 2016; Hillier 2012).

The first version of the CSA calculator was first developed on Excel thus not requiring specific programming skills. The input data required by the CSA calculator, were collected through a conventional survey based questionnaires applied among a sub-sample of CSA implementing farmers. They included questions on:

- Size of the family;
- CSA practices currently tested;
- Areas of the main crops;
- Number of animals (number of animal per batch, sales and purchases);
- Amount of input used (organic and mineral) and prices per crop and livestock batch
- Sale prices
- Management of crop residues (burning, compost….)

Table 1: *Main indicators of the CSA calculator at farm level*

CSA Pilar	**Indicator**	**Calculation**
Productivity	Caloric ratio of the farm (%)	Caloric supply/Caloric demand x 100
	Fodder ratio of the farm (%)	Fodder supply/Fodder demand x 100
	Cost benefit ratio (%)	Benefit/Cost x 100
Adaptation	Biodiversity index (%)	Assessment based on Gobbi, J., Casasola, F., 2003.
	Water balance (%)	Water supply/water demand x 100
	Nutrient balance (%)	Nutrient supply/nutrient demand x 100
Mitigation	Emission/Sequestration of CO_2	CoolFarmTool

II. Adaptation of the CSA calculator

The initial version of the tool used parameters estimated from the regional literature. This choice limits the number of required input data collected through surveys, however, it implies a higher literature review to estimate such parameters. For example, previously, the yields were not asked to the farmers and were considered as a parameter. We chose to ask directly the farmer about this value and base our calculations on this information rather than on a single regional value. Another adaptation of the CSA calculator was its calibration in 9 other countries (Ghana, Guatemala, Honduras, Nicaragua, Vietnam, Uganda, Bangladesh, India, Nepal). This meant identifying the types of crops, animals, fodder, inputs (pesticides, organic and mineral fertilizers, fodder), manure management systems found in each site in order to reframe the way the questions were asked, deleting some modalities of answers that did not make sense in the study site.

Another adaptation done after the Ghana pilot consisted in including it under the form of additional modules, in the ICT-based CSV monitoring application. The major implication in this case was that from this moment on, the units used for the surface areas of the main crops or the amount of input used in the application had to be predetermined. Before it was possible during the survey to use the units used by the farmers, such units may change from a crop to another.

III. Data collection

Enumerators and facilitators have been trained for data collection for the 9 countries. In each site 7 enumerators were trained. Special care was taken in selecting specific profiles of enumerators to implement the CSA calculator, emphasizing the need for high skills regarding how to make translations/conversions between the units locally used by the farmers and the ones used in the application. Data were collected in 7 of the 9 countries where the CSA calculator has been calibrated (Ghana, Guatemala, Honduras, Nicaragua, Uganda, Nepal and Bangladesh). In Vietnam and India, the data will be collected in 2019.

Table 2: *Number of surveyed farmers*

	Ghana	**Guatemala**	**Honduras**	**Nicaragua**	**Uganda**	**Nepal**	**Bangladesh**
Surveyed farmers	60	26	30	35	36	34	42

IV. Preliminary results across-sites

The calibration of the tool across sites allowed a first transversal comparison of the characteristics of farming systems highlighting the challenge of representing the whole farm when the production system is complicated.

We found that the land tenure has implication of the type of land use changes that can or not be conducted. For example, in Vietnam the land use is defined by the government, land use changes are consequently not allowed which has implication on emissions at farm level. Also, even if the home gardens were found in different countries they do not have the same size and importance from a country to another and do not have the same contribution to the food security of the family.

Table 3: *Main structural characteristics in the study sites*

	Colombia	**Ghana**	**Guatemala/Honduras/Nicaragua**	**Uganda**	**Vietnam**
Land tenure	Land owners	Land users	Land owners	Land users	Land users
Main cash crops	Coffee Sugar cane	Bambara beans Ground nuts	Coffee	Cassava Maize	Rice Cassava
Main staple crops	-	Maize Sorghum	Maize Bean	Cassava Maize	Rice Cassava
Main livestock	-	Small ruminants	-	Cattle	Buffalo Pig
Feeding management	-	Communal grazing	-	Communal grazing	Cut and carry

Fishery	No	No	No	No	Yes
Presence of home gardens	Yes	No	Yes	No	Yes
Presence of a forest area in the farm	No	No	No	No	Yes
Biodiversity	-	+++	++	++	+++

V. Systemic assessment of CSA effectiveness: Example of Ghana

Taking the example of Ghana, we present in this section the benefit of integrating the CSA calculator in the overall ICT-based CSV monitoring tool that comprises two other dimensions: an analysis of adoption, motivations and constraining factors at community level and gender disaggregated perception of farmers on the effects of CSA options on their livelihoods. We particularly show, how the data collected for the CSA calculator will be analyzed considering the typology of households present in each CSV (using information collected in modules M0 demographic module and M5 CSA practices module of the Monitoring survey).

5.1. Data analysis

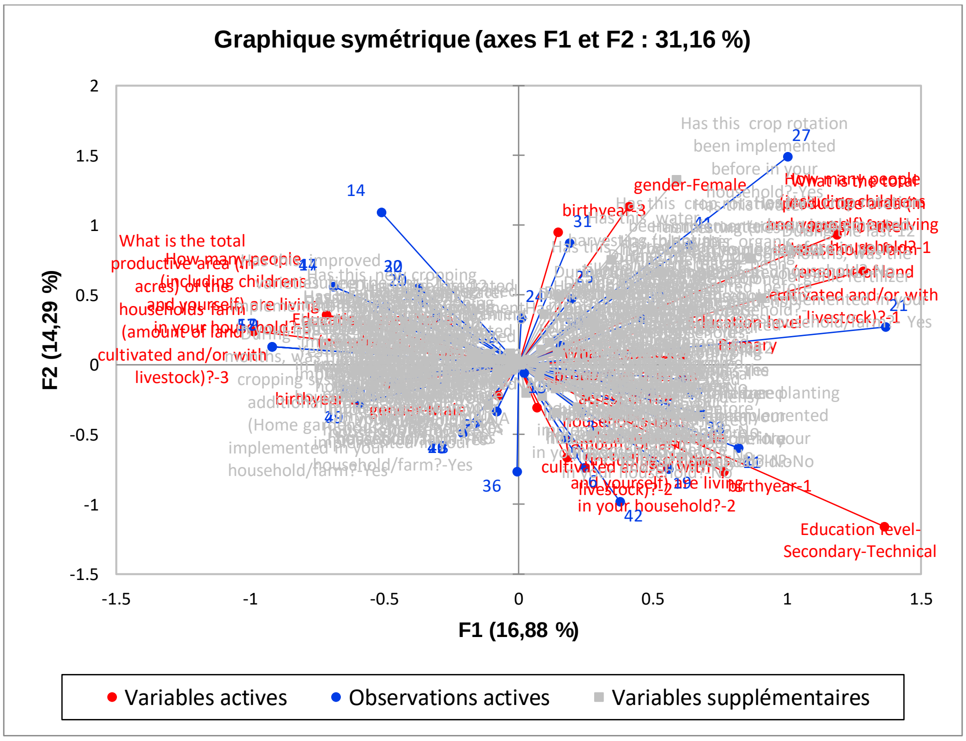
This typology of adoption of CSA practices, based on households socio-economic characteristics and CSA adoption trends is developed through a multiple correspondence analysis (MCA) (Greenacre, 1984) and a hierarchical clustering (HC) applied to data collected in M0 and M5 applied to the head of household (n-= 191). The MCA and HC allows to identify the main types of farming systems based on the socio-economic variables that may affect adoption of innovative practices. In the literature, household characteristics, such as gender, education, income, being affected by climate events are key in adaptation decisions (Alauddin and Sarker, 2014; Ariti et al., 2015; Barnes et al., 2013; Chandra Sahu and Mishra, 2013; Galdies et al., 2016).

We consider as active variables individual characteristics of the head of household (the gender, off-farm income, access to lean, being affected by food shortage), farm characteristics (productive area of the farm), variables related to climate (being affected by climate events) and access to services from key local stakeholders. Numerical variables were transformed into categorical variables according to the data distribution (average and quartiles). These active variables were considered as explanatory variables. Dependent variables (adoption of CSA practices) were used as supplementary variables (Table 4).

***Table 4**: Variables considered in the factor analysis*

Active variables	Gender Size of the household Size of the total productive area Climate related events Other main source of income Savings made from agriculture activities Access to loan or credit Food shortage
Supplementary variables	Crop rotation Improved varieties Integrated management Intercropping Mulching Reduced tillage Home gardens Organic fertilizer Tree planting Earth bunds Pits Ties ridges

5.2. Preliminary results in Ghana



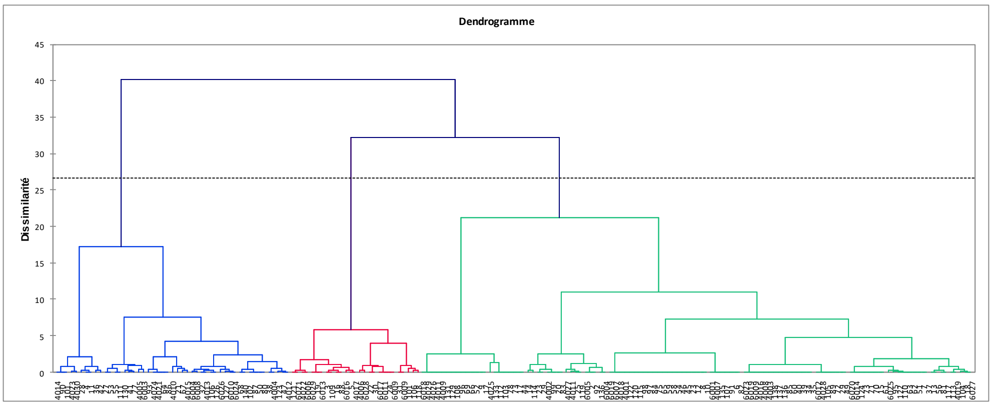


Figure 1: *Factor and cluster analysis to identify types of adoption*

We found three main classes:

1: the biggest group that we call the “**adopters”** are farmers mainly men with the higher productive area implementing practices, having no access to loan, were not affected by climate events

2: here we have the “**non-adopters”** that are farmers, mix men and women, that are not implementing practices and that did not have experience with these practices before, they have a low productive area, no access to loan, were not affected by climate events

3: here we have the “**poor-adopters”** that are farmers with an higher proportion of women than the other classes, with lower productive area, they are adopting practices, affected by climate, having access to loan, having problem of access to food, having additional income

The figure 2 shows the differences in terms of climate smartness for the farm the most representative members of the “adopting” types 1 and 3. Both farms implemented the same portfolios: crop rotation, improved varieties, integrated nutrient management, organic fertilizers, ties ridges. Additionally, the farm representative of type 1 is implementing reduced tillage

The farm representative of type 1 has the best performances under the three pillars. Indeed this farm covers the family requirement and generate a higher income than the farm representative of type 3 and it is more diverse. The amount of fertilizer used are the same between farms, however, farm 1 has less emission from the livestock sub-system. The introduction of CSA practices in both farms allowed them to increase their production area. However it may be noticed that more mineral fertilizers have been used in farm 1 for maize compared to the initial situation. This additional income generated may have been used to intensify the production.

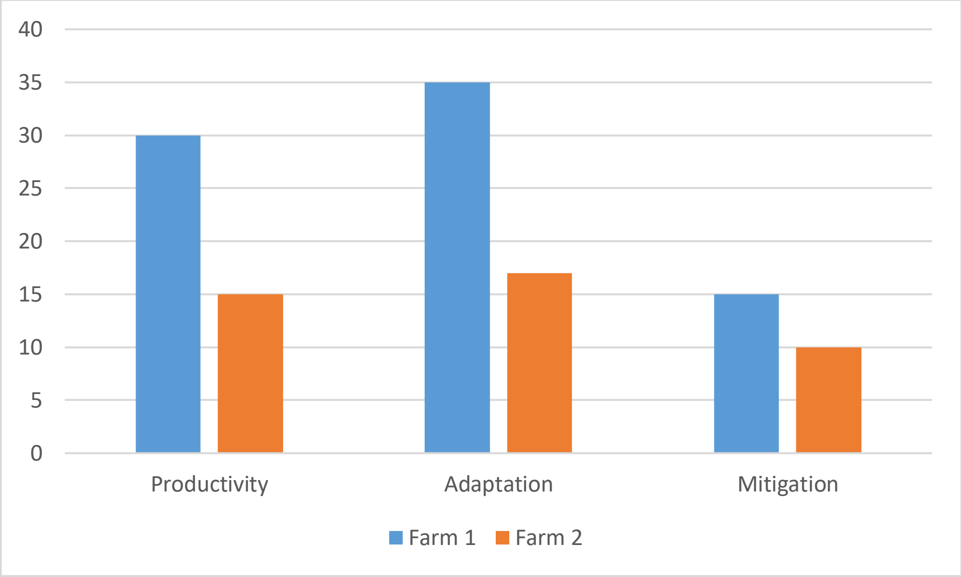


Figure 2: *Improvement of CSA practices linked to the introduction of practices*

VI. Main challenges of the inclusion of the CSA calculator in the ICT-based CVS monitoring tool

Going from an Excel tool to the application made the entry of data more rigid, particularly taking into account the units used for a given crop or for the inputs used, given that they are now coded. Indeed, even if we identified the main units found in a study site before the data collection, for a specific farmer, these units may change (for example a farmer may prefer defining his/her area in hectare rather than in *tarea*, the unit used in Guatemala). Consequently, the main challenge found was to identify in each study site an enumerator with at least a bachelor degree in agronomy or economy. This type of enumerator was generally used to collect quantitative data and particularly knew how to translate the units used by the farmer in the units coded in the application. In the different study sites, we found heterogeneous level between enumerators.

We have seen in the table 2 that the farms are more or less complicated with many sub-systems in Vietnam for example. In this case, the facilitator may decide to make an emphasis not on all the crops or animals of the farms but on the two or three main crops and animals of the farm. A rule for the crops can be to select the ones where the practices are implemented and corresponding to 50 to 70 % of the cropping areas. This rule should be defined by the facilitator of the site and keep constant from one year to another.

VII. Perspectives

We have as team different activities to implement for the next period:

- Development of a manual describing the whole ICT-based CSV monitoring tool (from the selection of enumerator, the calculations and the description of the data collected)
- A paper presenting the whole ICT-based CSV with its application in Ghana with deeper

analysis of the motivations of farmers to understand for example the motivations of farmers and better interpret why they are adopting CSA pratices and farmers perceived perception on them

- A paper on the transversal comparison of farming systems in the study sites

References

Acosta-Alba, I., Chia, E., Andrieu, N. (2019). The LCA4CSA framework: Using life cycle assessment to strengthen environmental sustainability analysis of climate smart agriculture options at farm and crop system levels. Agric. Syst., in press. https://doi.org/10.1016/j.agsy.2019.02.001

Alauddin, M., Sarker, M. A. R. (2014). Climate change and farm-level adaptation decisions and strategies in drought-prone and groundwater-depleted areas of Bangladesh: An empirical investigation. Ecological Economics, 106, 204-213. DOI 10.1016/j.ecolecon.2014.07.025

Antwi, E., K. Otsuki, O. Saito, F. Obeng, K. Gyekye, J. Boakye-danquah, Y. Boafo, et al. 2014. “Developing a Community-Based Resilience Assessment Model with Reference to Northern Ghana.” IDRiM 4 (1): 73–92. https://doi.org/10.5595/idrim.2014.0066.

Ariti, A. T., van Vliet, J., Verburg, P. H. (2015). Land-use and land-cover changes in the Central Rift Valley of Ethiopia: Assessment of perception and adaptation of stakeholders. Applied Geography, 65, 28-37. DOI 10.1016/j.apgeog.2015.10.002

Barnes, A. P., Islam, M. M., Toma, L. (2013). Heterogeneity in climate change risk perception amongst dairy farmers: A latent class clustering analysis. Applied Geography, 41, 105-115. DOI 10.1016/j.apgeog.2013.03.011

Chandra Sahu, N., Mishra, D. (2013). Analysis of perception and adaptability strategies of the farmers to climate change in Odisha, India. APCBEE Procedia, 5, 123-127. DOI 10.1016/j.apcbee.2013.05.022

Galdies, C., Said, A., Camilleri, L., Caruana, M. (2016). Climate change trends in Malta and related beliefs, concerns and attitudes toward adaptation among Gozitan farmers. European Journal of Agronomy, 74, 18-28. DOI 10.1016/j.eja.2015.11.011Hammond, J., S. Fraval, J. van Etten, J. G. Suchini, L. Mercado, T. Pagella, R. Frelat, et al. 2017. “The Rural Household Multi-Indicator Survey (RHoMIS) for Rapid Characterisation of Households to Inform Climate Smart Agriculture Interventions: Description and Applications in East Africa and Central America.” Agricultural Systems 151: 225–33. https://doi.org/10.1016/j.agsy.2016.05.003.

Greenacre, M.J., 1984. Theory and Applications of Correspondence Analysis. Academic Press, London, U K.

Hillier, J. 2012. “CoolFarmTool.” Aberdeen, UK: University of Aberdeen. https://coolfarmtool.org/.

Osorio-García, A.M., Paz, L., Howland, F., Ortega, L.A., Acosta-Alba, I., Arenas L., Chirinda N., Martinez-Baron, D., Bonilla Findji, O., Loboguerrero, A.M., Chia, E., Andrieu, N. Can an innovation platform support a local process of Climate-Smart Agriculture implementation? A case study in Cauca, Colombia. Agroecology and Sustainable Food Systems. Under revision.

Richards, M., R. Metzel, N. Chirinda, P. Ly, G. Nyamadzawo, Q. Duong Vu, A. de Neergaard, et al. 2016. “Limits of Agricultural Greenhouse Gas Calculators to Predict Soil N2O and CH4 Fluxes in Tropical Agriculture.” Scientific Reports 6 (1): 1–5. https://doi.org/10.1038/srep26279.

Richardson, R. B. 2010. “Ecosystem Services and Food Security: Economic Perspectives on

Environmental Sustainability.” Sustainability . https://doi.org/10.3390/su2113520.

Rodriguez, D., H. Cox, P. DeVoil, and B. Power. 2014. “A Participatory Whole Farm Modelling Approach to Understand Impacts and Increase Preparedness to Climate Change in Australia.” Agricultural Systems 126: 50–61. https://doi.org/10.1016/j.agsy.2013.04.003.ha

Sempore, A., N. Andrieu, P. Le Gal, H. Nacro, and M. Sedogo. 2016. “Supporting Better Crop-Livestock Integration on Small-Scale West African Farms: A Simulation-Based Approach.” Agroecology and Sustainable Food Systems 40 (1): 3–23. https://doi.org/10.1080/21683565.2015.1089966.