Using a positive deviance approach to inform farming systems redesign: A case study from Bihar, India

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\textbf{A B S T R A C T}

Improving farming systems in resource-poor contexts is often difficult as farmers face multiple challenges to implement the innovations developed by researchers. Viable solutions may however be present within local communities by positive deviant farmers, i.e. farmers that outperform positively compared to others. This study develops a positive deviance informed methodology to support redesign of farming systems, with the aim to improve farm productive, economic and environmental performances. We tested the methodology in Bihar, India, using survey data from 43 farms and the indicators of operating profit, soil organic matter balance, water use and dietary energy production. Positive deviant farms and practices were first identified and then recombined into a redesigned farm in consultation with farmers. The FarmDESIGN model was used to calculate current farm performance and to explore potential alternative farm configurations in the redesign. We found that outstanding performance on all indicators could only be reached by integrating high livestock density with an optimal combination of crop practices, which confirms the key role of interactions among components in mixed crop-livestock systems to improve all dimensions of farm sustainability. The redesigns outperformed all real farms on the indicators assessed. Farmers confirmed the viability of the redesigns in focus group discussions and their suggestions can serve as useful input for a next cycle of farm redesign. Since all suggestions are locally practiced and have proven to be accessible, affordable and recognizeable, we conclude that our methodology based on positive deviant farms and practices yields promising results with a large potential to boost agricultural development for resource-scarce smallholder farmers.

\textbf{1. Introduction}

The Indo-Gangetic Plains of India are the main food producing region of the country with intensive cereal-based agriculture sustaining millions of people with food and income. However, there is a strong productivity gradient from west to east, with Bihar being one of the poorest states (Jat et al., 2014; Laik et al., 2014) with about 41% of the population living below the poverty line (World Bank, 2016). The state’s economy is mostly based on the agricultural sector which contributes to one fourth of its Gross Domestic Product and employs 81% of its population (Government of Bihar, 2012). Bihar’s agriculture faces multiple challenges, including low farm income (Shirsath et al., 2017), natural resource degradation (Erenstein and Thorpe, 2011), and increasing drought occurrence due to climate change (Shirsath et al., 2017).

In recent years, the Government of India has introduced an ambitious reform agenda for Indian agriculture which includes the goals of doubling farmers’ income by 2022 and further improving national food security (Chand, 2017). Given Bihar’s high potential to significantly increase its agricultural production, the Government of India plans to transform this state into the ‘future food bowl’ of the country by boosting cereal and livestock production (Government of Bihar, 2012; Laik et al., 2014). To this aim, Climate Smart Agriculture (CSA) techniques and other sustainable intensification practices have been widely promoted in Bihar (Jat et al., 2014; Laik et al., 2014). However, despite extensive efforts and good results obtained in experimental trials, the
adoption of these new technologies remains low in Bihar as farmers are hindered by multiple constraints such as small landholdings and limited access to mechanization (Aryal et al., 2018).

Model-aided redesign of farming systems can substantially improve farm performances even in the context of low resource endowment and other socio-economic constraints. Instead of relying on the introduction of new technologies, the redesign can focus on using the room to manoeuvre inside the current farms by optimizing resource allocation and redistributing practices already in use (Dogliotti et al., 2014). From this perspective, whole-farm modelling represents a powerful tool to inform farm redesign because it can explore a large set of alternative farm configurations and evaluate the impact of these changes (Thornton and Herrero, 2001; Janssen and Van Ittersum, 2007; Le Gal et al., 2011; Jones et al., 2017). However, despite the fact that the redesign process can considerably benefit from large diversity of alternatives (van Noordwijk et al., 2001; Dogliotti et al., 2003), modelling studies usually focus on a rather small number of practices (Dogliotti et al., 2003; Dogliotti et al., 2005). On the other hand, the limited computing capacity of mathematical programming could not process large combinatorial problems and, therefore, a preliminary selection of practices is always required (Dogliotti et al., 2003; Groot et al., 2010).

The positive deviance approach can provide an interesting technique to explore the farm diversity and select a subset of efficient practices from the multitude of current farmers’ practices. Positive deviants are defined as individuals that achieve better outcomes than their peers despite having the same resources and constraints. The better performance can be achieved due to an innovative use of available assets, inputs and processes (i.e. positive deviant practices) (Marsh et al., 2004; Pant and Odamé, 2009). Compared to innovations developed and promoted by researchers, farmers’ positive deviant practices are already used in the biophysical and socio-economic context and therefore can be assumed accessible, affordable, tailored to local conditions and possibly transferable to other farmers (Marsh et al., 2004; Bradley et al., 2009). At the same time, they also already represent the most successful practices within the population and therefore represent a good starting point for a redesign procedure. However, although the positive deviance approach has been extensively used in the field of nutrition and health (Ahmadi et al., 2002; Bolles et al., 2002; Mackintosh et al., 2002; Marsh et al., 2002), its application in the agricultural context remains limited.

Existing studies on positive deviance in agriculture are mostly descriptive reviews, using normative approaches to identify positive deviants (Ochieng, 2007; Biggs, 2008; Pant and Odamé, 2009; Amankwah et al., 2012). Positive deviants are broadly defined as the ‘best’ farmers and are named by the community or local researchers, often without quantitative verification whether their performances are indeed better than the average. Furthermore, many studies focus on the single objective of profit (Amankwah, 2013; Savikurki, 2013) while the multi-objective nature of sustainability and agriculture requires a multi-criteria assessment of positive deviance, as introduced with the Pareto-optimality based method proposed by Modernel et al. (2018) and further employed by Steinke et al. (2019). Finally, up to now, positive deviant practices have been identified by qualitative comparison of farms and, to the best of our knowledge, there are no studies which have integrated the positive deviance approach in a redesign of farming systems. As such, this approach requires methodological specifications before it can be successfully implemented in the agricultural context.

This study develops a positive deviance informed methodology to support redesign of farming systems in Bihar on the four indicators of operating profit, water use, soil organic matter (SOM) balance and dietary energy production. The methodology is tested using 43 farms divided into five farm types and the whole-farm model FarmDESIGN. The aim is to improve overall performance on the four indicators using positive deviant farms and practices as a starting point and the methodology is divided into four steps: (1) to identify positive deviant farms, (2) to identify positive deviant practices, (3) to combine identified positive deviant practices in a positive deviance informed redesign for further improvement of the overall farm performance, and (4) to investigate the relevance of the proposed redesigns for local farmers. Positive deviant farms and practices were identified based on a quantitative methodology, with positive deviants defined as farms that perform better the population mean on each of the selected indicators. In the redesign, we aimed to further improve the performances of positive deviant farms to double beneficial indicators (or half impacting indicators) with respect to the population mean. This goal was defined in order to change the overall balance at state level of region-wise targets (such as water use or dietary energy production) and to suggest appealing improvements for all farmers, not only for the poorer part of the population.

2. Methodology

2.1. Study area and data collection

Agriculture in Bihar is characterized by mixed crop-livestock farming systems. The year is divided into three seasons: rabi (winter, October–April), zaid (spring, April–June), and kharif (monsoon, June–October). The predominant rotation is wheat-rice with wheat grown in rabi and rice grown in kharif, although maize is also very common and can be grown in any of the three seasons. In zaid, the short season between the harvest of wheat and the planting of rice, farmers generally grow some fast-growing crops or leave the land fallow. Cereals represent the main staple food for household food security, but other crops are also grown such as oilseeds, pulses and vegetables. Livestock mainly comprises cows or buffaloes for milk production, while goats and chickens are rare and, especially, goats, are associated with the poorest that cannot afford cows or buffaloes. Livestock is mostly fed wheat and rice straw obtained from cereal cultivation, possibly complemented with green fodder, collected grass and small amount of compound feed. As the straw is either sold or used on farm as feed, it has a substantial contribution to the farm income. In this way, it hampers the adoption of CSA techniques which require the use of straw as mulch (Erenstein et al., 2007; Singh et al., 2013). Average milk production per animal is low due to the large proportion of unproductive animals and the poor rations. In general, livestock management is largely inefficient and there is large potential for increasing livestock production (Devendra et al., 2000; Erenstein et al., 2007).

In 2010–2011, an extensive household survey was conducted on farming systems and livelihood pursuits among 269 farms in Bihar. Farms were classified into five farm types based on functional and structural characteristics: part-time farmers (type 1), wealthy farmers (type 2), small-scale crop and livestock farmers (type 3), medium-scale cereal crop farmers (type 4) and resource-poor agricultural labourers (type 5) (Table 1) (Lopez-Ridaura et al., 2018). For this study, 43 farms were further selected to collect input for the FarmDESIGN model. This in-depth survey was conducted by local researchers and based on the IMPACTLite survey from Rufino et al. (2013) and included detailed quantitative information on physical components (fields, animals, crops); inputs (labour, fertilizers, pesticides, seeds); outputs (income, yields, animal products) and management (adoption of CSA techniques) (Supplementary Material A). The 43 farms were located in the districts of Muzzafarpur (Bakhari (n = 4) and Dighra (n = 4)), Samastipur (Chandauli (n = 5), Digambra (n = 7), Kuboli (n = 3) and Repura (n = 5)) and Vaishali (Bajipur (n = 5), Barhia (n = 5) and Nirpur (n = 5)) (Fig. 1). The selected villages were similar in terms of farming systems, soil and climate. We aimed to select one farm per village for each type, when this was not possible the type was omitted for the village (Table 2). The in-depth surveys on the 43 farms were conducted in 2016–2018.

2.2. FarmDESIGN

FarmDESIGN is a static and exploratory whole-farm model that quantifies farm productive, economic and environmental performance on annual basis (Groot et al., 2012; Cortez-Arriola et al., 2016). The model can be used for both analysis of current farm performance and
exploration of alternative management options. In the exploration process, the model performs a multi-objective optimization using a Pareto-based Differential Evolution algorithm which uses the current farm configuration as a starting point (Groot et al., 2012). The model optimizes the multiple objectives according to the indicated constraints and generates a large set (e.g., 500, this can be specified by the user) of alternative configurations of farming systems by adjusting production activities and resource allocation, and evaluating their consequences on farm performances (Groot et al., 2012). As the Pareto-based multi-objective optimization does not present one single solution, the researcher can select one or multiple preferred farm configurations according to further criteria and/or in consultation with stakeholders. A detailed description of the model is provided by Groot et al. (2012) and Ditzler et al. (2019), while applications of the model can be found in Cortez-Arriola et al. (2014), Flores-Sánchez et al. (2014), Mandryk et al. (2014), Cortez-Arriola et al. (2016), Groot et al. (2016), Michalscheck et al. (2018) and Timler et al. (2020). The model with example datasets is available online at: https://sites.google.com/site/farmdesignmodel/home.

2.3. Selection of indicators

The following four indicators were selected for the analysis: (1) operating profit, (2) soil organic matter (SOM) balance, (3) water use, and (4) dietary energy production. These indicators were chosen in consultation with local researchers and represent the main priorities for agriculture in Bihar (Erenstein and Thorpe, 2011; Jat et al., 2018; Lopez-Ridaura et al., 2018). All indicators are expressed on an annual basis and per hectare in order to allow the comparison between farms with different landholding sizes and were calculated as follows:

1. Operating profit (USD ha⁻¹ year⁻¹) was calculated as the difference between the revenue obtained for crop and animal production and the costs including imported manure, fertilizers, pesticides, medical costs for livestock, feed costs and hired labour. All the economic data were converted from Indian rupees into USD using an exchange rate of 1 USD = 71.42 Indian rupees.

2. SOM balance (kg OM ha⁻¹ year⁻¹) was calculated as the difference between inputs of organic matter into the soil (from crop roots and residues, green manure, and farm-produced and imported manures) and losses of organic matter (by degradation of active soil organic matter, degradation of added manure, and soil erosion).

3. Water use (m³ water ha⁻¹ year⁻¹) was calculated as the sum of the amount of irrigation water applied to each crop.

4. Dietary energy production (adults ha⁻¹ year⁻¹) was calculated as the sum of dietary energy of each product used for human consumption. Dietary energy was calculated according to the Nutritional System Dietary Energy (DeFries et al., 2015) and was expressed as the number of consumer units (i.e. reference adults) who would be able to obtain 100% of their recommended Dietary Reference Intake for energy (Otten et al., 2006) from the total farm production. As indicators calculated on a kilocalorie basis are extensively used for food security (Frelat et al., 2016; Hammond et al., 2017a; Ritzema et al., 2017; Lopez-Ridaura et al., 2018), this study selected dietary energy production as a simple measure for national food security while it does not focus on farm food self-sufficiency or nutritional issues.

2.4. Methodological framework

The proposed methodological framework for positive deviance informed redesign is divided into four steps (Fig. 2). First, positive deviant farms and practices were identified by a three-sub-steps nested assessment and, then, in subsequent steps positive deviant farms were

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**Table 1**

Distribution of the 43 farms entered in FarmDESIGN divided per village and farm type. We selected one farm per village for each type and when this was not possible the type was omitted for the village.

<table>
<thead>
<tr>
<th>District</th>
<th>Village</th>
<th>Number of farms</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 3</th>
<th>Type 4</th>
<th>Type 5</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Muzaffapur</td>
<td>Bakhari</td>
<td>1 1 1 1 0 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Samastipur</td>
<td>Chaudali</td>
<td>1 1 1 1 1 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Digambre</td>
<td>1 1 1 2 1 2 7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Kuboli</td>
<td>1 1 0 1 0 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vaishali</td>
<td>Repura</td>
<td>1 1 1 1 1 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bajitpur</td>
<td>1 1 1 1 1 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bardha</td>
<td>1 1 1 1 1 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nirpur</td>
<td>1 1 1 1 1 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>9 8 9 9 8 43</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Fig. 1.** Map of India with the Indo-Gangetic Plains in grey and the state Bihar in detail with the districts Vaishali, Samastipur and Muzaffapur in pink. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Table 2: Description of the five farm types in Bihar. Values are medians for cultivated area, livestock density and mechanization score and averages for fraction of harvested crops sold to market. The description is adapted from Lopez-Ridaura et al. (2018).

<table>
<thead>
<tr>
<th>Type label</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 3</th>
<th>Type 4</th>
<th>Type 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short description</td>
<td>Part-time farmers</td>
<td>Wealthy farmers</td>
<td>Small-scale cereal crop farmers</td>
<td>Resource-poor agricultural labourers</td>
<td></td>
</tr>
<tr>
<td>Cultivated area</td>
<td>1 ha</td>
<td>2 ha</td>
<td>0.6 ha</td>
<td>1.2 ha</td>
<td>0.3 ha</td>
</tr>
<tr>
<td>Livestock density</td>
<td>1 head</td>
<td>2 heads</td>
<td>112 TLU ha⁻¹</td>
<td>1 head</td>
<td>28.2 TLU ha⁻¹</td>
</tr>
<tr>
<td>Mechanization score</td>
<td>5.2</td>
<td>6.4</td>
<td>3.6</td>
<td>4.4</td>
<td>1.9</td>
</tr>
<tr>
<td>Crops cultivated</td>
<td>Staple and also oilseeds and vegetables</td>
<td>Mostly staples³</td>
<td>Mostly oilseeds, vegetables</td>
<td>Mostly staples³</td>
<td>Mostly staple and also oilseeds and vegetables</td>
</tr>
<tr>
<td>Other characteristics</td>
<td>Primary income from off farm work, mainly as labourers on other farms. Most crop residues are either sold or used for fuel</td>
<td>Most of income from off farm is generated from livestock production sales (median 27%). Intensive use of crop residues as animal feed (75%). Milk is primarily for home consumption and does not represent a source of income.</td>
<td>Half of income from off farm is generated from livestock production sales (median 27%). Intensive use of crop residues as animal feed (75%). Milk is primarily for home consumption and does not represent a source of income.</td>
<td>Half of income from off farm is generated from livestock production sales (median 27%). Intensive use of crop residues as animal feed (75%). Milk is primarily for home consumption and does not represent a source of income.</td>
<td>Zero. Mostly home consumption</td>
</tr>
<tr>
<td>Income primarily dependent on food and cash crops (median 70%). Milk is primarily for home consumption and does not represent a source of income.</td>
<td>Rich and market-oriented farmers. Median income from off farm work is 60% and from off farm livestock 40%, respectively.</td>
<td>One-third</td>
<td>Half</td>
<td>Not provided</td>
<td>Not provided</td>
</tr>
</tbody>
</table>

1 TLU indicates Tropical Livestock Unit.
2 Mechanization score is calculated according to Lopez-Ridaura et al. (2018).
3 Staples in Bihar are wheat, rice and maize.
4 Based on the proportion found in the 269 surveyed farms by Lopez-Ridaura et al. (2018).
where $D_{pq}$ is the distance of the set of indicators of farm $p_k = (p_{1k}, \ldots, p_{nk})$ from the set of indicators of the ideal point $q_k = (q_{1k}, q_{2k}, \ldots, q_{nk})$, $md_k$ is the maximum discrepancy for the indicator $k$ (Eq. (2)), and $n$ is the number of indicators. The ideal point is unlikely to be achieved given trade-offs between target indicators but is used to further rank the solutions: the ideal point allows to rule out the extreme cases, rank the solutions on a continuous scale and identify the Pareto-optimal solutions which represent the best compromises (Piech and Rehman, 1993; Tiwari et al., 1999). However, the farms closest to the ideal point can still include unbalanced performances between indicators. We therefore introduce a threshold value for positive deviance in the next sub-step.

2.4.1.3. Comparison of farm performance with population mean. Finally, the farms with all indicators above the mean were defined as positive deviants. In these farms, having a high value in one indicator does not decrease the values of the other indicators, although they do not necessarily perform best on one of the indicators. As such, these are the farms with less trade-offs between indicators. This rule adds to the Pareto ranking and ideal point by defining a narrow set of positive deviants with outstanding performances for each indicator.

2.4.2. Identification of positive deviant practices

Positive deviant practices are the best practices which lead to positive deviant performance in a farm. To identify positive deviant practices, we used three sub-steps: 1) quantification of performance of individual practices; 2) Pareto ranking and determination of the distance to the ideal point; 3) quantification of the contribution of practices to the indicators at farm level.

Practices are defined as the combination of a production activity with a specific set of techniques and are divided into crop and animal husbandry practices. Crop practices consist of a crop with specific set of cultivation techniques, including irrigation (irrigated or non-irrigated), machinery (mechanized or manual planting/threshing), straw management (0%, 50% and 100% straw left on field as mulch), CSA techniques (traditional cultivation, zero tillage wheat, direct seeded rice), fertilization and pesticide application (low or high application), season (for crops that can be grown in different seasons such as maize or sorghum). The same crop cultivated with different cultivation techniques are considered different crop practices. For instance, wheat cultivation is classified into nine practices: traditional wheat with manual threshing, traditional wheat with mechanical threshing, and zero tillage wheat, each of them with three levels of straw allocation to soil of 0%, 50% and 100%. As a crop can last from one to several seasons, one crop practice can refer to one or more season (e.g. rice one season, yam two seasons, mango three seasons for several years). Rotations are formed of one to three successive crop practices in *rabi* (winter), *zaid* (spring) and *kharif* (monsoon), for instance “wheat-mungbean-rice”, “wheat-yam-yam(con-tinued)” with yam being planted in *zaid* and harvested in *kharif*, “mango-mango(continued)-mango(continued)” with mango being a perennial crop lasting for several years. Animal husbandry practices consist of an animal with related purpose (for milk or for meat).

2.4.2.1. Quantification of performance of individual practices. First, for each indicator the performances per hectare were calculated for crop
and animal husbandry practices. For crops, practices were individually entered in FarmDESIGN; as yields, prices and cultivation costs per ha did not differ among farm types we used average values from the 43 farms for each crop practice. OM inputs were used instead of SOM balance because crop practices usually last only one season while OM outputs from soil were calculated on annual basis. The crop practice was allocated to 1 ha. No manure was applied, as this is considered as an effect of the animal component, unless the crop specifically requires manure or other organic fertilizers, and these are usually imported (e.g. for tobacco). For animal husbandry, the performances of one adult bovine on one hectare was calculated using the formulas in Supplementary Materials A. The performances of goats and chickens were not considered because of the negligible effect on the indicators, rare occurrence on the farms and the culturally-determined reluctance towards rearing animals other than bovines (Thorpe et al., 2007).

2.4.2.2. Pareto ranking and ideal point. Second, practices were classified according to Pareto rank and ordinated based on the distance from ideal point, using the procedure explained above for farm performances (Section 2.4.1.2). Ordination of crop practices was performed for each season separately: *rabi*, *saiz*, *kharif*. The coordinates of the ideal point for crop practices represented the best performances among the three seasons (see Section 3.3 and Supplementary Materials F). As we only evaluated the performance of bovines, we could not perform the Pareto ranking or ordination from the ideal point of this single animal husbandry practice.

2.4.2.3. Contribution to the indicators at farm level. Finally, for each farm, the four indicators were partitioned into the relative contributions of individual crop and animal husbandry practices. Formulas were adapted from the model calculation as described in Groot et al. (2012) (Supplementary Materials B). Contribution of individual production activities to single indicators and to the overall farm performances were compared among positive deviant and non-deviant farms. We identified the practices in positive deviant farms that contribute to improving overall farm performance i.e. contributed for a substantial share in several indicators without decreasing any other: these are the positive deviant practices.

2.4.3. Positive deviance informed redesign
In the positive deviance informed redesign, we recombinated the previously identified positive deviant farms and practices in FarmDESIGN with the aim to redesign a farm which performed twice compared to the population mean for each of the indicators (i.e. around +100%; in case of water half the population mean i.e. around −50%). The redesign was initially performed on an individual farm and the resulting redesigned configuration was then adapted to the five farm types.

The four indicators were used as objectives to: (1) maximize operating profit, (2) maximize SOM balance, (3) minimize water use, and (4) maximize dietary energy production. The objectives were constrained to performance levels higher than either the original, or higher than twice the mean if they were already performing better. This forced the model to only consider alternative configurations with better solutions than the original (Groot et al., 2012). The decision variables were the areas allocated to crop rotations, the destination of crop residues and the amount of imported feed. Residue destination was restricted to common farmers’ practices in Bihar, e.g. wheat and rice straw could not be left on the field, according to Singh et al. (2013) and results from the interviews. The constraints were: (1) whole farm crop area was fixed, (2) the feed balance was fixed to acceptable deviation (dry matter ≤100% of intake capacity, energy within 95–105% of the requirements and protein within 100–130% of the requirement) (Groot et al., 2012; Cortez-Arriola et al., 2016), (3) minimum feed self-reliance for animal feed was 35% for energy and 20% for protein. The optimization process was run for 2000 iterations using the default values for amplitude of mutations \( F = 0.15 \) and crossover probability \( CR = 0.85 \) (Groot et al., 2007; Groot et al., 2010).

The redesign was performed using an iterative procedure:
1) One positive deviant farm was selected as a starting point for the redesign; this farm was selected in order to already present most of the positive deviant practices.
2) The causes of low scores on the lowest indicator(s) in the selected farm were identified based on the results on positive deviant practices (Section 2.4.2) and by comparing the farm configuration with configurations of farms with the highest value for the given indicator(s) (these extreme farms are usually not positive deviants as the highest performance in one indicator often comes with poor performances for other indicators).
3) Potential replacements were suggested for multi-objective optimization with FarmDESIGN i.e. replacement of an existing practice by a positive deviant practice. When introducing a new crop practice in the rotation, we took into account only rotations already present in the 43 farms thus ensuring agronomic feasibility. We did not take account of a pre-crop effect.
4) The alternative farm configurations obtained with the multi-optimization were sorted in order to check if a configuration was formed which complied with the goal to have all the indicators performing twice the population mean.
5) If such a configuration was not found in step 4, a new change was introduced in the farm and a new exploration was run, until a farm configuration was found with all indicators performing twice the mean. We only introduced one change at a time and kept the configuration as similar as possible to the original farm.

In order to present a recognizable example for all farm types, the obtained farm configuration was adapted for each farm type. To this aim, we repeated the procedure explained above for five model farms representing the five farm types using the obtained configuration as a starting point. Each model farm was assigned with the average area of the respective farm type as in Lopez-Ridaura et al. (2018) and the average available labour per farm type in this study. As a result, we obtained five positive deviance redesigned farms, one for each farm type.

2.4.4. Feedback from farmers
Fifteen focus group discussions were conducted with local farmers in the period of January–February 2019 in Nirpur (Vaishali district), Bakhari (Muzaffapur district) and Chaundali (Samastipur district). In each village, one focus group discussion per farm type was conducted with 10 representative farmers of the farm type, making a total of 15 sessions with 150 farmers. Farmers were recruited on the basis of a short household survey in each village and were assigned to a type as identified by Lopez-Ridaura et al. (2018). The focus group discussions were divided in three parts: in part 1, the designed farm was presented and farmers were asked for feedback on each element of the configuration; in part 2, farmers conducted a serious game in which they were asked to change the decision variables of the designed farm configuration, observe the effect of these changes on the indicators as calculated by the model and choose their preferred configuration among the alternatives produced; in part 3, farmers were asked for feedback on the designed farm in the view of the game’s outcome. In this study, the focus group discussions served to provide an initial feedback on the redesigned farm configuration and to collect their suggestions for subsequent redesign cycles. The complete description of the focus group discussions is available in Supplementary Materials C.

3. Results
3.1. Quantification of current farm performances
The 43 farms had a median area of 1.5 ha and showed a wide variety of crops. The most important crops were wheat (39% average
area), rice (33%) and maize (23.5%) (average area in one season). Furthermore, oilseed, pulses, fodder, vegetables, fruit trees and tobacco were cultivated. Farms had a median livestock density of 1.9 Tropical Livestock Units (TLU) ha\(^{-1}\) (median 2.4 TLU per farm). Most farms had cows or buffalos for milk production with an average milk yield per cow of 5.5 kg day\(^{-1}\) (calculated for the whole year) and the herd comprised on average 30% of non-productive animals (heifers or calves). Calculated average feed self-reliance was 60% for both energy and protein but decreased to 40% in farms with livestock density larger than 5 TLU ha\(^{-1}\). Farms presented a large within- and between-type variability (Fig. 4), and values of indicators did not significantly differ among farm types. In line with the fact that villages were selected among similar farming systems, soil and climate, we did not find significant differences among villages and therefore we do not further consider them in the analyses (Supplementary Materials D).

3.2. Identification of positive deviant farms

Farms exhibited a synergy between SOM balance and dietary energy production, but trade-offs between SOM balance and water use and between water use and dietary energy production (Fig. 5). Half of the farms (22 out of 43 farms) were classified as Pareto-optimal and occurred with similar frequencies in the different farm types (Fig. 5B). Distance from the ideal point ranged between 0.40 and 0.83 (on a 0 to 1 scale) (Fig. 6A). The first 16 farms closest to the ideal point were also Pareto-optimal (Supplementary Material E). Farm types did not show any pattern in relation to the distance from the ideal point (Fig. 6A). Six out of 43 farms had at the same time all indicators above the mean and were therefore assigned as positive deviants. They were all Pareto-optimal, among the eight closest farms to the ideal point and represented all farm types except for type 1.

3.3. Identification of positive deviant practices

One hundred forty three crop practices (i.e. the combination of a crop with specific set of cultivation techniques) including 45 different crops were cultivated in the 43 farms. Crop practices presented large variability in the indicator values, with an operating profit of 290–5044 USD ha\(^{-1}\) year\(^{-1}\), OM inputs of 1–747 kg OM ha\(^{-1}\) year\(^{-1}\), water use of 0–4550 m\(^3\) ha\(^{-1}\) year\(^{-1}\) and dietary energy production of 0–21.6 adults ha\(^{-1}\) year\(^{-1}\) (Supplementary materials F and G). The average performance of one adult bovine (1 TLU) on one hectare was 579 USD ha\(^{-1}\) year\(^{-1}\) of operating profit, 67 kg OM ha\(^{-1}\) year\(^{-1}\) of OM inputs, 0 m\(^3\) ha\(^{-1}\) year\(^{-1}\) of water use and 2.1 adults ha\(^{-1}\) year\(^{-1}\) for dietary energy. We present an overview of the performances of the most common crop and animal husbandry practices in Table 3.

Eleven out of 46 in rabi, 15 out of 47 in zaid and 16 out of 51 in kharif crop practices were ranked as Pareto-optimal. At overall level, no
Fig. 5. (A) Scatterplot matrix presenting the two-dimensional representation of the farm performances for the four indicators. Colors represent Pareto-optimal farms (green) and non-Pareto optimal farms (grey). Red lines represent relations between indicators; the two outliers for SOM balance (red circles) are not considered for the relation between the indicators. (B) Histograms representing the frequency of Pareto-optimal (green) and non-Pareto optimal farms among the five farm types. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 6. Ordination from the ideal point of (A) the 43 farms and (B) the 43 farms with the addition of the five positive deviance designed farms for each farm type. Farm codes represent villages (BD = Bardia, BJ = Bajitpur, BK = Bakhari, C = Chandauli, DH = Dighra, DM = Digambra, K = Kuboli, N = Nirpur, R = Repura) and farm types (types 1, 2, 3, 4, 5); positive deviance redesigned farms have codes RD1, RD2, RD3, RD4, RD5. Bars in different colors represent the scaled distance of the indicators operating profit (green), SOM balance (red), water use (blue) and dietary energy production (yellow). Square diamonds (♦) represent the distance from the ideal point of the farm. Note that the distance from the ideal point of the farm does not correspond to the simple sum of the scaled distances of the four indicators (see Eq. (1)). Dark bars with tick borders represent Pareto-optimal farms while light bar with thin borders represent non-Pareto optimal farms. Original positive deviant farms with all the indicators above the mean are circled in pink, while positive deviance redesigned farms with all the indicators twice the mean are circled in purple. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
clear trade-offs or synergies were revealed between indicators (Fig. 7). However, comparing performances of the indicators for single crop practices, crop practices excelling in one of the indicators showed strong trade-offs with other indicators, with none having all four indicators above the mean. Crop practice distance from ideal point varied from 0.46 to 0.89. All the Pareto-optimal crop practices closest to the ideal point were cereals (wheat and maize).

After analysis of the performances of practices, we evaluated the contributions of each practice on the indicators at farm level and identified the practices actually responsible for the highest/lowest performances for each indicator. For brevity, here we only present a summary of the main findings while the detailed analysis and bar graphs are presented in Supplementary Materials H. For operating profit, the most profitable farms either cultivated mango or tobacco or had high livestock density. Yam also significantly contributed to crop gross margin, despite the small dedicated area. For SOM balance, OM inputs mainly originated from crop residues, especially cereal straw and sesbania. Manure production was the most variable OM component and high manure production appeared essential to achieve positive SOM balance. For water use, high use directly correlated to the area dedicated to rice, while the lowest use related with large area of fallow and low water requiring crop practices, such as mustard, tobacco and yam. For dietary energy, the highest values were achieved in farms which combined a high cereal production with a large number of animals.

The in-depth analysis of the nine farms closest to the ideal point, which included the six positive deviant farms (i.e. farms with all the indicators above the mean), revealed the following set of positive deviant practices: high livestock density (5–6 TLU ha⁻¹), low or no (0–30%) rice, around 30% of wheat and 30% monsoon maize (average area in one season). In addition to the practices mentioned, yam and tobacco were identified as potential positive deviant practices. Yam was ranked as Pareto-optimal and received a distance to the ideal point of 0.64 being the closest crop practice after cereals. Monsoon maize without residues allocated to soil was ranked as Pareto-optimal and

### Table 3

Indicator performance, Pareto ranking (N = non-optimal, PO = Pareto-optimal) and distance from the ideal point of the most common crop and animal husbandry practices present in the 43 farms. Crop practices are divided into the three seasons rabi (winter), zaid (spring) and kharif (monsoon).

<table>
<thead>
<tr>
<th>Practice</th>
<th>OM input (kg OM ha⁻¹ year⁻¹)</th>
<th>Water use (m³ ha⁻¹ year⁻¹)</th>
<th>Operating profit (USD ha⁻¹ year⁻¹)</th>
<th>Dietary energy (adults ha⁻¹ year⁻¹)</th>
<th>Pareto</th>
<th>Distance to ideal point</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Rabi (Winter)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wheat 0%</td>
<td>159</td>
<td>2100</td>
<td>584</td>
<td>15.8</td>
<td>N</td>
<td>0.63</td>
</tr>
<tr>
<td>Tobacco</td>
<td>266</td>
<td>1000</td>
<td>1470</td>
<td>0</td>
<td>PO</td>
<td>0.69</td>
</tr>
<tr>
<td>Mustard</td>
<td>28</td>
<td>1000</td>
<td>394</td>
<td>8.7</td>
<td>PO</td>
<td>0.72</td>
</tr>
<tr>
<td>Mango²</td>
<td>5</td>
<td>1333</td>
<td>541</td>
<td>1.07</td>
<td>N</td>
<td>0.82</td>
</tr>
<tr>
<td><strong>Zaid (Spring)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yam - first season¹</td>
<td>88</td>
<td>500</td>
<td>3827</td>
<td>19</td>
<td>PO</td>
<td>0.46</td>
</tr>
<tr>
<td>Sesbania</td>
<td>705</td>
<td>0</td>
<td>−78</td>
<td>0</td>
<td>PO</td>
<td>0.69</td>
</tr>
<tr>
<td>Sorghum¹</td>
<td>136</td>
<td>0</td>
<td>−257</td>
<td>0</td>
<td>N</td>
<td>0.69</td>
</tr>
<tr>
<td>Mungbean</td>
<td>224</td>
<td>0</td>
<td>333</td>
<td>2.2</td>
<td>PO</td>
<td>0.72</td>
</tr>
<tr>
<td>Mango¹</td>
<td>5</td>
<td>1333</td>
<td>541</td>
<td>1.07</td>
<td>N</td>
<td>0.82</td>
</tr>
<tr>
<td><strong>Kharif (Monsoon)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yam - second season²</td>
<td>88</td>
<td>500</td>
<td>3828</td>
<td>19</td>
<td>PO</td>
<td>0.46</td>
</tr>
<tr>
<td>Monsoon maize 0%¹</td>
<td>161</td>
<td>1200</td>
<td>559</td>
<td>17.6</td>
<td>N</td>
<td>0.60</td>
</tr>
<tr>
<td>Rice 0%¹</td>
<td>125</td>
<td>4550</td>
<td>204</td>
<td>14.6</td>
<td>N</td>
<td>0.80</td>
</tr>
<tr>
<td>Sorghum</td>
<td>136</td>
<td>0</td>
<td>−257</td>
<td>0</td>
<td>N</td>
<td>0.82</td>
</tr>
<tr>
<td>Mango¹</td>
<td>5</td>
<td>1333</td>
<td>541</td>
<td>1.07</td>
<td>N</td>
<td>0.82</td>
</tr>
<tr>
<td>Animals</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dairy cow</td>
<td>73</td>
<td>0</td>
<td>579</td>
<td>2.1</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

¹ 0% indicates that no residues are left on field as mulch.
² Mango lasts for several years. The performance per season was obtained by dividing the overall yearly performance by the three seasons.
³ Yam lasts for two seasons (it is planted in zaid and harvested in kharif) and therefore appears in both seasons. The performance per season was obtained by dividing the overall two-season performance by the two seasons.
⁴ Sorghum lasts one season and can be grown both in zaid and in kharif.

![Fig. 7](image-url). Performances of crop practices. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)
received an ideal point distance of 0.6. Finally, despite the relatively large distance to the ideal point (0.79), tobacco may also be considered a promising crop practice, because it is a Pareto-optimal crop practice and appears twice out of nine farms mentioned above. The in-depth analysis of the nine farms closest to the ideal points is presented in Supplementary Materials I.

3.4. Positive deviance informed redesign

Based on the crop practice analysis, the following crop rotations were proposed for the positive deviance redesigned farms: Mustard-Yam-Cn ('Cn' indicates that yam continues for two seasons), Wheat-Mungbean-Maize, and Tobacco-Sorghum-Maize. The shares of each crop rotation were comparable between the types (Table 4). Livestock density ranged from 4.7 TLU ha\(^{-1}\) (type 2) to 6.3 TLU ha\(^{-1}\) (type 3). Farm types 1, 2 and 4 required hiring additional labour for livestock management.

The five positive deviance redesigned farms performed twice the mean for each indicator. When adding them to the 43 farms, six farms out of 48 were ranked as Pareto-optimal and the distance from the ideal point ranged from 0.26 to 0.83 (Supplementary Materials J). The five farms were closest to the ideal point (distance 0.26–0.30, Fig. 6B), and for types 1, 3 and 5 the designs were classified as Pareto-optimal. The detailed steps for the design procedure are presented in Supplementary Materials K.

3.5. Feedback from farmers

The focus group discussions yielded consistent results among villages (Table 5): farmers from the same farm type attending different focus groups made similar remarks and some major comments were repeated among all farm types.

When introducing the positive deviance redesigned farm (part 1), farmers agreed in all the focus groups that the configuration was familiar and realistic. The performance in terms of operating profit, water use and dietary energy production of the designed positive deviants were above their expectations.

During the game (part 2), farmers chose their preferred configuration almost exclusively according to the profit and the degree of similarity with their own current farms. Despite farmers mentioning decreasing water tables and rainfall and high irrigation costs during the sessions, water use rarely informed their choices. Farmers never included SOM balance as a selection criterion, but said that they would cope with negative SOM balance by adding organic amendments.

In the discussion after the game (part 3), farmers stated that they were interested in the high profit offered by the redesigned farm, but multiple components were considered undesirable (Table 5). Only type 3 farmers found the suggested farm configuration entirely feasible and useful. High livestock density represented the main issue for types 1, 2 and 4 that were constrained by feed import and labour. Type 4 farmers were not willing to reduce wheat because this is their main crop and type 5 farmers did not agree to reduce wheat and rice for food security.

Table 4

<table>
<thead>
<tr>
<th>Farm configuration and performance</th>
<th>Original farm</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 3</th>
<th>Type 4</th>
<th>Type 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crops</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total area (ha)</td>
<td>0.32</td>
<td>1.1</td>
<td>2.0</td>
<td>0.6</td>
<td>1.2</td>
<td>0.3</td>
</tr>
<tr>
<td>Rotations area (%)</td>
<td>28% Wheat-Fallow-Fallow</td>
<td>46% Mustard-Yam-Cn</td>
<td>45% Mustard-Yam-Cn</td>
<td>47% Mustard-Yam-Cn</td>
<td>46% Mustard-Yam-Cn</td>
<td></td>
</tr>
<tr>
<td></td>
<td>28% PotatoMaize-Cn-Sorghum</td>
<td>18% Tobacco-Sorghum-Maize</td>
<td>18% Tobacco-Sorghum-Maize</td>
<td>18% Tobacco-Sorghum-Maize</td>
<td>16% Tobacco-Sorghum-Maize</td>
<td></td>
</tr>
<tr>
<td></td>
<td>9% Mango trees</td>
<td>7% Banana trees</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Animals</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cows (n)</td>
<td>1</td>
<td>5</td>
<td>8</td>
<td>3</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>Calves/Heifers (n)</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Livestock density (TLU ha(^{-1}))</td>
<td>5.3</td>
<td>5.2</td>
<td>4.7</td>
<td>6.2</td>
<td>4.8</td>
<td>5.7</td>
</tr>
<tr>
<td>Milk yield per cow (kg day(^{-1}))</td>
<td>6.5</td>
<td>6.5</td>
<td>6.5</td>
<td>6.5</td>
<td>6.5</td>
<td>6.5</td>
</tr>
<tr>
<td>Purchased wheat bean (kg FM year(^{-1}))</td>
<td>1610</td>
<td>4945</td>
<td>9231</td>
<td>3231</td>
<td>5340</td>
<td>1011</td>
</tr>
<tr>
<td>Purchased maize grain fed to animals (kg FM year(^{-1}))</td>
<td>0</td>
<td>2104</td>
<td>4002</td>
<td>1171</td>
<td>1240</td>
<td>407</td>
</tr>
<tr>
<td>On-farm maize grain fed to animals (kg FM year(^{-1}))</td>
<td>44%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>On-farm maize straw (%)</td>
<td>50%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Self-reliance for energy (%)</td>
<td>36.0%</td>
<td>38.7%</td>
<td>41.8%</td>
<td>35.6%</td>
<td>40.7%</td>
<td>36.0%</td>
</tr>
<tr>
<td>Self-reliance for protein (%)</td>
<td>22.0%</td>
<td>26.5%</td>
<td>28.2%</td>
<td>23.0%</td>
<td>26.6%</td>
<td>23.0%</td>
</tr>
<tr>
<td>Labour</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own labour surplus (h year(^{-1}))</td>
<td>1480</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1250</td>
</tr>
<tr>
<td>Extra hired labour (h year(^{-1}))</td>
<td>0</td>
<td>1200</td>
<td>1930</td>
<td>0</td>
<td>1030</td>
<td>0</td>
</tr>
<tr>
<td>Farm performance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating profit (USD ha(^{-1}) year(^{-1}))</td>
<td>2989</td>
<td>4307 (+84%)</td>
<td>3934 (+68%)</td>
<td>4884 (+80%)</td>
<td>4209 (+80%)</td>
<td>4205 (+79%)</td>
</tr>
<tr>
<td>SOM balance (kg OM ha(^{-1}) year(^{-1}))</td>
<td>28</td>
<td>135 (+95%)</td>
<td>124 (+79%)</td>
<td>125 (+81%)</td>
<td>124 (+79%)</td>
<td>122 (+76%)</td>
</tr>
<tr>
<td>Water use (m(^3) ha(^{-1}) year(^{-1}))</td>
<td>3534</td>
<td>2509 (+49%)</td>
<td>2523 (+49%)</td>
<td>2492 (+50%)</td>
<td>2521 (+49%)</td>
<td>2467 (+50%)</td>
</tr>
<tr>
<td>Dietary energy (adults ha(^{-1}) year(^{-1}))</td>
<td>31.7</td>
<td>48.9 (+88%)</td>
<td>47.6 (+83%)</td>
<td>50.1 (+93%)</td>
<td>48.2 (+86%)</td>
<td>46.6 (+80%)</td>
</tr>
</tbody>
</table>

1 PotatoesMaize is an intercropping of the two crops maize and potato.
2 PotatoMaize and Yam are sown in spring and last till the monsoon season ('Cn' indicates a continuation of the crop into a second season).
Table 5

<table>
<thead>
<tr>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 3</th>
<th>Type 4</th>
<th>Type 5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Livestock</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not considered feasible. constrained by food import</td>
<td>Not considered feasible, constrained by food import and labour</td>
<td>Not willing</td>
<td>Willing but constrained in the lowlands</td>
<td>Willing but constrained in the lowlands</td>
</tr>
<tr>
<td>Willing</td>
<td>Not willing because of governmental ban</td>
<td>Rice and potato should be added. Eventually mango orchard and vegetables should be added.</td>
<td>Rice and potato should be added. Eventually mango orchard and vegetables should be added.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Monsoon maize</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Willing</td>
<td>Willing but wanted some rice during the good price</td>
<td>Willing but constrained in the lowlands</td>
<td>Willing but constrained in the lowlands</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Tobacco</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Willing as soon as the good price will be back</td>
<td>Willing but constrained in the lowlands</td>
<td>Willing but constrained in the lowlands</td>
<td>Willing but constrained in the lowlands</td>
<td></td>
</tr>
<tr>
<td>Variety of crops can be added. Rice and possibly vegetables should be added.</td>
<td>Rice and potato should be added. Eventually mango orchard and vegetables should be added.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Yam</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Willing</td>
<td>Willing but constrained in the lowlands</td>
<td>Willing but constrained in the lowlands</td>
<td>Willing but constrained in the lowlands</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Wheat</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Willing but constrained in the lowlands</td>
<td>Willing but constrained in the lowlands</td>
<td>Willing but constrained in the lowlands</td>
<td>Willing but constrained in the lowlands</td>
<td></td>
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<td></td>
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</tr>
</tbody>
</table>

Farmers were interested in replacing rice with monsoon maize but stated that this is not feasible in the lowlands. The recent price drop in tobacco forced farmers to stop cultivating the crop, but they were willing to grow it again if the price would recover. Finally, farmers asked for more crop diversification.

4. Discussion

This study aimed to identify and redesign positive deviant farming systems in Bihar, using data from 43 farms classified in five farm types. Because of large within-type variability, farm types did not significantly differ in terms of average indicator performances nor frequencies of exceptionally good performances when expressed per hectare. This suggests that the different performances in terms of profit and potential food availability between farm types found by Lopez-Ridaura et al. (2018) were mostly driven by farm size while farm efficiency (i.e. performance per ha) was similar across farm types. Exceptional performances across different farm types were also reported in other studies and suggest that focusing on farm typology might limit the identification of options to improve farm performances (Ondersteijn et al., 2003; Flores-Sanchez et al., 2011; Cortez-Arriola et al., 2015; Hammond et al., 2017b; Michalscheck et al., 2018; Moderndal et al., 2018; Steinke et al., 2019). These findings justify the decision in our methodology to use average performances from all farm types and identify positive deviant farms and practices across all farms instead of focusing on individual farm types.

The nested assessment allowed to identify six positive deviant farms. While Pareto ranking and calculating the distance to the ideal point were sub-steps that added useful information, the comparison with the population mean was finally required to narrow down the selection to a small number of best performing farms for all indicators. Pareto ranking identified more than half of the farms as Pareto-optimal; this is a significantly larger percentage than the 41 Pareto-optimal farms out of 280 in Moderndal et al. (2018) and 12 out of 521 in Steinke et al. (2019), also considering that more indicators were used in those studies, thereby increasing the probability of equal Pareto ranks (Groot et al., 2010). Although the ideal point distance successfully ruled out Pareto-optimal farms with extreme performances (i.e. farms which excel in one indicator but perform very poorly in all the others), all farms were relatively far from the ideal point. In line with the largely widespread Pareto optimality and the far distance from the ideal point, even the six positive deviant farms with all the indicators above the mean were not substantially deviating from the population mean on each indicator. This suggests that all farms, including the six positive deviants, were locked into strong trade-offs among indicators and performances can be still substantially improved in the redesign.

The diverse practices in the 43 farms presented widely differential performances with some practices showing very high performances for single indicators, but without clear trends among the four indicators (Fig. 5). Crop practices had widespread Pareto optimality and far distances to the ideal point, and no practices were found with all indicators above the mean. As such, none of the crop practices could be the single success factor for positive deviance. Nevertheless, livestock could solve these trade-offs as it increases operating profit, SOM balance and dietary energy production from a given area with negligible additional water use. High livestock density (5–6 TLU ha\(^{-1}\)) seemed the key feature of the six positive deviant farms, even though it needs to be complemented with a specific set of crop practices to achieve best performances. Livestock is often pointed as the way forward to achieve overall farm sustainability as it can simultaneously improve productive, economic and environmental performances (Devendra et al., 2006; Petersen et al., 2007; Wilkins, 2007; Herrero et al., 2010; Thornton and Herrero, 2015) and was suggested as positive deviant practice by Steinke et al. (2019).

During the redesign step, the selected positive deviant farms could be further improved when high livestock density was combined with an optimal combination of crop practices. This is in line with the idea that interactions and complementarity among practices are more important than the practices themselves (Tittoneill, 2014a; Thornton and Herrero,
Adding the positive deviance redesigned farms to the set of actual farms reduced the number of Pareto-optimal cases. As the Pareto frontier moved forward, the scope for improvement within the farms increased from 50% to 86% when including the redesigns (Fig. 8). All the redesigned farms scored the closest distance to the ideal point, decreasing the minimum distance from 0.40 to 0.26. This demonstrates that the designed configurations had a superior overall performance. However, increasing livestock density reduced farm feed self-reliance: SOM balance and dietary energy seemed to originate more from the net feed import rather than the internal recycling of residues or positive interactions among farm components (Cortez-Arriola et al., 2014; Flores-Sánchez et al., 2014; Cortez-Arriola et al., 2016).

During the focus group discussions, farmers showed interest in the considerably higher profit offered by the positive deviance redesigned farms, but some farm types also raised concerns regarding the elements that were different from their current farms. For example, types 1 (part-time farmers), type 2 (well-endowed farmers) and type 4 (cereal-crop farmers) showed concerns about higher labour and feed import costs when livestock density would increase. While farmers raised concrete concerns, implicit but inherent goals and values also contributed to their decision making (van der Ploeg, 1994). For instance, the underlying causes of these concerns may be risk and vulnerability aversion related to dependency on feed import for livestock. These implicit goals (e.g. increasing farm resilience) combined with intrinsic drivers, activities and their social and market network define the farming style of a farmer (Renting et al., 2009; van der Ploeg et al., 2009). Farmers tend to adhere to their current farming style: for example, type 4 (medium-scale cereal crop farmers) favoured larger wheat area and type 5 (resource poor agricultural labourers) preferred staple crops and did not like tobacco because of its high input requirements. As such, the redesigned farm appeared to be most suitable for type 3 farmers which already base their livelihood strategy on livestock, while it would require some adjustments to better fit other farm types.

The three innovative aspects of the proposed methodology in this study are: (1) three-sub-steps nested assessment for identification of positive deviant farms; (2) quantitative analysis for identification of positive deviant practices; (3) integration of redesign component into the positive deviance approach. First, based on a clear definition of positive deviance, the proposed nested assessment for positive deviance expands the Pareto-optimality based method by Modernel et al. (2018) and identifies positive deviants without relying on subjective weighting or expert knowledge. Second, positive deviant practices were identified by quantifying the contribution of individual practices and their interactions. Compared to the common use in the field of nutrition of statistical inference (e.g. correlation or chi-square test between positive deviant performances and practices) (Ahrari et al., 2002; Mackintosh et al., 2002; Bradley et al., 2009), the use of a detailed farm survey combined with a modelling approach has two advantages: it tests for the underlying causes of positive deviance and works with a smaller sample size. Finally, the integration of the redesign component allowed to explore the multitude of practices (143 in total) from the community to find the most efficient combination. Because of computational limits, a similar exploration could not be performed by the model alone with (iterative) Linear Programming or Multiple Goal Linear Programming and would otherwise require resorting to preselection of practices by experts (cf. Dogliotti et al., 2005; Dogliotti et al., 2014). This application expands the potential of FarmDESIGN with respect to other studies which only optimize within the current farm configuration (Cortez-Arriola et al., 2016; Ditzler et al., 2019) or after adding a limited set of new alternatives (Flores-Sánchez et al., 2014; Mandryk et al., 2014; Michalscheck et al., 2018; Timler et al., 2020). To the best of our knowledge, this is the first study to integrate the positive deviant approach in a redesign of farming systems. Farm redesign may be in conflict with the idea that positive deviants are powerful agents of change because they are real and thus proved to be realistic (Marsh et al., 2004; Bradley et al., 2009). However, the redesign is based on existing positive deviant farms and practices used among farmers while the feedback-loop was added to guarantee sensible and feasible suggestions.

Future studies should use our results from focus group discussions to inform a second cycle of redesign. General improvements include risk analysis for tobacco, more crop diversification and selection of suitable crops to replace rice in the lowlands. Other indicators and objectives could be assessed, such as increasing feed self-reliance and reducing the labour burden (as mentioned by farmers), and reducing greenhouse gas emissions from animals. In addition, the preliminary redesigned configuration should be further tailored to each farm type (Landais, 1998; Ojem et al., 2006; Andersen et al., 2007; Tittonell et al., 2010; Righi et al., 2011; Tittonell, 2014b; Descheemaeker et al., 2016; Haileslassie et al., 2016). We acknowledge that livestock density may not be appropriate for all farm types but, given the governmental goal to increase milk production in Bihar (Government of Bihar, 2012; Laik et al., 2014), it would be relevant to further discuss the implications and drawbacks of such a change with farmers and other stakeholders. Given the current low efficiency of the livestock component (Devendra et al., 2000; Erenstein et al., 2007), significant gains could be achieved by exploring options to optimize livestock density and reduce feed import (e.g. better herd management, higher feed quality and protein intake, increased on-farm feed production, etc.). The game could be further improved to include both farmers and other stakeholders in the redesign process (Vervoort et al., 2010). As last step, pilot positive deviant farms could be implemented in the villages to test and showcase the positive deviance redesigned farms in reality.

5. Conclusions

This study identified and redesigned farming systems in Bihar departing from existing, well-performing farms and based on best...
practices from the community. Using this positive deviance approach, we were able evaluated the multitude of practices present and selected few effective practices for the redesign. We found that outstanding performance for all indicators could only be reached by integrating high livestock density with an optimal combination of crop practices, which confirms the key role of interactions among components in mixed crop-livestock systems to improve multiple dimensions of farm sustainability. The redesigns outperformed all real farms in terms of the indicators assessed and showed inspiring examples for the community as they were configured out of viable interventions which already showed their validity. Focus group discussions revealed that the redesign was especially interesting for farm type 3 (small-scale crop and livestock farmers), while we recommend a second design cycle for the other farm types. We conclude that it is possible to simultaneously improve farm productive, economic and environmental performances by focusing on the room for manoeuvre inside the diversity of current farmers’ practices. These results show that the methodology could yield valuable suggestions for farm optimization to support sustainable development in agroecosystems and improvements of smallholder farmer livelihoods.

Author contributions

RAT: conceptualization, methodology, visualization, supervision, writing (original draft). VC: conceptualization, methodology, formal analysis, visualization, data curation, data collection for focus group discussions, writing (original draft). DB: resources, data collection. MLJ: resources. Funding acquisition, project administration. RKL: resources, funding acquisition, project administration. SLR: investigation, conceptualization, writing (review and editing), supervision, funding acquisition. JCG: conceptualization, software, investigation, methodology, writing (review and editing), supervision, project administration, funding acquisition.

Declaration of Competing Interest

None.

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