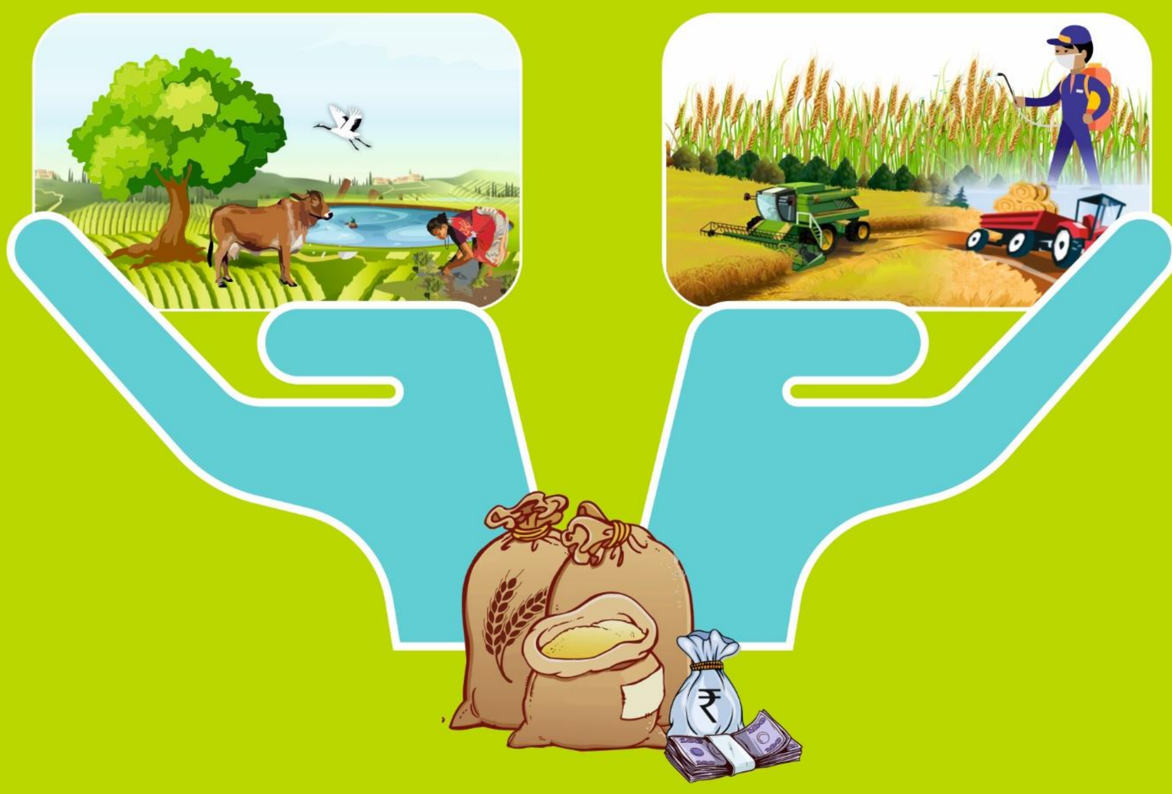
Development and Application of a Farm Assessment Index (FAI)

-Towards a Holistic Comparison of Organic and Chemical Farming



November, 2018

DEVELOPMENT & APPLICATION OF A FARM ASSESSMENT INDEX (FAI):
Towards A Holistic Comparison of Organic and Chemical Farming

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PREFACE

It was in an internal meeting in ASHA (Alliance for Sustainable & Holistic Agriculture) in 2011 that a small thought was first articulated – that we need a HDI equivalent (Human Development Index) in agricultural sciences, and what it (HDI) managed to do to expose GDP (Gross Domestic Product) as a narrow but much-used indicator of growth and development in our world today. For several working in the domain of ecological agriculture, the narrow focus mainly on yields in the mainstream agricultural development paradigm was disturbing and they wanted an assessment tool that was more holistic, that had the potential to capture overall performance of a particular agricultural paradigm on numerous fronts, beyond yields. This, it was felt, would be useful to farmers and policy makers too, to make decisions that are rooted in sustainability.

ASHA representatives reached out to Organic Farming Association of India (OFAI), and also some scientists like (late) Dr Om Prakash Rupela to collaborate with us in this. They also began reaching out to several organisations working with farmers in different states, in promoting organic farming. Some states and locations were shortlisted where we could take up the comparison of organic farms with chemical farms, using a composite index that looks at social and environmental impacts too. Sitting in Dharamitra's campus in Wardha in 2012, an initial intense workshop was undertaken, about the scope and methodology of such a research endeavour. It was decided that a one-season or one-year study will not do. That it has to be over several seasons. There was no access to any funds at this point of time but the team decided to plod on with the idea taking shape slowly.

After visiting several places, the collaboration of Chetana Vikas and Dharamitra in Maharashtra, Tribal Health Initiative in Tamil Nadu, Chetna Organic project of Forum For Integrated Development in Odisha and Savayava Krushikara Sangha in Karnataka was enlisted for taking up field based research in four states. The contribution of these organisation to obtaining high quality field data, by extending the time of their senior staff voluntarily, to oversee the work of field enumerators regularly, is sincerely acknowledged. Field enumerators were local staff and their work is gratefully acknowledged.

The cooperation extended by all the farmers who participated in the study, in both the organic farm samples as well as the conventional ones, is noteworthy and sincere thanks are extended to them.

Data collection began, using a survey-based methodology, with the questionnaires administered at three different points of an agricultural season, after an orientation to the field enumerators from all the 4 states and after a piloting of the questionnaires evolved.

It was in 2013 that IIT-Bombay's CTARA came into the picture and this was a great boost to the whole effort. Prof Om Damani of CTARA and his doctoral student Siva Muthuprakash were instrumental in bringing in the theoretical framework to the development of the composite index and a more thorough sorting of indicators to be used. The methodology also shifted to inclusion of a farm diary to be maintained for each farmer by the field enumerators and not just a 3-time survey with questionnaires. It was a unique collaboration between a PhD student supported by an able guide and a set of civil society organisations, that started unfolding thereafter. Dr Srijit Mishra who was with IGIDR in Mumbai and later with NCDS in Bhubaneswar added to the methodological rigor required for a study like this. Within the collaborating organisations were scientific brains of Ashok Bang of Chetna Vikas and Dr Tarak Kate of Dharamitra, who are both ecological agriculture science experts. The insights and inputs of Kapil Shah of Jatan (Baroda) throughout the research project were very useful and valuable. While Siva Muthuprakash focused on the states of Tamil Nadu and Maharashtra for the purposes of his PhD, ASHA and OFAI focused on Odisha and Karnataka, to continue with the original 4-state effort. The “composite index” was also formally renamed as “Farm Assessment Index” or FAI.

While Dr OP Rupela passed away succumbing to cancer in 2015, his contribution to this study is enormous and significant, starting from discussions on indicators to be included, to framing of questions in the Questionnaire. The study also benefited from the inputs of Dr N Devakumar, who was with the Regional Institute of Organic Farming in University of Agricultural Sciences, Bangalore.

In the entire effort, the support of Swissaid is notable. Starting from the initial pilot phase in 2012-13, they supported the study through their partner organisations like Indian Social Action Forum, Centre for Sustainable Agriculture, Forum For Integrated Development and Sahaja Samrudha. Joint review workshops on an annual basis and payment of honorarium to field enumerators was done with this support. Association for India’s Development (AID) also pitched in with a small grant at the beginning of this effort. Based on a proposal put in by IIT-B, NABARD extended its support to the research project for two seasons in the state of Maharashtra. This also enabled soil sample analyses to be taken up.

This research report is long over-due, after having completed its formal processes of wrapping up in 2017 and with Siva Muthuprakash submitting his PhD thesis in April 2018. A major part of this work was carried out and submitted by the first author for his partial fulfilment of the degree of Doctor of Philosophy to CTARA, IIT Bombay, under the supervision of Prof. Om Damani, IIT Bombay, Mumbai. We advise any citation to this report should accompany the reference to the PhD thesis as per the details below

“Siva Muthuprakash (2018), Development and Field Application of the Farm Assessment Index (FAI) for Evaluation of Farming Systems, PhD Thesis, Centre for Technology Alternative for Rural Areas, IIT Bombay, Mumbai.”

Siva also developed an alternative, more user-friendly online tool for any stakeholder including farmers, to feed in data on their farming system along chosen parameters, obtain a Farm Assessment Index value and monitor progress or compare with other systems themselves. This demonstrated clearly that a simpler version of FAI is possible to evolve, for mass application.

It is hoped that the Farm Assessment Index developed here, on a stock-and-flow based framework, will indeed be adopted by the Indian National Agricultural Research System (NARS) so that research results are appraised holistically before they are disseminated and deployed on a large scale. The collaborators of this study are enthused by some recent announcements to this effect by the Indian Council for Agricultural Research (ICAR) and sincerely encourage policy makers to use more comprehensive indices like FAI in their decision-making so that agricultural development is not lopsided, or short-sighted.

- All Collaborators of this Research Project

November, 2018

1. Introduction

In India, the existing agricultural programs and interventions focus mostly on increasing the crop yield and overall production, overlooking the long-term undesirable outcomes. For example, Green Revolution has helped India in achieving self-sufficiency in food grains, but it has long been realized that the input intensive farming has caused serious environmental and health impacts (NAAS India 2011; Planning Commission 2002).

Therefore, there has been an increasing attention towards the assessment of agricultural sustainability because of growing threats to human health, ecosystem, and livelihood of farmers. Assessment plays an important role in effective design and strengthening of public policies and programs. The methodology for the assessment depends on the availability of financial resources, time and other constraints and may involve surveys, interviews, field measurements, modelling and simulation, etc. (Speelman et al. 2007). The key features of a sustainability assessment are to integrate the planning, monitoring and decision support tools, and provide useful guidance for the transition towards sustainability (Kates et al. 2012; Ness et al. 2007)

1.1. Indicators and Indices

Indicators are often used as a standalone tool to understand, evaluate and monitor the state of a given system. They act as a bridge to understand complex systems (Monteith 1996). They translate scientific knowledge into manageable units of information that can aid the decision-making process (United Nations 2001; Rossing et al. 2007; Heink and Kowarik 2010).

While scientific community prefers detailed data, policymakers need a composite index which can be easily communicated and unambiguously interpreted by the wider masses (Hammond et al. 1995). Composite index is an aggregate of several base indicators which helps in summarizing the information provided by all the base indicators. It allows us to communicate an overall judgment about the state of the system (Gómez-Limón and Sanchez-Fernandez 2010).

Aggregating indicators of various dimension into a single number is often debatable, and the arbitrary nature of weighing might disguise serious failings (Sharpe 2004). However, aggregation can be justified if it fits the intended purpose and accepted by peers and stakeholders (Rosen 1991; Roy and Chan 2011). Subjectivity is the major aspect of concern in the design of composite indicators. However, the subjectivity is accepted as a part of the research process and is often essential for field applications (Munda, Nijkamp, and Rietveld 1995).

1.2. Farm Assessment Studies

Since the last decade, there has been several farm sustainability frameworks and studies ranging from field level to national level. The scope of these studies has varied widely, as shown in Table 1.

Table 1 Farm sustainability studies with various scope of study

S No	Scope of the study	References
1	Design of framework for indicator selection	(Smyth et al. 1993; Walker and Reuter 1996; Bossel 2000; López-Ridaura et al. 2005; Van Cauwenbergh et al. 2007; Pannell and Glenn 2000; Haberl et al. 2004)
2	A set of indicators identified for farm assessment	(Calker et al. 2005; Sauvenier et al. 2005; Roy and Chan 2011; Dantsis et al. 2010),
3	Case studies using the selected indicators	(Rigby et al. 2001; Astier et al. 2011; NABARD 2012; Srinivasa Rao et al. 2018)
4	Policy recommendations using indicator study	(Gómez-Limón and Sanchez-Fernandez 2010; Speelman et al. 2007; Ceyhan 2010; Merante, Van Passel, and Pacini 2015)
5	Design of assessment tools	(Viglizzo et al. 2006; Andrieu, Piraux, and Tonneau 2007; Wiek and Binder 2005; Meul et al. 2008)

In India, agricultural development and farm sustainability have been studied in a few regions using different set of indicators (Sharma and Shardendu 2011; NABARD 2012; Chand, Sirohi, and Sirohi 2015). A composite Index of Climate Resilient Agriculture (ICRA) has also been designed by aggregating a set of 30 sustainability indicators to provide a framework to measure the climate change adaptation and mitigation levels in agriculture (Srinivasa Rao *et al.*, 2018). However, the existing indicator studies either lack a supportive framework, or they are based on frameworks that depend on pre-set attributes and criteria, rather than a systemic selection process. Both the absence of a framework as well as frameworks based on pre-set attributes often lead to redundancy and gap in system representation, making the methodology less reliable. Besides, most of the existing frameworks do not explain the rationale behind the choice and selection of sustainability themes on which the entire indicator selection is dependent (Werf and Petit 2002).

In contrast to the pre-set criteria approach, in this work, a holistic set of indicators were identified by using a stock and flow model of the farming system, covering socio-economic and ecological dimensions (Siva Muthuprakash and Damani 2017). We design a composite metric called Farm Assessment Index (FAI) by aggregating the holistic set of indicators identified for comparing farming systems. The robust design of FAI helps in comparison of a wide range of farming systems across various crops and regions. As a case study, the proposed methodology has been used to assess the farming practices of organic and conventional farmers from four regions in India.

2. Stock and Flow Framework

A conceptual framework guides any research process by adding rigor to an idea or a concept. The concepts of Stock and Flow and System Dynamics are often used to predict future scenarios like long term impacts of agricultural practices (Li, Dong, and Li 2012; Shi and Gill 2005). Stock describe the characteristics of the system that are accumulated over long term, and Flow describe the transient and dynamic characteristics of the system (Sterman 2000). Stock and Flow models help us in capturing the characteristics of the system as a whole, along with its causal linkages which will help in understanding the relative importance of the indicators. It provides a structural basis for the reasoning of the inclusion or exclusion of related indicators. It helps in differentiating the short term and long term characteristics of the system. It also helps to capture, represent and reproduce the indicator selection process for any system with a set of guidelines. These guidelines aid in visualizing various dimensions of the biophysical processes and the spatio-temporal boundaries across these dimension.

The outline of our framework is given in Figure 1. Note that, while the indicator selection process is shown as a linear one, in practice, it will often be an iterative one. In this framework, stock variables inside the system capture the stability and resilience of the system, and the variables from biophysical flows across the system-environment boundary capture both the desirable outcomes and undesirable impacts. The framework also aids in selection of appropriate proxy indicators for hard to measure primary indicators by tracing their forward and backward linkages rather than avoiding the complex indicators all together. A proxy indicator is a substitute variable representative of the actual indicator and its trends.

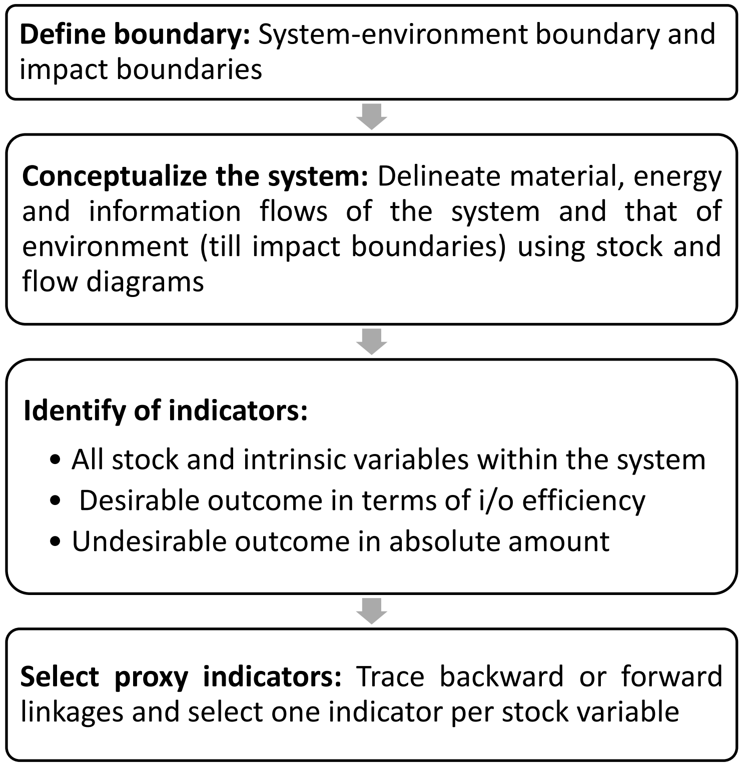

Figure 1 Outline of stock and flow based framework for indicator selection

2.1. Defining the system and its boundary

The initial step in the construction of a stock and flow diagram is to define the system and carefully delineate the system-environment boundary. We conceptualize the environment of the system by distinguishing the ecological and socio-economic dimensions. Any biophysical outflow of the system is associated with its own impacts in social and economic dimensions. While in theory, impacts of the system can be traced indefinitely in space and time, in practice, it is required to set a boundary for the environment as well. Further, it may be ideal to have a uniform boundary across all three dimensions but in reality, we often have imbalanced scenarios across the dimension as the changes along ecological dimension reflect in socio-economic dimension after a significant delay.

For example, as shown in Figure 2, the nutrient runoff from a farming field is taken as material outflow from the system to its environment and a part of its downstream linkages in social and economic dimensions. The nutrient runoff causes water contamination, which in turn increases the GHG emission from water bodies. In this case, water contamination leading to drinking water problems are observed after a short delay while GHG emission leading to secondary health impacts are realized after a significant delay. Further, the economic aspect of drinking water contamination or the health impacts appears after even longer delay.

While full-cost accounting can help in filling the gap by assigning economic value for the unpriced cost and benefits (FAO 2014), it may not be possible to account for all the relevant economic and social impacts like distributional impacts, human health and well-being (Weidema, Finnveden, and Stewart 2005). Therefore, it is necessary to have independent boundary along different dimensions depending upon the scope and objective of the study which varies with time and space. We use the term 'impact boundary' to represent the dimensional boundary of the environment.

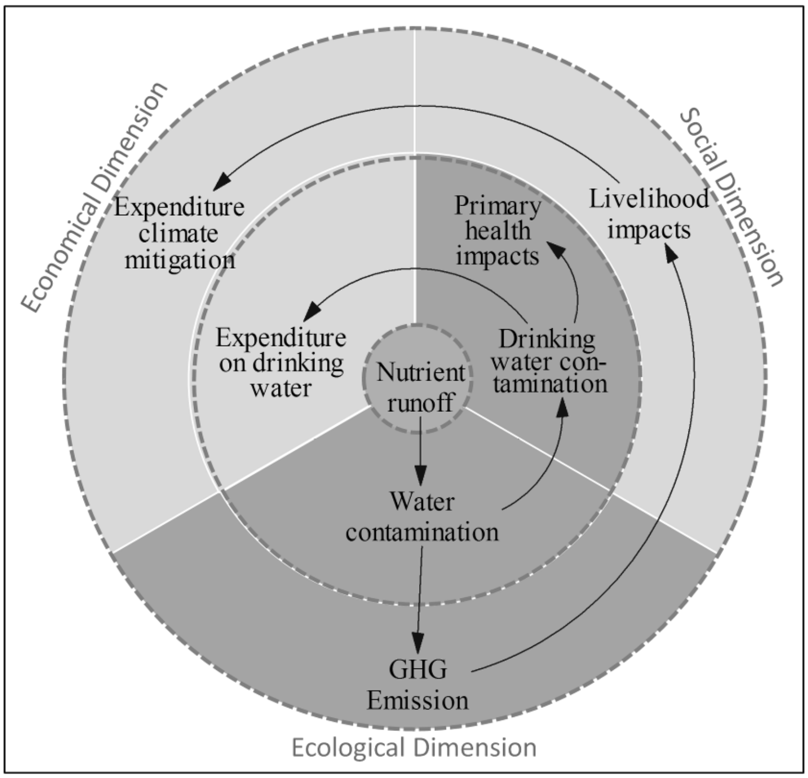

Figure 2 Varying boundaries along different dimensions for an outflow variable
(Grey colored annuli represent the variables outside the impact boundary)

While farm is often considered as the smallest enterprise in agriculture, analyzing or comparing sustainability of farm with different type of crops is difficult and scarcely conclusive (Gómez-Limón and Sanchez-Fernandez 2010). We take the field as our system and consider the actual boundary of the field as the system boundary as majority of decisions by farmers varies at the field level. The impact boundaries vary among outflow and inflow variables as mentioned in the framework and are determined based on the objectives of the study with the inputs from the stakeholders like policy makers, scientists, field officers and farmers.

2.2. Conceptualization of the system

Once the boundaries are defined, the initial step is to conceptualize the system as a black-box (Nathan and Reddy 2011) and detail the list of inputs and outputs of the system which will help in identifying the start and end points of interest. Then, all the relevant processes and their feedback loops involving material, energy, and information flows of the system are identified (Wolstenholme 1983). Then each process is delineated by introducing stocks and flows which might in turn bring focus on yet unconsidered processes involving more variables. Stocks are the variables whose value depends on the past behaviour of the system and they accumulate material or information over time. They represent the inertia of the system and change only as a result of flows. Flow variables cause changes in system state, and they either flow into or out of the stock.

For example, in Figure 3, the nutrient in an arable soil is a stock which is affected by the inflows like nutrient input and natural synthesis, and outflows like nutrient uptake by crops, microbes, etc., and nutrient runoff. Various factors like fertilizer input, biological fixation, irrigation etc. affect the nutrient stock only by affecting the relevant flows.

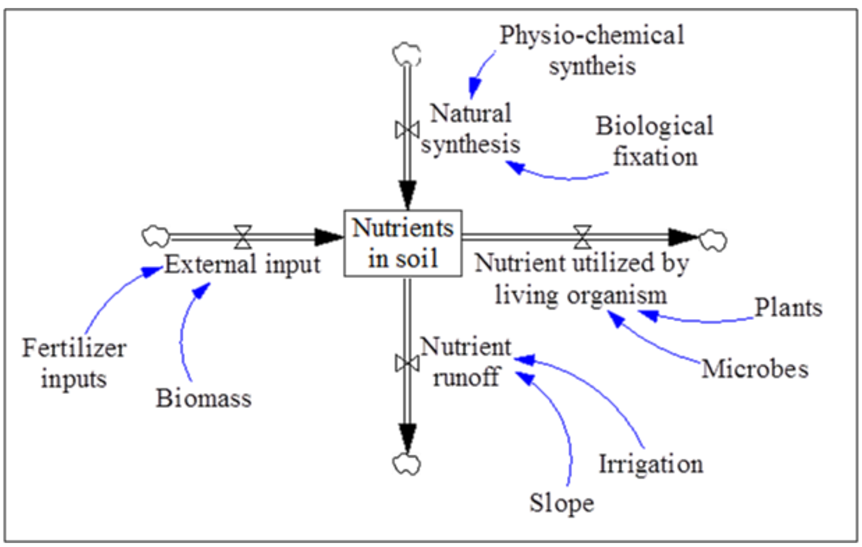

Figure 3 Example of stock and flow diagram

The stock and flow diagram (SFD) with all significant processes and phenomena of the system forms the conceptual model for visualizing various independent and interdependent processes. This helps us in capturing all the essential characteristics of the system and guides us in identification of indicators.

Since the physical boundary of the field is taken as the system boundary, the input flow starts with materials like seeds, water, nutrients, pesticides, etc., and ends with desirable outputs like harvest of target product and byproducts, and undesirable outcomes like water contamination, soil health impacts etc.

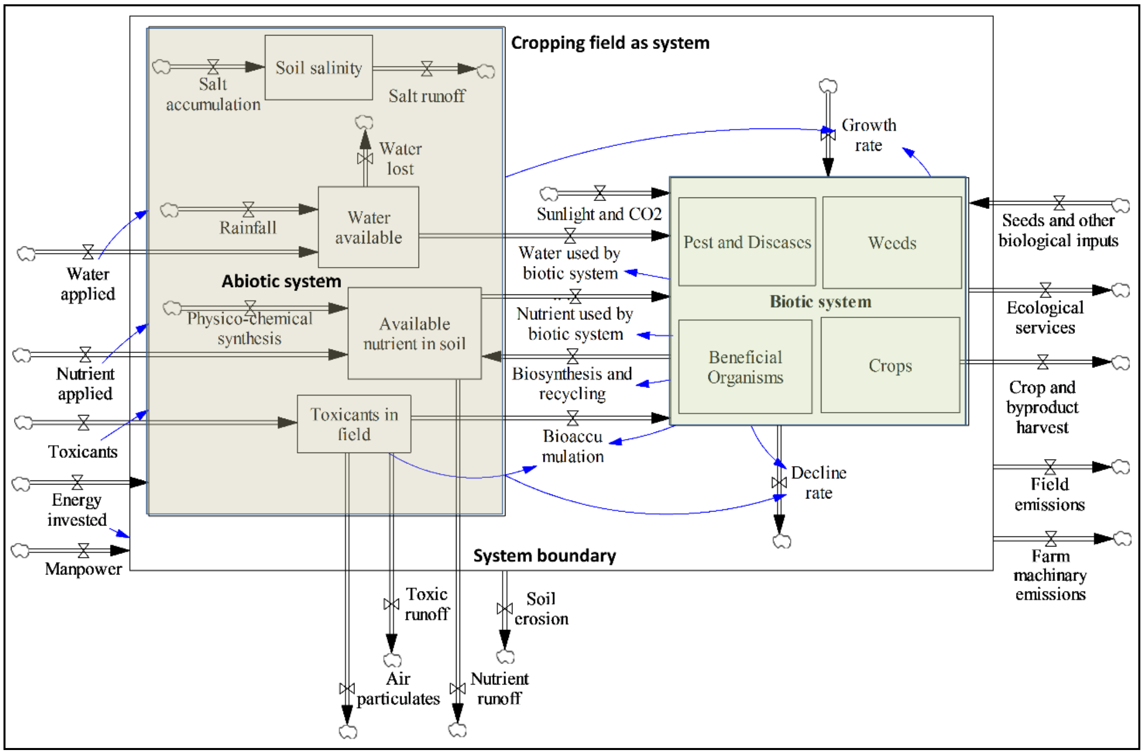

Figure 4 A simplified stock and flow diagram for farming system

The minimum temporal scale for the evaluation of agricultural system is one cropping season and it is taken as the unit period for flow. Figure 4 gives a simplified stock and flow diagram of the farming system which shows the nutrient and energy inflows and outflows of the field with two separate components: abiotic and biotic components within the field.

The material flows including nutrient, water, toxicants and seeds, enter the field to contribute to either abiotic or biotic stock. Then they flow either to agro-ecological environment in the form of runoff, emissions, ecological services etc., or flow to the human interface as farm produce. Though the materials flow through their corresponding stocks in the system, these material stocks affect various intrinsic variables like soil pH, soil compactness etc., which also constitute the characteristics of system. Since there are numerous interactions among the stocks of abiotic and biotic component within the field, these interactions are not portrayed in Fig 5 to maintain the readability of the diagram.

2.3. Identification of indicators

Although all the variables in a system can be taken as indicators, it leads to unwarranted redundancy due to interdependent and correlated variables. It is necessary to capture the state of the system in totality while avoiding over or under accounting of any system characteristics. Therefore, it is essential to systematize the process of indicator identification.

Basis for identification of indicators

In any production system, short-term desirable outcomes often get the major focus while several desirable and undesirable outcomes that are not perceived to be important in short term, are neglected. For example, in case of agriculture, conventional indicators like yield and income are flow variables that capture only the immediate outcome of farming, and fail to capture the sustainability related attributes like soil quality that has strong inertia and changes slowly with time.

The production process involves material, energy and information inflows that eventually result in a variety of outputs and outcomes. While the inflows to the system are the resources consumed, the outflow will include intended outputs along with unintended outcomes. The unintended outcomes can be either beneficial or harmful, and they can be either within or outside the system. While the intended outputs are visible and measured easily, the unintended outcomes may or may not be apparent in short term, but they impact the sustainability of the system in long run. Since the stock variables describe the state of system that have accumulated the past impacts, they should be the major focus in the indicator set to account for the long term sustainability. Therefore, first, the stock variables that are present within the system boundary are taken as indicators.

Following the stock variables intrinsic variables of the system are taken as indicators. Intrinsic variables are those variables which represent the characteristic of the system that emerge out the interaction between a set of underlying stocks. Then the input and output flows across the system boundary are the variables of interest. Flow variables constitute the bio-physical interactions between the system and its surrounding. As discussed earlier, each bio-physical flow variable is associated with its own impact on economic, social and ecological attributes which may be desirable or undesirable.

A production system can be considered to perform better if there is either an increase in desirable outcomes, or a decrease in undesirable outcomes. In order to evaluate the performance of any system with respect to its desirable outcome, it is appropriate to measure their output efficiency with respect to the inputs (Jahanshahloo et al. 2012). Although not backed by conceptual reasoning, European Commission (European Commission 2001) has also recommended the usage of stocks followed by efficiency parameters and equity of resources. While there has been a long debate on efficiency indicators and the resource depletion in life-cycle thinking (Klinglmair, Sala, and Brandão 2014), the stock and flow based framework focuses on the production efficiency of only those components which lie within the system boundary.

In case of undesirable outcomes, eliminating them altogether may not be feasible as it may work against the main objective of the system. For example, it may not be possible to totally curb the GHG emissions from a thermal power plant but it is feasible to minimize it. Therefore, the objective should be to restrict the harmful outcomes within the safety limits or permissible standards. Hence, the undesirable outcomes are measured in absolute amount of impact caused. This approach is comparable to the use of biomass flows and balance of the farm by Andrieu et al. (Andrieu, Piraux, and Tonneau 2007) to identify the indicators where the indicators are focused on the changes to characteristics of resources. In short, the indicators associated with desirable outcomes should be measured in terms of input-output efficiency while the undesirable outcomes need to be measured in terms of absolute values.

While material and physical characteristics of the system can be modeled using various techniques, social characteristics like personal values, power etc., demand qualitative approaches (Mingers and Rosenhead 2004). Accounting for the social aspects of a system is relatively challenging due to the qualitative nature of social dimension which is often intangible and lacks consensus (von Geibler et al. 2006). The complex and often conflicting nature of qualitative variables demand an active participation of all the stakeholders in order to capture the social aspects of the system (Midgley and Reynolds 2004). Since the objective of our study is to develop a set of indicators with wider applicability, we have considered only the descriptive characteristics like producer and consumer health and avoided the normative variables like custom, values etc., for the social dimension.

Uncontrolled attributes like rainfall, sunlight etc., that originate outside the system boundary but affect crop production, are considered as extraneous variables that constitute the parameters of system. These variables are not taken as indicators and ideally need to be constant while comparing different systems.

2.4. Identifying proxy indicators

While it may be ideal to measure all the identified indicators for a comprehensive analysis, there is a trade-off between the extent of information captured and the ease of monitoring (Rigby et al. 2001). There are a few scenarios where selection of indicators may be challenging. Identification of proxy indicators that could capture these indicators with a simpler measure is desirable. A proxy indicator is a substitute variable used when the desired data is unavailable or too complex to measure. We select appropriate proxy indicators for hard to measure primary indicators by tracing their forward and backward linkages rather than avoiding complex indicators all together. It should be representative of the variable of our interest and have a close approximation to the target indicator.

For example, stock variables like water contamination, bioaccumulation, health impacts, etc. are non-point pollution caused due to the usage of farm inputs, such as fertilizers and pesticides. Given that these stock variables are influenced by various extraneous factors, it is neither appropriate to attribute all the changes in these variables to farming practices, nor it is feasible to identify the impacts corresponding to farming practices alone. For example, though an open-well may be situated within an organic farm, it might be contaminated due to the sub-surface leaching of contaminants from neighbouring farm. Therefore, using the backward linkages, the amount of toxicants applied to the system is considered relative to the impact caused, and hence the toxicant applied can be taken as a proxy.

3. Design of Farm Assessment Index (FAI)

The construction of a composite index involves four distinctive steps viz. indicator selection, normalisation, weighing and aggregation.

3.1. Indicator selection

Farm Assessment Index (FAI) uses the comprehensive set of indicators identified using the stock and flow framework. The comprehensive set of indicators identified and selected across the economic, social, and ecological dimensions are listed in Figure 5. The numbers (in %) in Figure 5 represent the weightage of each indicator used in this study for FAI, and it will be discussed later in Section 4.3. Followed by indicator selection, the first step in the application of indicators is to define them based on the objectives and scope of the application.

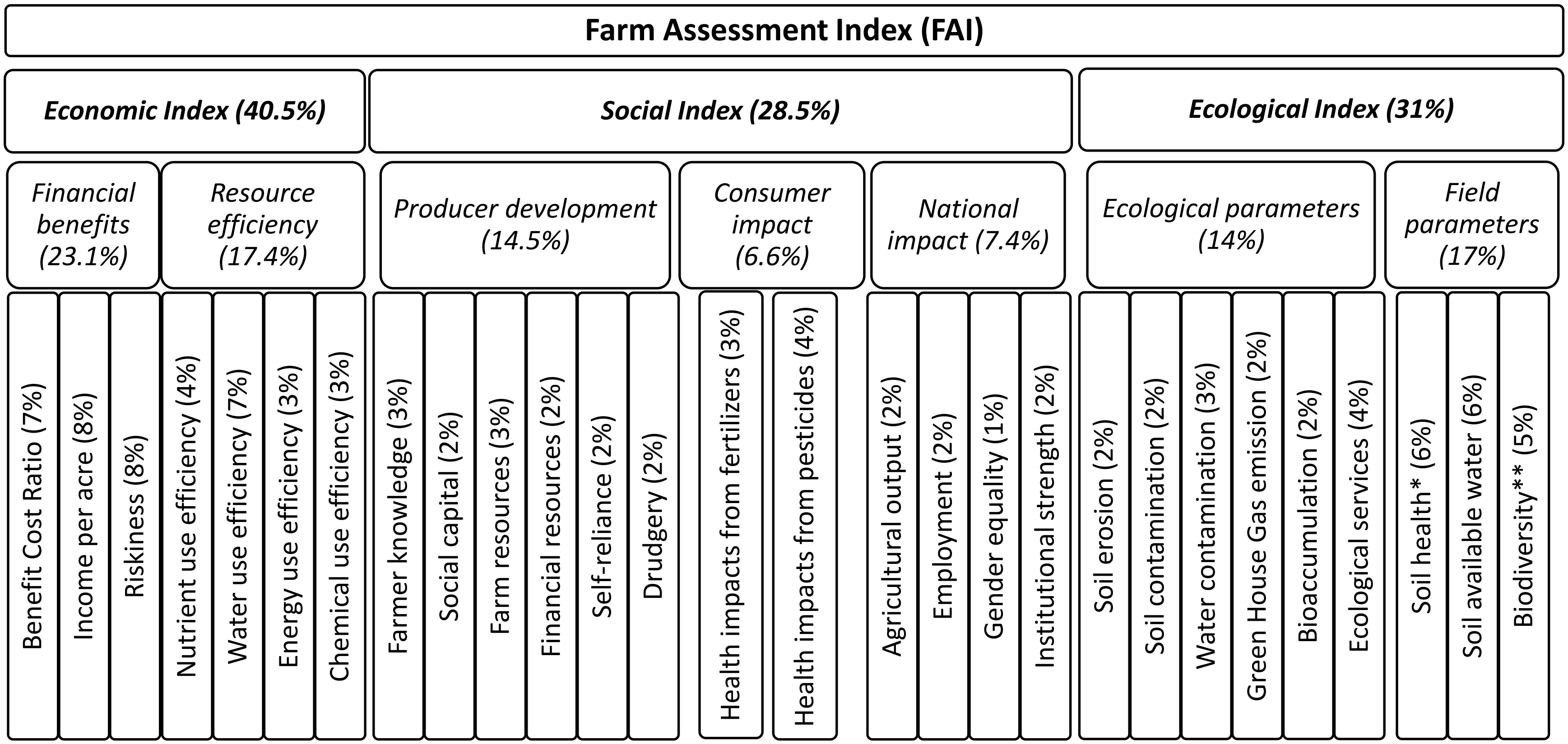

Figure 5 Hierarchical classification of indicators in FAI and their weightage assigned in the case study

*has at least five sub-indicators including soil nutrients (nitrogen, phosphorous and potassium), soil pH and soil salinity
** has at least two sub-indicators including crop diversity and non-crop diversity

3.2. Indicator definition

Indicators are to be defined in the spatio-temporal context with the participation of stakeholders (Bockstaller et al. 2008). For example, water use efficiency can be defined in several ways such as yield per unit water consumed by the crop, or yield per unit water applied to the field. A trade-off is made between the level of detailing and feasibility depending upon the end application and utility of the indicator. Depending on the definition of indicators, an appropriate method to estimate each indicator is selected.

While it is desirable to measure all the indicators identified, in this study, we define and estimate 17 variables covering a set of 26 indicators. Table 2 gives the definition of the indicators along with their unit of measurement and method of estimation.

Table 2 Indicator definition with the unit of measure and their estimation methodology

S No	Indicators	Definition (All variables are calculated on per acre basis)	Unit	Estimation
1	Income per acre	The total value of the farm produce minus the paidout cost for cultivation	₹/acre	Field survey
2	Benefit-cost ratio	The ratio of total value of farm produce to paidout cost of cultivation	Dimensionless (DMNL)	
3	Crop yield	Total crop produce including intercrops	kg/acre	
4	Self-reliance	The ratio of self-borne cost to total cost of cultivation	Dimensionless	
5	Drudgery	The ratio of gross income to the expenditure on labours including self-borne labours (Gross income per unit labour)	Dimensionless	
6	Riskiness	The total cost of cultivation with the cost imputed for self-borne labour and inputs	₹/acre	
7	Financial resources	Paidout cost of cultivation	₹/acre	
8	Employment	The ratio of expenditure on total labour to the total cost of cultivation	Dimensionless	
9	Nutrient use efficiency	The nutrient balance between total nutrient applied and nutrient consumed by the crop for unit production	kg/acre	

10	Fertiliser Impact Quotient (FIQ)	Fertiliser Impact Quotient (FIQ) is defined as the estimate of nutrient balance between total nutrient applied and nutrient consumed with respect to the crop yield. It captures the direct and indirect impacts like soil and water contamination, health hazards etc., caused due to fertiliser usage	Dimensionless	
11	Pesticide Impact Quotient (PIQ)	Pesticide Impact Quotient (PIQ) is an estimate of impact based on the potential toxicity of active ingredients and dosage applied. It captures the direct and indirect impacts like health hazards, soil and water contamination, etc., caused due to pesticide usage	Dimensionless	Field survey and PIQ tool
12	Soil Organic matter	Amount of organic content in the soil	% of soil	Laboratory testing
13	Total Nitrogen	Nutrient in the soil	PPM of N	
14	Available phosphorous		kg P/Ha	
15	Available potassium		kg K/Ha	
16	Soil pH	pH of the soil	Dimensionless	
17	Soil salinity	The salinity of the soil	DS/cm	

We use direct survey-based estimation for socio-economic and ecological indicators, and use laboratory techniques for the estimation of soil parameters. In defining the socio-economic indicators, we use the term “paidout cost” to represent the actual expenditure of the farmer without imputing any cost for self-borne labour and inputs (for example, farmyard manure from farmer's field or kitchen waste). In the case of total cost of cultivation and total labour expense, the market value of home borne material inputs and the opportunity cost of self-borne labour are included.

Most of the indicators estimated from the data collected through survey are relatively simple and direct to estimate, but the estimation of PIQ and FIQ are relatively complex. PIQ uses the toxicological database of pesticides and the dosage applied to measure the impacts of pesticide application on producers, consumers and the agro-ecology (Kovach et al. 1992). PIQ is estimated based on the amount of pesticide application, nature and concentration of active ingredients, and the maximum recommended dosage. An online tool designed by Eshenaur et al., (2016), is used to calculate the impact caused by each pesticide with respect to its active ingredients and application dosage. The impact caused by the maximum recommended dosage P_{max} is assumed to be within the acceptable limit and hence it is set to be the mid-point reference during normalisation. Double the P_{max} is considered to be unacceptably hazardous dosage and therefore taken as the upper threshold above which PIQ is capped as zero.

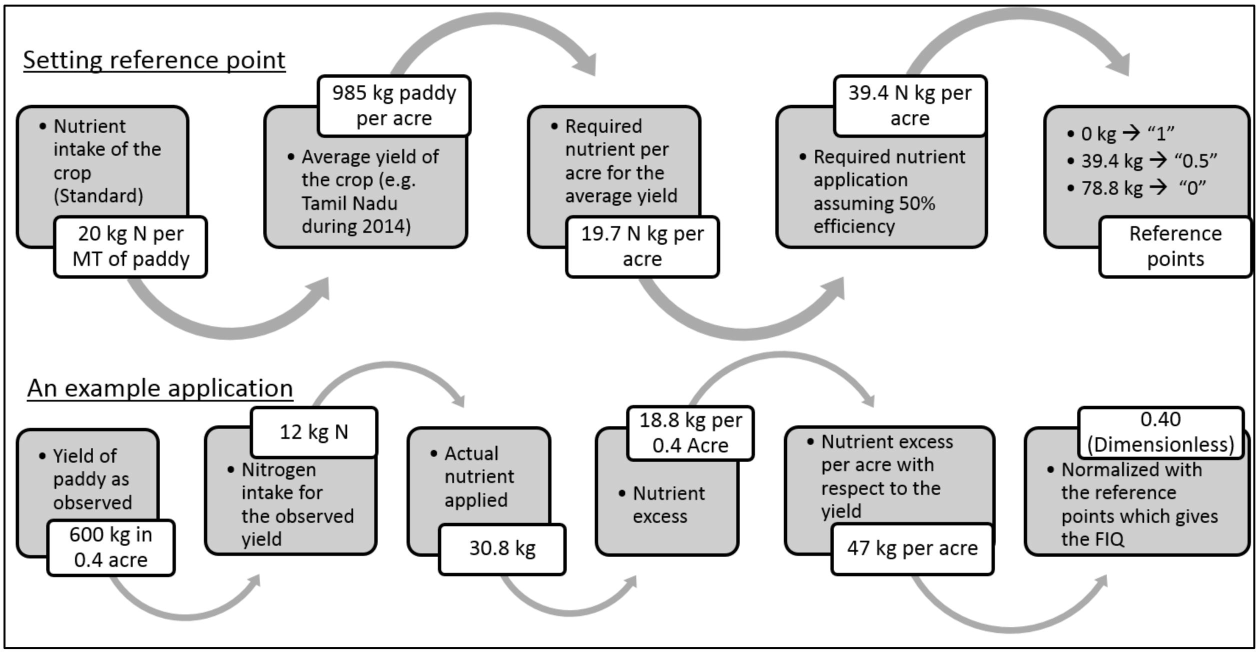

Figure 6 Methodology for calculation of Fertilizer Impact Quotient (FIQ) with an example

FIQ is a measure based on nutrient excess in the field. It is calculated using the quantity of nutrient applied, crop yield, average nutrient consumption rate of the crop, and the average yield of the crop. Figure 6 shows a detailed scheme of FIQ calculation for paddy crop along with an example of data application. The nutrient requirement (F_{avg}) for the average crop production is calculated using the standard crop specific nutrient consumption data. In Figure 6, paddy consumes 20 kg of N per tonne of grain production. A regional average yield of 985 kg per acre would consume 19.7 kg of nitrogen per acre. Since 50% fertiliser use efficiency is considered to be efficient farm management, double the F_{avg} is taken as the '0.5' reference and double of '0.5'reference value is set as the '0' reference point, and above which FIQ is capped as zero. Correspondingly, double of 19.7 kg that is 39.4 kg is set as "0.5" (mid-point reference) reference and its double 78.8 is set as "0" reference. Thereby, a field with nutrient excess equivalent to the amount of nutrient consumed by the crop will get a score of "0.5" and a field with a nutrient excess of four times the nutrient consumed by the crop will be rated "0". These reference points help us to score a range of farms that have very high efficiency to low efficiency. In the example given in Figure 6, a plot of 0.4 acre size has harvested 600 kg of paddy whose corresponding nutrient intake is calculated as 12 kg. With the actual nitrogen application of 30.8 kg, the nitrogen excess for the plot of 0.4 acre size is 18.8 kg. This translates to an excess of 47 kg of nitrogen per acre which is compared with the reference points to obtain the FIQ as 0.40.

3.3. Normalisation of indicators

Normalisation of indicators is a prerequisite for aggregation of indicators with different units in order to express them in relative terms and make them suitable for aggregation (OECD 2008). Normalisation is a mathematical procedure for converting different scales of measures into a comparable scale. While there are several methods to normalise indicators, it is desirable to maintain the simplicity of the index in terms of both construction and interpretation (Singh et al. 2009). After considering a range of mathematical methods (Nardo et al. 2005; Andreoli and Tellarini 2000; Sauvenier et al. 2005), the min-max method with a pre-set reference, is selected for the normalisation of indicators. Min-max method of normalisation has the advantage of retaining the actual relationship between the samples with a continuous and linear function. It is also widely used in indicator studies (Nathan and Reddy 2011; NABARD 2012; Hajkowicz 2006; Gómez-Limón and Sanchez-Fernandez 2010). In this method, the value of any given indicator is transformed within the range '0' to '1' using either of the following equations (Ceyhan 2010).

$$V_b = \frac{x_i - min_i(x)}{max_i(x) - min_i(x)} \quad \text{or} \quad V_c = \frac{max_i(x) - x_i}{max_i(x) - min_i(x)}$$

where V_b and V_c are the normalised indicator value for benefit and cost indicator respectively, x_i is the actual indicator value, $max_i(x)\ and\ min_i(x)$ are the maximum and minimum value for a given indicator 'i'.

In contrast to many existing studies (Gómez-Limón and Sanchez-Fernandez 2010; NABARD 2012; van Asselt et al. 2014; Dantsis et al. 2010) , where the reference points [$max_v(x)\ and\ min_v(x)$] for normalization are taken within the sample set under consideration, scientific or legislative standards and national or state averages from government databases, are used for selecting the reference points. This approach has the advantage of contextualising the assessment locally but still allowing the comparison of a wide range of farming systems across various crops and regions. This method maintains the simplicity of FAI estimation even when the size of the sample under evaluation is expanded by avoiding the need to change the min and max points with the change in the sample.

Data on crop specific and state specific average is used for setting the reference point of socioeconomic indicators like cost of cultivation, labour expense, yield etc. In case of PIQ, pesticide specific maximum recommended dosage provided by manufacturers is used to determine their reference points. Crop specific nutrient consumption per unit yield is used to set their reference points for FIQ. In case of soil parameters, reference points were set based on their scientific thresholds based on published literature.

3.4. Weighing of indicators

Trade-offs among various objectives play a crucial role in sustainability evaluation as the criteria selected for most agro-ecological and socio-economic issues are rarely absolute (Kruseman, Ruben, and Kuyvenhoven 1996). Since weighing of indicators determines the priorities of objectives and stakeholders, the process of weighing gets the primary attention of decision makers. Weightage to indicators can be done by a variety of statistical or normative methods (OECD 2008; Gómez-Limón and Sanchez-Fernandez 2010). In order to ensure the socio-political context and policy relevance, Delphi technique where the weights are assigned to the indicators through consensus, is used in the design of FAI. Delphi method is a group communication process with an objective of converging opinions and building consensus among stakeholders along with an expert panel. The subjectivity involved in the Delphi method of weighing adds the social preference factor and makes it more relevant for practical application (Gómez-Limón and Sanchez-Fernandez 2010).

Assigning relative weightages for all the indicators at a single level is a challenging task due to the diversity and number of indicators to be compared. Hierarchical weighing of attributes reduces the splitting biases that are implicitly added to indicators by decision makers for increasing or decreasing the importance of a particular indicator (Weber, Eisenführ, and Von Winterfeldt 1988; Pöyhönen and Hämäläinen 1998). In order to ensure the robustness of weighing, indicators are organised into a hierarchical structure, and the relative importance is assigned at each level.

The Delphi workshop was conducted with bureaucrats, scientists, academician, members from non-governmental organizations, and many other stakeholders including field coordinators, field officers and farmer representatives. A consensus was built over the classification of indicators and allocation of weightage for each indicator in the FAI as shown in Figure 5.

3.5. Aggregation of indicators

The normalised indicators need to be aggregated to arrive at composite indices that can summarise the information about the system. The method of aggregation would have the final impact on the composite index as it can impose total or partial or no compensation among indicators (Munda 2005; Nardo et al. 2005). Compensation refers to the compromise of low performance of one indicator with better performance of another indicator during aggregation (Andreoli and Tellarini 2000). A linear summation of the product of normalised indicator value and its weight would imply total compensation or substitutability among the indicators. A geometric sum would permit partial compensation, and multi-criteria methods will permit a range of compensation for different indicators (Gómez-Limón and Sanchez-Fernandez 2010). A set of axioms MANUSH (Monotonicity, Anonymity, Normalisation, Uniformity, Shortfall sensitivity, Hiatus sensitivity to level), has been proposed for evaluating robust aggregation methods (Mishra and Nathan 2018).

Although the weighing method and aggregation method are independent of each other, the level of impact imparted by the weightage over the final index will depend on the method of aggregation (Ebert and Welsch 2004). Since the linear summation provides the most intuitive form of aggregation for the stakeholders while assigning the weightage, simple weighted mean is used for aggregation of indicators.

Further, FAI uses progressive aggregation (Sauvenier et al. 2005), where the weighting and aggregation are done at each hierarchical level individually. Indicators are aggregated at each level using simple weighted mean and the aggregate of indicators at each level has its own meaning and utility. Three separate indices viz. economic index, social index and ecological index are calculated at the dimensional level. The aggregate of indicators across all the dimensions forms the FAI of the farming system.

4 Comparison of Organic and Chemical farming

The FAI was applied to evaluate farming practices of 200 farmers across four states in India. Regional host organizations were identified in each of the four states to facilitate the reach to local farmers, selection of farmers for the study, and collection of the farm data.

4.1 Selection of farmers

Purposive sampling, where the samples are selected based on the characteristics of the population and the objectives of the study, was done for selecting the set of farmers. Farmers were selected so as to form the best comparative pairs of organic and chemical plots. The main criteria for selecting organic farmers in the study was to ensure that the paired organic and chemical plots has similar farming conditions (soil, water availability, crop pattern, plot size etc.) at closest possible locations.

Figure 7 shows the field sample locations across four states. The samples in Tamil Nadu, Odisha and Karnataka were located within 2- 4 villages in 10 km range. In case of Maharashtra, sample farms are spread over 100 km in 22 villages around Wardha in Nagpur, Chandrapur and Wardha district, as depicted by a larger green circle.

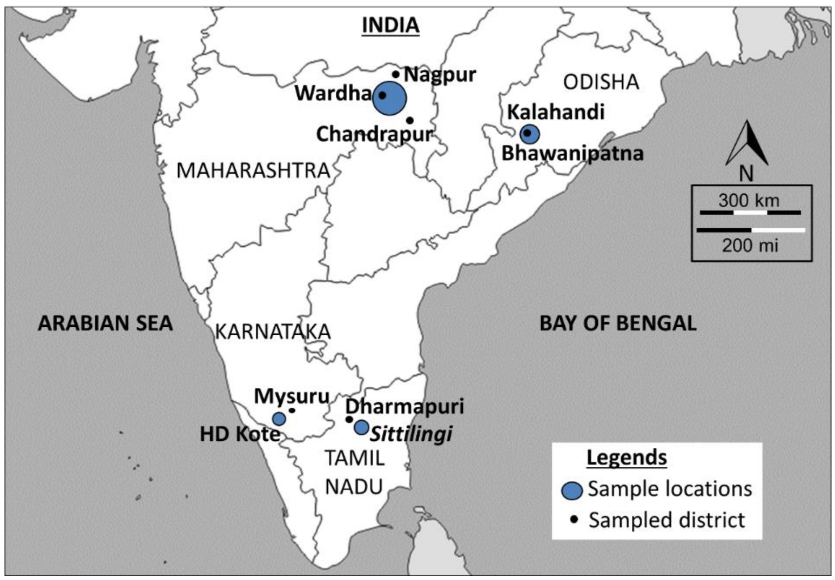

Figure 7 Location of fields samples in four different states

4.2 Data collection and processing

An extensive questionnaire was used to collect all the details of inputs including machinery usage, materials used and labour, along with their actual and opportunity cost. Since the time taken for each survey was long and the chances of recall error were very high if the entire data is collected at the end of the season, a farm diary was maintained to document the day to day farm activities with the help of field researchers. A field officer visited all the farmers once every three days to collect information regarding their farm activities. At the end of the season, the data was compiled into a spreadsheet based tool (Supplementary 1) for estimation of indicators and computing the FAI. Data gaps and extreme entries were identified and resolved by revisiting the farm diaries and telephonic discussion with farmers. The spreadsheet tool has been prepared in such a way to make a detailed data entry about the farm activities and automate the estimation of indicators and composite indices.

Estimation of soil parameters like nutrient content, soil pH, salinity etc. requires soil sample analysis. A representative set of soil samples were analysed due to limitations in resources and logistics. Two rounds of sixty composite soil samples were collected soon after the crop harvest from 10 organic and 10 chemical plots in Maharashtra during the month of April 2015 and 2016. Each composite sample is prepared by mixing three or four sub-samples. Each of these sub-samples are collected and analyzed as per the manual of soil testing in India (DAC 2011).

5 Results and Discussion

Data from 100 organic and 100 chemical farmers covering a total of 764 plot data were collected and analysed. Table 3 gives the details on the number of plots in each crop during different year in different states. Though the data collection was done for three years (June 2013 – May 2016) in all the states, the first-year data had several gaps in all the states except Tamil Nadu. In order to avoid misinterpretation of farms, the first-year data from Maharashtra, Odisha and Karnataka were not included in the data analysis.

Table 3 Number of plots under major crops

State	**Year**	**2013-14**		**2014-15**		**2015-16**	
	Crop	**Organic**	**Chemical**	**Organic**	**Chemical**	**Organic**	**Chemical**
Tamil Nadu	Turmeric	19	27	30	26	28	27
	Paddy	18	21	25	18	21	19
Maharashtra	Cotton			19	21	14	19
	Soybean			19	19	22	21
	Wheat			14	8	11	14
	Gram			8	7	11	13
Odisha	Cotton			30	30	30	30
	Paddy			22	27	18	28
Karnataka	Cotton			8	6	7	9
	Sub-Total	85		337		342	
	Total	**764**					

First, we discuss the comparison of organic and chemical farms with respect to individual indicators, followed by the description on various composite indices, then its statistical comparison using meta-analysis, and finally the sensitivity analysis of FAI with respect to each indicator.

5.1 Trends in indicators

Although FAI helps us in summarising the overall ranking of farming system, trends of individual indicators are also important. Radar chart is one of the commonly used tools to compare multiple parameters like indicators of various farming systems. This chart requires a uniform scale of measure across all the parameters under study. We use the normalized indicators to present the crop wise and year wise results with respect to the organic and chemical farming systems. It is important to note that cost indicators like risk, paidout cost etc., are normalized with a negative function and so higher the score, the better they are. The mean of normalized indicator values and their corresponding indicator means are given in this section. Further, several observations and inferences from the patterns of individual indicators as also discussed.

Cotton in Maharashtra

Figure 8 shows the trend of various indicators in cotton cultivation over two years in villages around Wardha, Maharashtra.

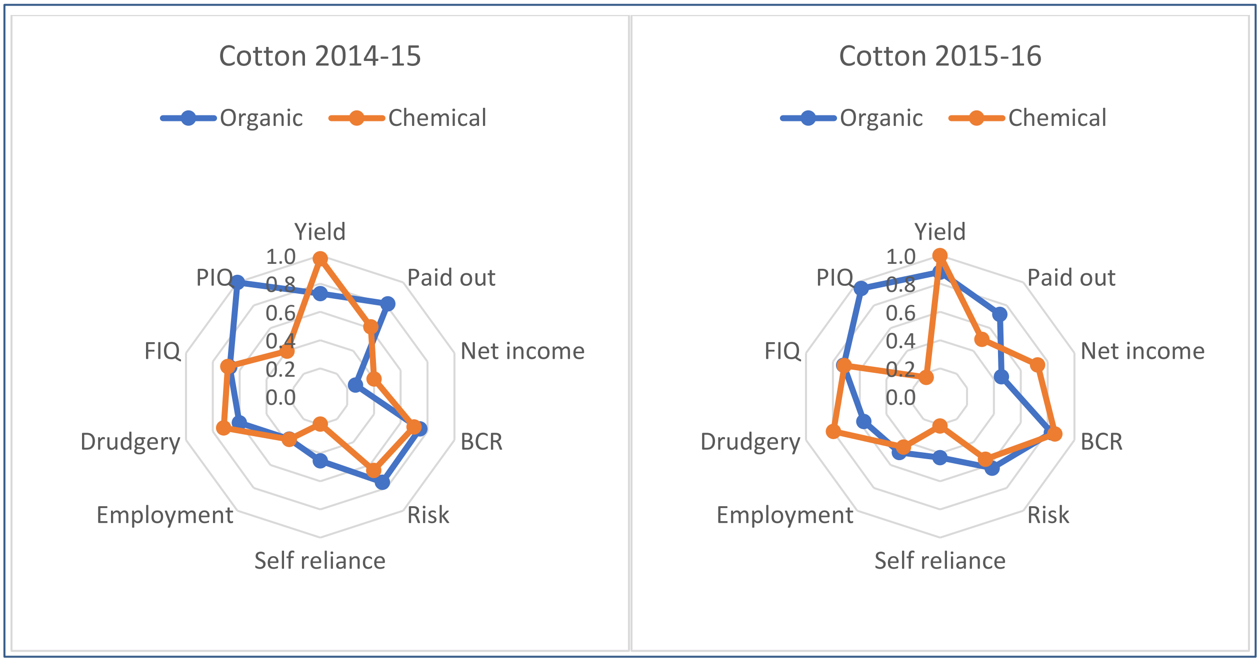

Figure 8 Radar charts for individual indicators of cotton cultivation in Wardha, Maharashtra

- Yield and net income have been significantly higher for chemical farms in both the years. The main reason for the huge yield gap can be attributed to the use of BT seeds by chemical farmers.

- The net income has increased during the second year for both organic and chemical farms in spite of higher paidout expenditure. This higher income is due to the increase in crop yield.
- Paidout cost, BCR, and risk have been better in organic farms as the chemical farms are input and capital intensive. Further, the majority of these inputs are from the market and hence the self-reliance of chemical farms is significantly lesser than that of organic farms.
- While employment was similar in both organic and chemical farms, drudgery in chemical farms was better than that of organic farm. This difference is due to higher farm produce in chemical farms and its corresponding increase in income per unit labour expense.
- While FIQ has remained same over both the years, PIQ has dropped down during the second year due to increase in pesticide use during the second year. It can be noted that the FIQ of organic farms has scored lesser than any other crop. This is mainly due to the relatively lesser consumption of phosphorous by cotton and it corresponding excess phosphorous has affected the FIQ in organic farms as well.

Similarly, each crop in different states has a range of insights across various indicators and are described in detail in the full report of this work.

5.2 FAI and dimensional indices

Table 4 gives the crop-wise mean score of the indices for each crop along with the comparative statistics between organic and chemical farms. In the case of Maharashtra, FAI scores of organic plots were relatively higher than that of chemical farming, but in most cases, they were not statistically different (p-values >0.05). Since the p-values are relatively higher for individual years, combining the results over the years using meta-analysis will help in aggregating the statistical evidence and increase the confidence level of the results (Borenstein et al. 2009).

Meta-analytic thinking contextualises the current results with past findings and aid the planning of future research (Cumming 2013). The combined p-values estimated using Fisher's method, indicate that the FAI scores of organic plots are significantly higher in both cotton and soybean at 95% confidence level with the combined p-value of 0.037 and <0.001 respectively. In contrast to FAI, the economic index of chemical farm for both cotton and soybean was not statistically different from that of organic farms (combined p-value >0.05).

Table 4 Mean scores of FAI and dimensional indices of organic and chemical plots with comparative statistics *(O: Organic plot; C: Chemical plot; M: Combined p-value)*

Crop	Year	Statistic function	FAI			Economic index			Social index			Ecological index		
Maharashtra			***O***	***C***	***M***	***O***	***C***	***M***	***O***	***C***	***M***	***O***	***C***	***M***
Cotton	2014-15	Mean Score	0.64	0.59	***0.037***	0.56	0.60	***0.069***	0.70	0.55	***< 0.001***	0.69	0.61	***< 0.001***
		P- value	0.089			0.323			< 0.001			0.009		
	2015-16	Mean score	0.66	0.60		0.60	0.69		0.71	0.51		0.69	0.56	
		P- value	0.067			0.040			< 0.001			< 0.001		
Soybean	2014-15	Mean score	0.61	0.56	***< 0.001***	0.52	0.52	***0.233***	0.65	0.57	***< 0.001***	0.70	0.62	***< 0.001***
		P- value	0.079			0.932			0.009			< 0.001		
	2015-16	Mean score	0.62	0.48		0.55	0.47		0.66	0.49		0.69	0.49	
		P- value	< 0.001			0.066			< 0.001			< 0.001		
Tamil Nadu			***O***	***C***	***M***	***O***	***C***	***M***	***O***	***C***	***M***			
Turmeric	2013-14	Mean score	0.82	0.70	***< 0.001***	0.72	0.61	***< 0.001***	0.73	0.69	***< 0.001***			
		P- value	< 0.001			0.022			0.059					
	2014-15	Mean score	0.91	0.55		0.86	0.64		0.87	0.55				
		P- value	< 0.001			< 0.001			< 0.001					
	2015-16	Mean score	0.90	0.47		0.83	0.50		0.86	0.50				
		P- value	< 0.001			< 0.001			< 0.001					
Paddy	2013-14	Mean score	0.67	0.53	***< 0.001***	0.43	0.33	***< 0.001***	0.66	0.54	***< 0.001***			
		P- value	< 0.001			< 0.001			< 0.001					
	2014-15	Mean score	0.79	0.53		0.65	0.44		0.73	0.52				
		P- value	< 0.001			< 0.001			< 0.001					
	2015-16	Mean score	0.69	0.50		0.43	0.40		0.72	0.53				
		P- value	< 0.001			0.488			< 0.001					
Odisha			***O***	***C***	***M***	***O***	***C***	***M***	***O***	***C***	***M***			
Cotton	2014-15	Mean Score	0.6	0.55	***0.004***	0.59	0.71	***0.143***	0.62	0.48	***<0.001***			
		P- value	0.07			0.005			<0.001					
	2015-16	Mean score	0.79	0.66		0.8	0.83		0.8	0.56				
		P- value	<0.001			0.03			<0.001					
Soybean	2014-15	Mean score	0.84	0.68	***0.027***	0.79	0.56	***0.043***	0.77	0.62	***0.001***			
		P- value	<0.001			<0.001			<0.001					
	2015-16	Mean score	0.84	0.77		0.77	0.69		0.77	0.69				
		P- value	0.006			<0.001			<0.001					
Karnataka			***O***	***C***	***M***	***O***	***C***	***M***	***O***	***C***	***M***			
Cotton	2013-14	Mean score	0.79	0.54	***0.11***	0.82	0.67	***0.844***	0.77	0.66	***0.004***			
		P- value	0.017			<0.001			<0.001					
	2014-15	Mean score	0.73	0.67		0.69	0.8		0.73	0.63				
		P- value	0.424			0.112			0.047					

In case of Tamil Nadu, FAI of organic plots were significantly higher than that of chemical plots for both turmeric and paddy for each of the three years at 95% confidence level (p-value <0.001). Similar to FAI, the crop-wise mean scores of dimensional indices were also significantly higher at 95% confidence level for the organic farms except for economic index of paddy in the year 2015-16. The meta-analysis gave the combined p-values as less than 0.001 for all the indices indicating organic farms were doing significantly better than chemical farms when compared holistically.

Similar to Maharashtra, in Odisha, the meta-analysis helped to improve the statistical evidence that FAI of organic cotton farms to be significantly higher than chemical farms. In contrast, the economic index of chemical farms in cotton were not statistically different from organic farms even after combining the data for two years. In case of paddy, the combined p-values reiterated that the organic farms had significantly higher FAI and dimensional index scores than chemical farms.In case of Karnataka, there was no significant difference between organic and chemical farms in both FAI and economic index, even after the meta-analysis of two years. This is probably due to the limited sample size during both the years.

Significance testing with p-values as used conventionally prompts dichotomous thinking that focuses on making a choice between alternatives. In order to move beyond the dichotomous question “is there an effect?” toward the estimation question of “How much effect”, we estimate the *effect size* (ES) of the mean difference between organic plots and chemical plots for various indices. ES is a measure of magnitude (“size”) along with the direction (“effect”) of any estimation statistics (Cumming 2013). ES gives a cognitive advantage in understanding and communicating the results among researchers and readers. Point and interval estimates of ES are recommended for a better interpretation and discussion of results (APA 2010).

Figure 9 gives the *forest plots* of mean difference among chemical and organic plots for various indices. It gives the ES of mean difference with 95% confidence interval (CI), for each crop and each year individually as well as the combined effect size (Q) over the years, using the random effect method (Cumming 2013). Aggregation of ES from similar studies helps to improve the statistical power and increases the likelihood of detecting the differences among groups (Ellis 2010). The positive ES in most cases indicates that the scores of various indices for organic plots are higher than chemical plots. Though the point estimate of ES of FAI for cotton cultivation is positive for both years in Maharashtra and Odisha, CIs show that there are chances of zero mean difference during each year. However, combining the results from both years gives a positive Q value with 95% CI. In case of Karnataka, FAI of cotton farms had a positive effect size but the confidence interval was very large due to limited number of samples.

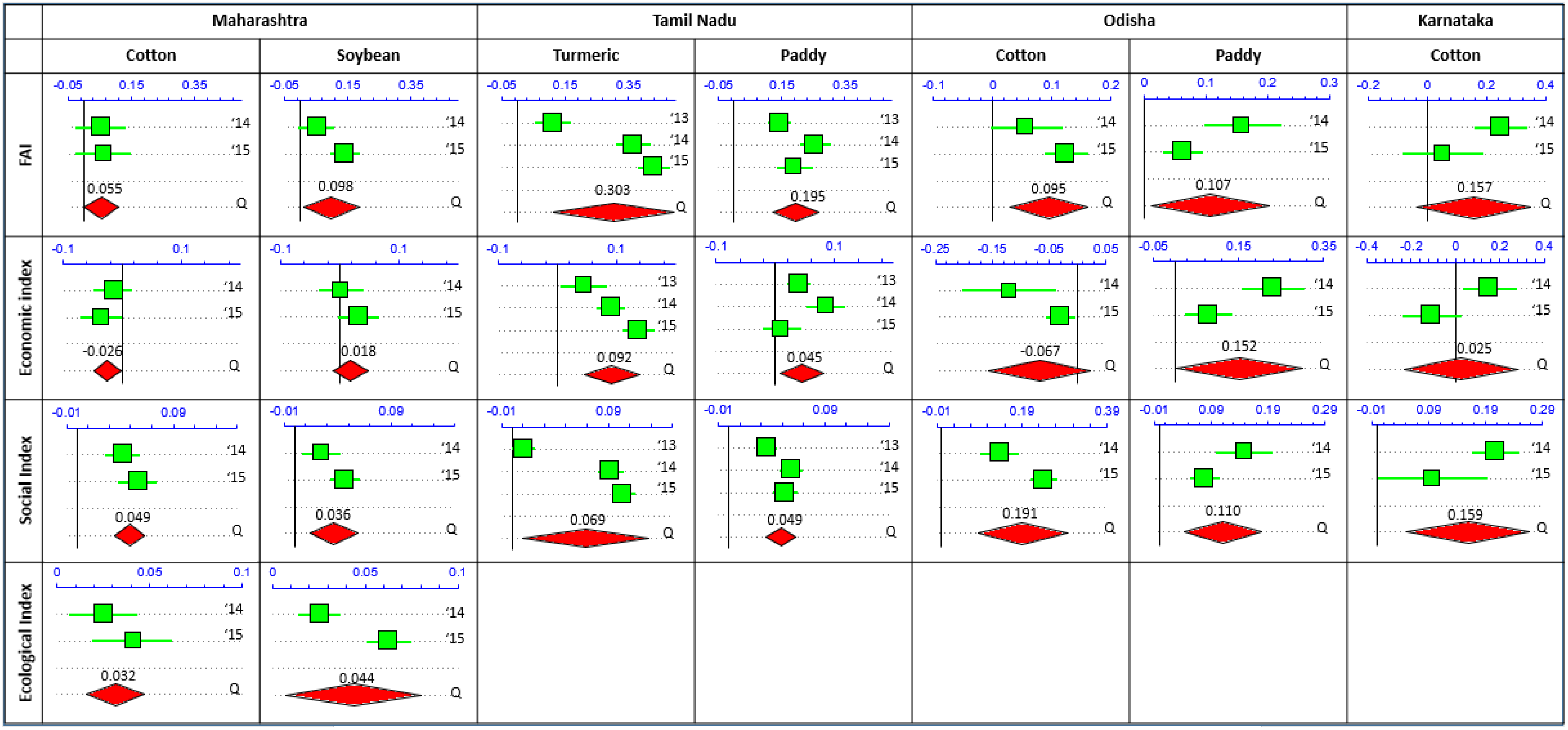

Figure 9 Forest plot of FAI and dimensional indices of various crops from four Indian states

Note: The unit of scales are the corresponding index scores and the measuring axis varies for each index. The green squares represent the effect size (ES) of the mean difference between chemical and organic plots with 95% confidence interval (CI) as indicated by the green bars on either side of the square. Red diamonds give the combined ES (Q) of the mean difference over the entire study period using the random effects model. A positive ES indicate that organic farms have scored higher than chemical farms during the respective year. A positive Q value indicate that organic farms have scored higher than chemical farms when compared over the years.

The major advantage of the forest plot over the p-values is the indication of the magnitude of the mean difference between the organic and chemical plots (Q = 0.03 to 0.3). The combined effect size (Q) of results over the years show that organic plots have scored significantly higher in all the indices across all the crops in all the states except for the economic indices of cotton in all the three states and soybean in Maharashtra.

5.3 Sensitivity analysis

Sensitivity analysis helps in understanding the robustness of a composite indicator and influence of individual indicators (Saltelli et al. 2006). We use OAT (One At a Time) based sensitivity analysis which helps to identify the most influential and crucial indicators for the estimation of FAI. Two different approaches namely, change in ranking based method and decomposition of variance were adopted to analyse the field data.

The Change in Rank (CR) method is based on the impact caused by an individual indicator to the overall ranking of sample fields. It is carried out by removing one indicator at a time and comparing the newly computed FAI ranking of samples with the original FAI ranking (Jain and Rao 2013). A change in rank indicates the role of a particular indicator in altering the preference of one farming practice over the other. An indicator is considered to be most influential if its removal has caused the maximum change to the FAI ranking of the sample. The change in rank essentially means that there is a significant variation in that specific indicator across the sample and the range of significance depends on the weightage given to the indicator. Conversely, if the removal of an indicator did not affect the rank, the indicator has not varied to a level which might affect the FAI ranking.

In the decomposition of variance method, sensitivity of each indicator is quantified using two measures viz. first order sensitivity (S) and total effect sensitivity (ST) based on variance as defined below.

$$S_i = \frac{V_i}{V}$$

$$ST_i = \frac{V - VC_i}{V}$$

where V_i is the variance of i^{th} indicator, V is the variance of FAI and VC_i is the conditional variance which is the variance of FAI after removal of the i^{th} indicator. S is calculated as the fractional contribution of individual indicator variance to the total FAI variance. ST estimates the overall contribution of an indicator to FAI variance including the interaction effects. The values of S and ST provides the relative contribution of individual variance to the overall FAI variance. Higher S and ST values for an indicator imply a greater impact of the indicator on FAI (Ligmann-Zielinska et al. 2014).

Table 5 and 6 provide the results from state level sensitivity analysis across the crops using the change in rank method (CR) and decomposition of variance method for different categories over two years. An indicator with higher CR and higher S (first-order sensitivity) and ST (total effect sensitivity) values indicates a greater impact of the indicator over FAI. The tables are colour coded for a quick inference. Red implies maximum impact followed by yellow gradient and green for the least impact indicator. The results from decomposition of variance method (S and ST) were found to be consistent with that of change in ranking (CR) method in most cases.

Table 5 Sensitivity analysis of indicators for Tamil Nadu and Maharashtra across various crops

State	**Tamil Nadu**						**Maharashtra**					
Year	**2014-15**			**2015-16**			**2014-15**			**2015-16**		
Indicator	**CR**	**S**	**ST**	**CR**	**S**	**ST**	**CR**	**S**	**ST**	**CR**	**S**	**ST**
Farm expenditure	3.35	0.01	0.08	3.89	0.01	0.06	1.85	0.01	0.01	1.82	0.01	0.04
Self-borne	0.91	0.00	0.04	0.72	0.00	0.02	1.28	0.00	0.04	1.24	0.00	0.04
Paidout cost	0.79	0.00	0.04	0.55	0.00	0.03	0.97	0.00	0.03	0.82	0.00	0.04
Net Income	2.83	0.05	0.21	2.23	0.05	0.28	4.77	0.08	0.22	5.16	0.10	0.17
BCR	1.54	0.02	0.14	2.13	0.02	0.14	3.67	0.06	0.24	3.82	0.06	0.18
Employment	0.77	0.00	-0.01	0.51	0.00	-0.01	0.54	0.00	0.00	0.61	0.00	0.02
Drudgery	0.91	0.00	0.06	0.63	0.00	0.08	1.59	0.01	0.07	1.26	0.00	0.01
Yield	1.17	0.00	0.03	0.97	0.00	0.04	1.85	0.01	-0.01	2.08	0.01	0.00
PIQ	3.52	0.12	0.48	6.34	0.14	0.45	9.82	0.29	0.33	13.89	0.46	0.51
Total FIQ	6.40	0.20	0.51	8.57	0.19	0.48	8.18	0.25	0.37	6.84	0.15	0.17

Table 6 Sensitivity analysis of indicators for Odisha and Karnataka across various crops

State	**Odisha**						**Karnataka**					
Year	**2014-15**			**2015-16**			**2014-15**			**2015-16**		
Indicator	**CR**	**S**	**ST**	**CR**	**S**	**ST**	**CR**	**S**	**ST**	**CR**	**S**	**ST**
Total expenditure	3.32	0.02	0.17	5.53	0.05	0.24	0.43	0.01	0.13	0.38	0.02	0.11
Self-borne	1.01	0.00	0.03	2.68	0.01	0.07	0.00	0.00	0.01	0.00	0.00	0.00
Paidout cost	1.38	0.00	0.09	1.43	0.01	0.14	0.00	0.00	0.03	0.13	0.00	0.03
Net Income	8.04	0.09	0.02	11.98	0.22	-0.40	0.14	0.02	0.20	0.75	0.04	0.02
BCR	3.34	0.02	0.11	1.17	0.01	0.03	0.00	0.01	0.10	0.38	0.01	0.06
Employment	0.57	0.00	0.00	1.23	0.00	0.02	0.14	0.00	0.01	0.00	0.00	0.02
Drudgery	1.38	0.00	0.04	1.04	0.00	0.01	0.00	0.00	0.02	0.25	0.00	0.00
Yield	1.89	0.01	-0.04	4.11	0.02	-0.10	0.00	0.00	0.00	0.00	0.00	0.00
PIQ	16.6	0.37	0.34	28.81	0.95	0.49	1.43	0.27	0.51	1.63	0.28	0.37
Total FIQ	16.4	0.34	0.38	16.43	0.45	-0.23	1.71	0.21	0.47	2.38	0.40	0.64

In general, the sensitivity analysis shows that the crucial indicators influencing FAI score in most cases are PIQ, FIQ, net income and riskiness. In case of Tamil Nadu, FIQ is found to have the highest influence on the index for both the years. Net income and riskiness are found to be the second and third most influencing indicators for the year 2014-15 (Table 5). However, PIQ and riskiness are found to be the second and third most influencing indicators during the year 2015-16 in Tamil Nadu. In Maharashtra, net income is found to have the highest influence on the index followed by PIQ and FIQ during both the years (Table 5). In Odisha and Karnataka, the highest influencing factor were found to be PIQ, FIQ, net income and riskiness (Table 6).

Further crop-wise sensitivity analysis (refer full report for tables) indicates that riskiness, FIQ, yield and PIQ are the top influencing factors in turmeric cultivation for the year 2014-15, and in the year 2015-16 it is riskiness, FIQ, PIQ and net income. In the case of paddy, PIQ, riskiness, net income and FIQ are found to be the top four influencing factors respectively. PIQ emerges to be the most influencing factor in cotton cultivation as well, followed by FIQ, net income and BCR indicators respectively. Similarly, in soybean cultivation, PIQ is found to be the most influencing indicator followed by net income, BCR and riskiness. FIQ did not have much impact in case of soybean due to less fertiliser application, but in the case of paddy, the lesser influence of FIQ is due to a corresponding increase in yield. Net income and FIQ were the most influencing indictors in wheat cultivation during 2014-15 and 2015-16 respectively. Similarly, net income and PIQ were the most influencing indicators in Bengal gram cultivation during 2014-15 and 2015-16 respectively. In case of Odisha, the PIQ, the FIQ and the net income were found to be the most influencing indicators during both the years for cotton. Net income and FIQ were found to be the most crucial indicators in paddy field samples from Odisha. It is notable that the PIQ has not made any significant difference among the sample farmers in wheat cultivation from Maharashtra and the paddy cultivation in Odisha.

6 Conclusion

We have designed a stock and flow based framework to identify a holistic set of indicators for evaluation of any farming system. In contrast to the existing frameworks for indicator identification that are based on pre-set attributes, this framework has been designed for a systemic identification of indicators. It aides in identifying and selecting indicators that cover both short and long-term characteristics of the system across socio-economic and ecological dimensions. It also helps us to capture the stability and resilience of the system. This framework improves the transparency and reliability of the process of identification and selection of indicators. In addition, the framework aids in the selection of appropriate proxy indicators for hard to measure primary indicators by tracing their forward and backward linkages.

A comprehensive set of indicators was identified using the framework and validated at a stakeholder workshop. A set of proxy indicators was identified to capture the maximum possible primary indicators across socio-economic and ecological dimensions, using a minimal resource usage. These indicators were transformed using min-max normalization followed by hierarchical weighing and progressive aggregation using weighted mean to form the Farm Assessment Index (FAI), which is used as a single holistic measure for any farming system. In addition, three dimensional indices *viz.* economic index, social index, and ecological index, were also calculated. These indices help in relative rating of farming systems and practices, and identification of appropriate policy interventions. The indicators are normalized using preset reference points based on the crop and region, which make the estimation of FAI simple by avoiding the change in normalized value with change in sample. The use of crop and region based reference points for normalization also helps to contextualize the farm assessment but still allowing the comparison of a wide range of farming systems across various crops and regions.

We applied the FAI to compare the organic and chemical farming systems of 200 farmers from the states of Maharashtra, Tamil Nadu, Odisha and Karnataka. The results from FAI application indicate that the focus on yield or income as the sole indicator will not lead to sustainable farming practices. Agricultural policies need to shift towards more holistic interventions with an emphasis on human health, livelihood of farmers and sustenance of agro-ecology.

In case of Maharashtra and Odisha, field data shows that in spite of variations in trends of individual indicators like yield, cost of cultivation, income etc., organic farms have significantly higher FAI than that of chemical farms with a combined effect size ranging from 0.03 to 0.30. Popular economic indicators like yield and income are predominantly higher in case of chemical farms, but the inclusion of other indicators like riskiness and resource use efficiency makes the economic index of organic and chemical farms relatively similar. Organic farms have scored better in both social and environmental indices. Pesticide and fertilizer impact quotients have been the critical factor affecting both social and ecological indices of chemical farms. Further, social index score has also been affected due to higher paidout expenditure in chemical farms.

In the case of Tamil Nadu, the FAI of organic farms were significantly higher than that of chemical farms for both turmeric and paddy farms over three years. The gap between the FAI of organic and chemical farms is larger in Tamil Nadu than in Maharashtra. This is due to low net income and poorer PIQ in chemical farms. The economic index of turmeric is significantly higher for organic farms due to premium pricing for organic produce. In case of Karnataka, the sample size was too less to have any statistical inference for the indicators and composite indices.

The variance in FAI among the farmers within the chemical group was significantly higher than that of organic farms both in Maharashtra and Tamil Nadu. Also, less input intensive crops like wheat and gram have significantly higher index scores than that of input intensive cotton cultivation under chemical farming. Thus, the designed FAI will be a useful tool for assessment of farming practices as well as selection of crops, thereby aiding the design of farm policies. Field application of FAI has shown that organic farming practices have scored better in most cases and need to be encouraged for a long-term social viability of farming and ecological sustainability of agriculture.

Sensitivity analysis showed that PIQ, FIQ, income and riskiness are the major determinants of FAI and thereby corresponding primary indicators are identified to be the most crucial indicators in the comparison of organic and conventional farming systems. Thus, agricultural policies need to shift towards a more holistic set of indicators emphasizing human health, the livelihood of farmers and sustenance of agro-ecology. Further, field application of FAI has shown that organic farming systems have scored better in most cases and they need to be encouraged for the long-term social viability of farming and ecological sustainability of agriculture. FAI and similar holistic tools should be used for designing appropriate and sustainable farm policies.

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About FAI and its application

Traditionally, crop yield has been the main focus of agricultural policies and technological interventions. While there have been continuous efforts to improve farming practices towards food and farm sustainability, a metric to assess and promote farming system in a holistic manner has been missing. In order to address this need, we have developed a *Stock* and *Flow* based framework for a systemic identification of both short and long-term indicators across the socio-economic and ecological dimension. In this framework, stock variables inside the system capture the stability and resilience of the system, and the variables from biophysical flows across the system-environment boundary capture both the desirable outcomes and undesirable impacts. The framework also aids in the selection of appropriate proxy indicators for hard to measure primary indicators by tracing their forward and backward linkages rather than avoiding complex indicators altogether. This stock and flow based framework is used to identify a holistic set of indicators for comparing farming system. These indicators are classified under three widely accepted dimensions: economic, social and ecological dimension. The indicators under each dimension are aggregated to give three dimensional indices. These dimensional indices are further aggregated to give a single holistic index called Farm Assessment Index (FAI).

The FAI was applied to evaluate farming practices of a set of 100 organic and 100 chemical farmers, across Maharashtra, Tamil Nadu, Odisha and Karnataka. The major crops including cotton, soybean, wheat, bengal gram, turmeric and paddy cultivated over three years (2013 – 2016) totalling to 764 plots are studied. While there have been variations in yield and income trends, FAI score of most organic farms is better than corresponding chemical farms. Even in the cases where the gross income from chemical farms is relatively higher, the economic index is higher for organic farms due to their higher benefit-cost ratio, lower risk, as well as better resource use efficiency. Similarly, in case of the social and environmental index, organic farms have scored higher than chemical farms given the impacts caused by excessive fertilizer and pesticide usage in chemical farms.

The results from FAI application demonstrate that the focus on yield or income as the sole indicator for policy decisions will not lead to sustainable farming systems. Policy makers and technocrats need to shift towards holistic measures emphasising human health, livelihood of farmers and sustenance of agro-ecology. Further, the comparative studies have shown that organic farming practices need to be encouraged for improving the long-term socio-economic viability of the farmers and ecological sustainability of agriculture.

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