



Research article

Farmers' perspectives on drivers of rice yield in the Fogera Plain of Ethiopia

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ABSTRACT

In Ethiopia, rice productivity varies over locations. However, there is limited understanding about rice yield drivers for design appropriate policies and strategies to enhance rice productivity. This study focuses on assessing the patterns of rice yield and its drivers. Data were collected from 220 households and field measurements were made accordingly. Descriptive statistics, the Kruskal-Wallis test, and biplot were used to assess yield groups, drivers ranking, and driver yield group association, respectively. Four yield groups were identified 2.1 (Y1) t ha⁻¹, 3.0 (Y2) t ha⁻¹, 4.1 (Y3) t ha⁻¹, and 5.2 (Y4) t ha⁻¹. Water stress, low soil fertility, lack of draft animals, shortage of credit, pests, weak extension, and weeds were yield affecting drivers in Y1. Similarly, labor shortage, increase input price, credit, and weed marketing were yield-limiting drivers in Y2 while flooding, poor marketing, and the lack of storage were the drivers in Y3. Poor seed system, post-harvest losses, lack of farm tools, price fluctuation, lack of storage, and poor marketing were drivers in Y4. This study showed that the major drivers that significantly affect yield varied among the yield groups. Perceived drivers of the different yield groups have a better understanding and prospect for strategic target policy and intervention support to minimize yield losses thereby increasing productivity.

1. Introduction

Smallholder farmer agricultural productivity in developing countries is limited by diverse biotic and abiotic constraints (Makuvaro et al., 2017). Across the different Sub Sahara African countries, four adjacent drivers, i.e., soil fertility decline, climate change and variability, access to services, demand for food and fuel, are found the most important drivers of agricultural expansion (Nugun et al., 2021). The constraints posed by the complexity of abiotic, biotic, and socioeconomic factors reduce yields and productivity of food crops for smallholders in the developing world (Dixon et al., 2001). Farmers' fields in rainfed rice ecosystem are characterized by a high degree of heterogeneity in terms of topography, and soil conditions along topo-sequences and across sites (Boling et al., 2008). The national level policies, extreme climatic events, biotic stress, population increase, and urban expansion are major drivers of farming systems changes in Ethiopia (Kebede et al., 2019). The environmental, socio-economic conditions, and production systems of rice vary greatly from country to country as well as from location to location which

affected the performance of rice production and influences the potential of improving future rice production (Rao et al., 2017).

Differences in rice full production capacity is strongly correlated with irrigation, accessibility input, market influence, agricultural labor, and slope (Neumann et al., 2010). With this, rice yield differs among countries depending on many production limiting factors such as seed availability, variety, irrigation system, use of fertilizer and pesticides, water quality, climate, and whole crop management practices (GRiSP, 2013). Rice productivity largely depends on the degree of biophysical, socio-economic, and policy factors (Molua, 2008). Affholders et al. (2016) distinguished that the as reported by Abdul-Gafar et al. (2016), the rice yield performance difference in Nigeria and China is perceived by farmers to be biotic, abiotic, and socioeconomic drivers. Similarly, Banerjee et al. (2014) suggested that the maize yield gap and yield variations among farms in India is associated by farmers ethnic origin, availability of family labor, land ownership, legumes in cropping sequence, irrigation constraints, seed type, plant population, labor and capital investment, and use of organic manure.

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As specific drivers dictate the productivity and yield performance of different regions, region-specific management changes and interventions are required to close the observed crop yield gap (Mueller et al., 2012). Wheat yield gap in Ethiopia is attributed due to lack of appropriate technology, pests, diseases, weeds, and shortage of input levels for water-limited production system (Silva et al., 2021). Maestrini and Basso (2018) reported that the drivers of spatial and temporal variability of crop yield depends on interaction between climate, soil, topography, and management practices. Understanding the small-scale farm production constraints is also essential in designing intervention plans and targets to enhance smallholder farm yield output (Arias et al., 2013).

Rice is one of the priority commodity crops for ensuring food security in Ethiopia (MoARD, 2010). Average rice productivity in Ethiopia is estimated at 2.81 t ha⁻¹ (FAO, 2019), which is much lower than the World's average of 4.7 t ha⁻¹. This is because the Ethiopian rice production sector is still characterized by smallholder farms that depend on rain-fed production systems, a shortage of improved varieties, the lack of improved agronomic packages, low input use, drought, low temperature, low soil fertility, weeds, insect pests and diseases, inadequate irrigation schemes and facilities, erratic rainfall, and inefficient pre-and post-harvest management (MoARD, 2010; Gebey et al., 2012). The lowland rice production in Fogera Plain is affected by moisture stress especially, the late start and early cessation of rainfall (Tadesse et al., 2013). It is hypothesized that combinations of all these driving factors result in high variability in rice yields over space and over time.

In Fogera Plain, rice productivity varies over locations and over years across the rice ecosystem. We expect to find specific drivers for distinct yield groups across farm households in study area. Rice yield driving factors have not been properly evaluated and well documented, and their feature remains unknown for agricultural development intervention in the rice-producing area in Fogera Plain. This demands for making a detailed understanding and having information about yield group-specific drivers generated through a detailed characterization of biophysical and socioeconomic drivers across the rice ecosystem.

Thus this paper presents yield categories and drivers of rice production in the Fogera Plain, Ethiopia generated through a detailed characterization of biophysical and socioeconomic drivers across the ecosystem.

2. Methodology

2.1. Description of the study area

The survey was conducted for two years (main rainy season) of 2017 and 2018 in Libo Kemkm and Fogera districts, North-Western Ethiopia. The study areas are found in the Fogera Plain around the eastern part of Lake Tana Sub-Basin. It is located within latitudinal and longitudinal ranges between 11°40'N and 12°20'N and 37°30'E to 38°00'E. The districts receive average annual minimum and maximum temperatures of 13.17 °C and 28.08 °C with a mean of 20.63 °C. The mean annual rainfall is 1278.92mm (National Meteorological Service Agency, 2018).

2.2. Sampling procedure

Based on the rice ecosystem, a stratified random sampling procedure was employed. The sampling approaches were three stages sampling: The first stage of sampling study areas was a total of six rice-growing districts out of which two districts of Fogera Plain (Fogera and Libo Kemkem) were randomly selected. In the second stage, districts were stratified as low land and upland rice ecosystem. In the third stage, the peasant associations (PAs) were selected randomly within the stratified low land and upland rice ecosystem. Lastly, households (HHs) were randomly selected per PA in Table 1. In the multivariate statistical tools-based research under different (HHs) and varied factors, the sample size is determined at least 10 times or more as large as the number of variables (Nunnally, 1978). Accordingly, the sample size for this study area was 240 households framed as samples from the upland and low land ecosystems. The

Table 1. Sampled households (HHs) per ecosystem.

PAs per District	Ecosystem	PAs	HHs per Ecosystem	FGD per Ecosystem	HHs per FGD
Fogera (37PAs)	Upland (9PAs)	3	45	1	8
	Low land (19PAs)	5	75	2	16
Libo (31PAs)	Upland (12PAs)	5	55	2	16
	Low land (6PAs)	3	45	1	8
Total		16	220	6	48

Notes: PAs, peasant association; HHs, households; FGD, focus group discussion.

questionnaire was pre-tested with farm households in the intermediate farm villages and revised to make it relevant to the purpose of this study. Data were carefully inspected for their quality and completeness. Boxplots were used to detect outliers for remove them to improve multivariate analysis. Therefore, 20 questionnaires were removed and were not considered for analysis in Table 1.

Data were collected through interviews with trained enumerators, development agents, and agricultural extension experts. In the household survey, households were provided with a list of rice drivers and asked to rank in order of importance. Using focus group discussion and in-depth interviews, the list of criteria from the farmers' perspective was developed. A preference ranking matrix was used for weighing the criteria. The criteria were weighed through focus group discussion. Comparative judgments were made on the relative importance by comparing each other from the list of drivers and the dominant ones were ranked based on the order of importance. In cases of lack of consensus, group members voted. This was repeated to compare and contrast until the entire list of drivers was identified. These judgments were used to assign relative weights to the order of importance across farm diversity.

The number of focus groups per ecosystem was three. Eight households members per focus group participated. A total of 24 households participated in three FGD sessions per ecosystem, where each group consisted of 8 households. A total of 48 households were involved in FGD sessions in Table 1. The number of participants per focus group discussion from the different social groups. Respondents' order of priority pattern and preference on drivers of rice production was ranked on a scale of 5 (the most priority) to 1 (very rarely or least priority). Furthermore, two district agricultural experts, one value chain expert, one extension officer, and five development agents (DA's) were considered key informants in each district. Key informant selection was based on their special positions, experience, and knowledge that help to supplement in-depth analysis, and also cross-check the household survey.

2.3. Data collection

Rice yield data were obtained from multi-locations in 2017 and 2018 from different household farm plots. The survey captured the farmers' biophysical and socio-economic drivers such as water stress, low soil fertility, weed, insect pest and disease, birds, over flooding, lack of seed supply system, post-harvest losses, shortage of credit access, increased input price, poor marketing system, price fluctuation, shortage of draft animals, lack of storage facility, labor shortage, and lack of farm tools within rice production ecosystem.

2.4. Data analyses

The relative yield was calculated as a ratio of the average yield in each yield group to the total mean yield of the yield groups. Descriptive statistics, the Kruskal-Wallis test, and biplot analysis were to assess yield groups, drivers ranking, and driver yield group association, respectively. Households' perception analysis was employed using preference ranking of drivers and the data are ordinal that is treated by non-parametric tests.

Ordinal (ranked) data were subjected to analysis using the Kruskal-Wallis test, with a follow-up of least significant difference (LSD) for comparison of means at $\alpha = 0.05$. The frequency data associated with the categories of a single preference variable were compared using the one-way Chi-Square. SPSS Version 22 and XLSTAT15 to analyze data.

3. Results and discussion

3.1. Patterns of rice yield groups

Four major types of yield groups were identified from 220 farm households' farm plot yield data. The cluster centroids' yield groups' $t\ ha^{-1}$ were 2.1 (Y1), 3.0(Y2), 4.1(Y3), and 5.2(Y4) valued as low, medium, high, and very high, respectively. The lowest and the highest mean yield of rice yield groups lie between 2.1 (Y1) and 5.2 $t\ ha^{-1}$ (Y4) in Table 2. In a similar study conducted by Abdul-Gafar et al. (2016), rice yield performance had three major rice yield groups in Nigeria low-yield (2.4 $t\ ha^{-1}$), medium-yield (4 $t\ ha^{-1}$), and high-yield (5.1 $t\ ha^{-1}$), and in China low-yield (2.4 $t\ ha^{-1}$), medium-yield (4.1 $t\ ha^{-1}$), and high-yield (5.8 $t\ ha^{-1}$). The descriptive statistics of the farm plot, mean yield value, and relative yield percentage are described in Table 3. Regarding rice productivity, the frequency and proportion of farm households across rice yield groups were: yield group one 69 (31.40%), yield group two 84 (38.18%), yield group three 40 (18.18%), and yield group four 27 (12.27%), respectively. In this study, relative rice yield ranged from 58.33 to 144.44% across the rice ecosystem in Fogera Plain in Table 3. The relative yield result indicated that there was productivity variation among HHs across the rice ecosystem due to socioeconomic and biophysical drivers in Tables 4 and 5. As reported by Yau and Hamblin (1994) the relative yield is calculated as a ratio of entry yield (average yield) at each yield group to the total mean yield of the yield groups.

3.2. Drivers of rice yield

The households that were found in each yield group helped to rank rice-associated drivers according to the level of importance in Tables 4 and 5. Using the Kruskal-Wallis nonparametric test, the priority level of drivers was assessed. The overall drivers were prioritized by households as shown in Tables 4 and 5. In this study, 17 different drivers and four yield groups were identified. Based on the order of priority: biophysical drivers such as water stress, weeds, insect pest, and disease, over flooding, and low soil fertility was highly significant ($P \leq 0.001$) among four yield groups in Table 4. Similarly, socio-economic drivers such as lack of seed supply system, post-harvest losses, limited credit access, poor marketing system, price fluctuation, lack of storage facility, labor shortage, lack of farm tools, and shortage of draft animals were also highly significant ($P \leq 0.001$) among four yield groups in Table 5. This indicated that the rice yield associated drivers occurred more frequently with a highly significant rank mean than other factors. However, an increase in input price, poor extension support, and bird damage drivers were non-significant ($P \geq 0.05$) among the four yield groups in Tables 4 and 5. With this, Waddington et al. (2010), reported that the rice production drivers in sub-Saharan Africa are: depletion of soil fertility, weak information system, shortage of finance, lack of high yield varieties, shortage of N fertilizer, bird damage, weed competition, and inadequate water

Table 2. Farm plots clustering and variance decomposition for the optimal classification of rice yield.

Class	Yield ($t\ ha^{-1}$)	Sum of weights	Within-class variance	Average distance to the centroid
1	2.10	84.000	0.114	0.266
2	3.00	69.000	0.072	0.232
3	4.10	40.000	0.059	0.191
4	5.20	27.000	0.200	0.358

Table 3. Descriptive statistics of rice yield groups in 2017 and 2018.

Yield group ($t\ ha^{-1}$)	Frequency	Relative frequency (%)	Mean yield ($t\ ha^{-1}$)	Relative yield (%)
Y1	84	38.18	2.10	58.33
Y2	69	31.40	3.00	83.30
Y3	40	18.18	4.10	111.10
Y4	27	12.27	5.20	144.44
Total	220		3.60	

Notes: Yield groups' ($t\ ha^{-1}$), yield group 1 (y1), yield group 2 (y2), yield group 3 (y3), and yield group 4 (y4), Relative yield (%).

management. In relation to this, crop yield gap in Ethiopia is mainly attributed due to low input use (Assefa et al., 2020) and technological limitations in variety selection, planting date and density, crop residue management, weeds, pests, and diseases problems (Silva et al., 2021). As informed by Ringler et al. (2010), Gebregziabher et al. (2011), and Mekonnen (2012), the constraints for the production and flow of cereal crops in Ethiopia are tenure insecurity; weak extension and financial system, imperfect agricultural markets; inappropriate pricing and incentive policies; and inadequate information system, limited access to both agricultural inputs and markets for outputs, shortage of draft power and farm inputs; scarcity of labor, limited access to capital and markets, increasing temperature, and decreasing precipitation.

In relation to this, Jellason et al. (2021) suggested that vital agricultural expansion drivers across the different Sub Sahara African countries are soil fertility decline, climate change and variability, access to services, and demand for food and fuel. Similarly, Peng et al. (2009), reported that the key rice production drivers in China are a decline in arable land, increasing water scarcity, global climate change, labor shortage, and increasing demand for high-quality rice. With this, rice production drivers in Thailand are identified by many authors as a lack of experience in organizational management, high costs of production, lack of working capital (Khodphue and Sreshthaputra, 2008), weak information systems, poor product design (Sakolnakorn and Naipinit, 2013), and lack of knowledge and skills on the part of the entrepreneur (Purateera et al., 2009). A similar result reported by van Ittersum et al. (2013) revealed that the wheat yield limiting drivers are water stress, nutrient deficiency, insect pests, diseases, temperature, solar radiation and rainfall. Similarly, in high yielding areas tend to be more susceptible to yield losses due to weeds, pests, diseases and potential for waterlogging and the subsequently higher costs and risks of production (Gobbett et al., 2016).

3.3. Rank means of yield drivers

The degree of variation and relative importance of rice yield drivers' were identified among yield groups across the ecosystem. The rice yield drivers' rank means in Tables 4 and 5, along with the rice yield groups are presented in Figure 1. According to the order of priority in the 1st yield group (Y1), farmers perceived that the highest rank means drivers were: shortage of draft animals (153), low soil fertility (148), water stress (144), insect pest and disease (142), lack of credit access (137), weeds (126), and poor extension service (122) compared with Y2, Y3, and Y4 yield groups. The highest rank means drivers perceived by the 2nd yield group Y2 farmers were: labor shortage (141) and increase in input price (123) compared with Y1, Y3, and Y4 yield groups. On the other hand, poor market system (147) and over-flooding (161) were the highest ranks mean drivers perceived by Y3 farmers as compared with Y1, Y2, and Y4 yield groups. Likewise, regarding farm households' perception of drivers ranking, the 4th yield group (Y4) had the highest rank mean for poor seed supply system (192), lack of farm tools (175), post-harvest losses (173), lack of storage facility (168), and price fluctuation (160) compared with (Y1), (Y2), and (Y3) yield groups in Figure 1 and Tables 4 and 5. With this, in Nigeria socio-economic constraints and China's abiotic constraints as the major drivers of rice yield group differences among households (Abdul-Gafar et al., 2016).

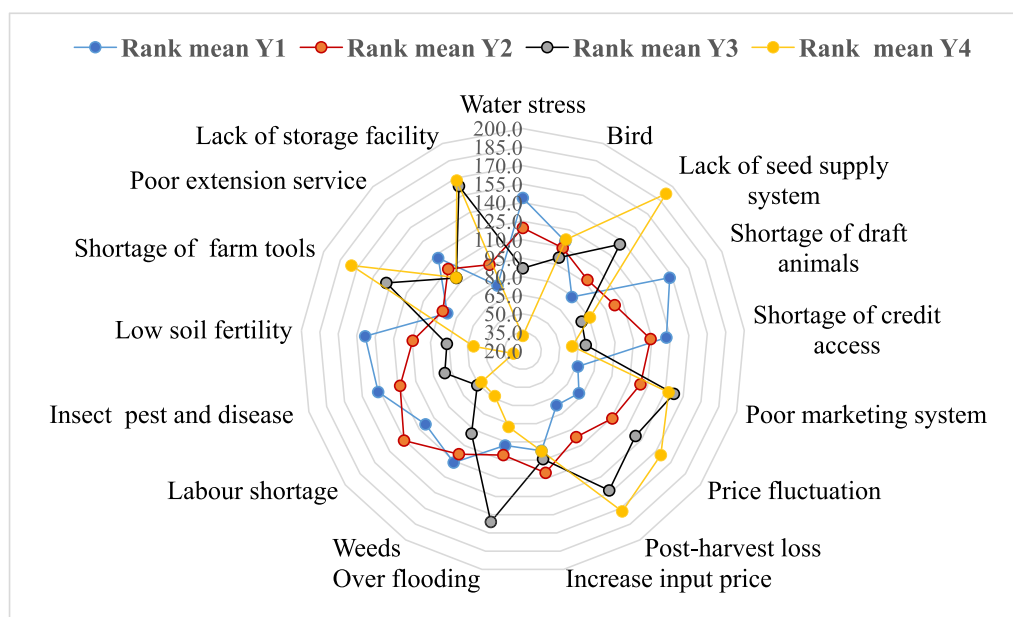
Table 4. Rice yield biophysical drivers.

Drivers	Y1 (69) = 2.1 (t ha ⁻¹) Rank mean	Y2 (84) = 3.0 (t ha ⁻¹) Rank mean	Y3 (40) = 4.1 (t ha ⁻¹) Rank mean	Y4 (27) = 5.2 (t ha ⁻¹) Rank mean	χ^2	P
Water stress	143.84	119.54	86.88	32.17	75.536	0.00
Birds	115.04	109.32	100.98	116.69	1.711	0.635
Pest and disease	141.72	123.23	85.66	27.91	75.890	0.00
Low soil fertility	148.15	109.49	81.74	60.02	52.516	0.00
Over flooding	97.92	105.80	160.89	82.61	35.495	0.00
Weeds	126.34	118.32	98.79	63.04	23.379	0.00

Table 5. Rice yields socio-economic drivers.

Drivers	Y1 (69) = 2.1 (t ha ⁻¹) Rank mean	Y2 (84) = 3.0 (t ha ⁻¹) Rank mean	Y3 (40) = 4.1 (t ha ⁻¹) Rank mean	Y4 (27) = 5.2 (t ha ⁻¹) Rank mean	χ^2	P
Poor marketing system	66.32	119.00	147.14	142.69	59.626	0.00
Price volatility	76.94	110.81	134.33	160.00	45.749	0.00
Post-harvest loss	71.78	102.10	152.85	172.85	75.543	0.00
Increase input price	102.27	120.42	109.15	102.67	5.093	0.165
Lack of seed supply system	79.00	97.70	136.65	192.07	78.466	0.00
Shortage of draft animals	152.80	103.10	73.19	80.69	55.529	0.00
Labour shortage	118.66	140.48	66.20	62.02	59.149	0.00
Shortage of farm tools	88.29	92.35	143.43	174.94	55.529	0.00
Poor extension service	121.69	109.65	99.88	100.28	4.336	0.227
Lack of storage facility	76.72	94.77	163.04	167.91	78.547	0.00
Shortage of credit access	136.72	123.89	71.18	60.11	50.601	0.00

Notes: Yield group (t ha⁻¹), Yield group1 (y1), Yield group2 (y2), Yield group3 (y3), and Yield group4 (y4).



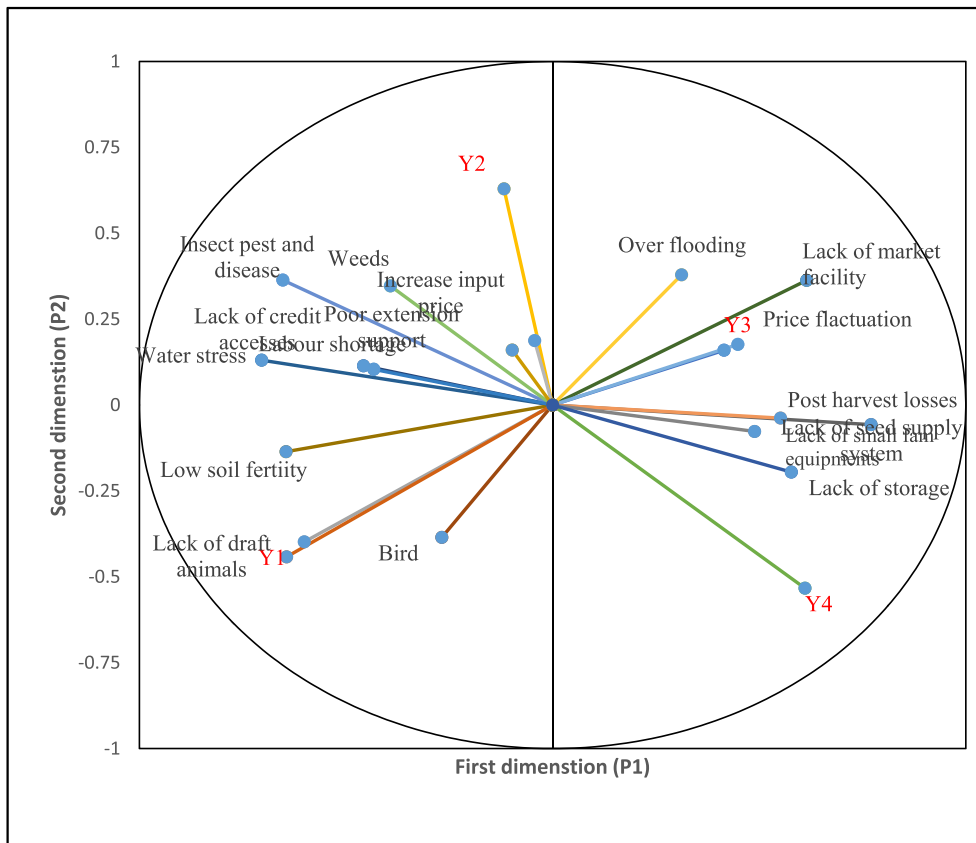
Note: The yield groups ; 2.1 (Y1), 3 (Y2), 4.1(Y3), and 5.2(Y4)

Figure 1. Households' perceptions of drivers rank mean across yield groups.

3.4. Distribution of drivers across yield groups

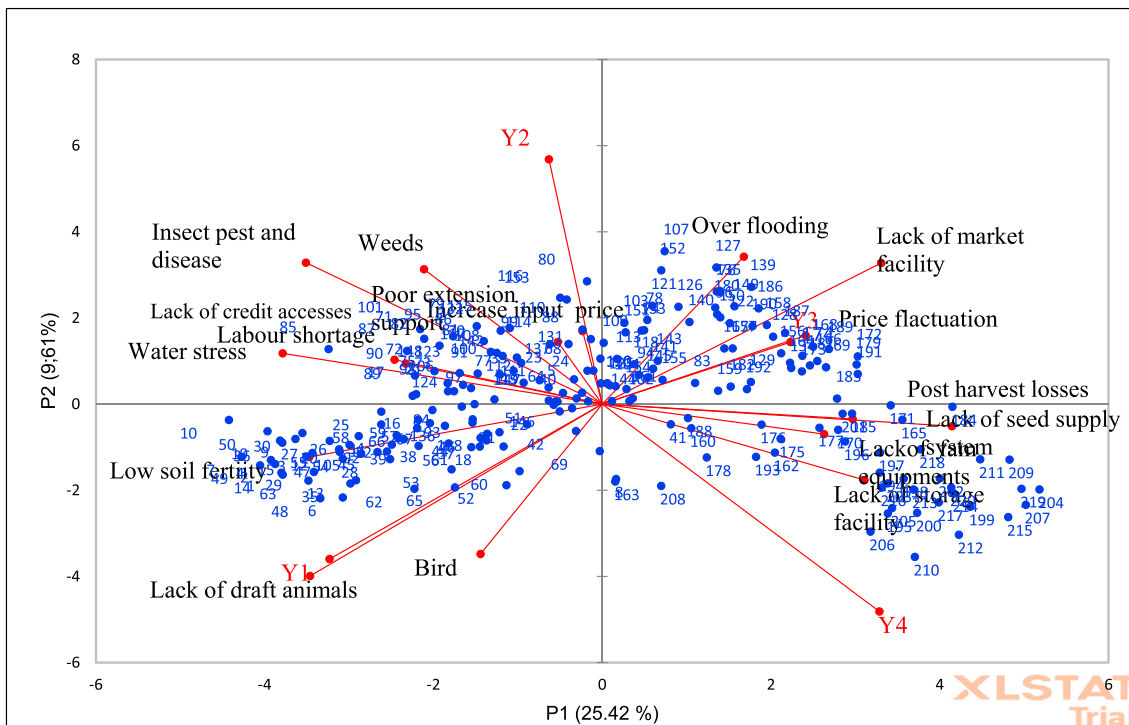
The biplots pattern of the variables (loading plot and score plot) in Figures 2 and 3 are presented with 4 yield groups, 17 drivers, and 220 farm households. The multivariate analysis pattern of the variables indicated that the drivers, i.e., poor extension services, over flooding,

bird problem, increased input price, and price fluctuation are found near to the origin (x, y) and had smaller loading and low contribution for drivers rank mean. The drivers (water stress, poor seed supply system, post-harvest losses, shortage of credit, insect pests and disease, weeds, lack of storage facility, shortage of farm tools, lack of market facility, and shortage of draft animals) are found far from the origin and had higher



Note: the yield groups t ha-1; 2.1 (y1), 3(y2), 4.1(y3), and 5.2(y4)

Figure 2. Loading plot showing driving factors associated with yield groups.



Note: dots and numbers are used to show the observations (farm households), the yield groups (t ha-1); 2.1 (y1), 3(y2), 4.1(y3), and 5.2(y4)

Figure 3. Score plot showing overall variation among 220 farm households across drivers and yield groups.

Table 6. The Cumulative principal components.

	F1	F2	F3	F4	F5	F6	F7
Eigenvalue	5.339	2.019	1.750	1.397	1.195	1.112	1.088
Variability (%)	25.422	9.614	8.334	6.652	5.689	5.293	5.179
Cumulative %	25.422	35.037	43.371	50.023	55.712	61.005	66.184

loading and high contribution for drivers rank mean. As described by Kohler and Luniak (2005), the biplot analysis help to examine the multivariate pattern of the variables in the data matrix providing the inter-unit distances and their distant positions from their origin, variance, and correlations of variables of large datasets. Accordingly, in this study, each yield group associated with the specific drivers was explained by the first two-dimension principal components biplot axes (axes P1 and P2) in Figure 2. In Figure 2 yield associated drivers included yield group (Y1) with water stress, low soil fertility, lack of draft animals, pests and diseases, weeds, shortage of credit, poor extension, and bird problems; yield group (Y2) with high input price, labor shortage, limited access to credit, and weeds; yield group (Y3) with a poor market system, over flooding, and lack of storage; and yield group (Y4) with poor seed system, post-harvest losses, lack of farm tools, lack of storage, price fluctuation and poor market access. This implies that the loading plot in Figure 2 indicated that rice productivity varies across farm households due to the variation of socioeconomic and biophysical drivers for each yield group.

Similarly, the score plot along the biplot axis in Figure 3 and principal component (PC) in Table 6 showed overall farm households variation and distribution across drivers and yield groups. The first principal component (PC1) was found to be the most influential. It explained 25.42% of the total variance followed by the second principal component (PC2) which explained 9.61% of the total variance. Both PC1 and PC2 explained 35.03% of the total variance. The cumulative first seven principal components with Eigenvalues > one together that explained 66.2% of the variability (Table 6). As reported by Giller et al. (2006), the challenge of crop yield production constraint studies that attempt to average out problems and their losses over diverse environments due to spatial and temporal variation in biophysical factors. The complexity of abiotic, biotic, and socioeconomic constraints reduces crop yield and productivity for smallholders in the developing world (Dixon et al., 2001). The agricultural productivity of smallholder farmers in developing countries is limited by diverse biotic and abiotic constraints (Makvarov et al., 2017).

4. Conclusion and policy recommendations

Rice yields in our case study area are grouped into four major types and valued as low 2.1 t/ha (Y1), medium 3.0 t/ha (Y2), high 4.1 t/ha (Y3), and very high 5.2 t/ha (Y4), respectively. Driving factors affecting rice yield levels differed across households. The differences in rice productivities are meaningfully correlated with rice yield drivers. The study revealed that yield group one (Y1) rice production drivers, water stress, low soil fertility, lack of draft animals, pests and diseases, weeds, shortage of credit, poor extension, and bird problem is interdependent. Hence, appropriate intervention strategies and management options to improve rice productivity must take into consideration. Similarly, the study finding directed that yield group two (Y2) drivers, increase input price, credit, labor shortage, and weed were yield-limiting factors, the policies of which will depend on access to credit and subsidy on input price to improve rice productivity. While over flooding, poor marketing, and the lack of storage were the drivers in yield group three (Y3), whereas there is need of appropriate strategies to enhance market networking, improve storage facility, and flood management by rice producers must take this mutually dependent into consideration. Similarly, yield group four (Y4), poor seed system, post-harvest losses, lack of farm tools, price fluctuation, lack of storage, and poor marketing were drivers in yield group four (Y4), applicable strategies, technology, and

management options to improve seed production system, market networking, storage facility, and post-harvest technology by rice producers must consider this interdependence.

The results from the analysis indicated that the specific rice yield group drivers dictate the rice yield performance variation among farm households. It is imperative to consider the yield group associated drivers in the study area, which might be relevant in supporting a more prominent and meaningful use in farm context-specific application of appropriate policy, intervention strategies, technology, and rice management options to close the observed yield gaps and minimize yield losses and thereby increase productivity in the Fogera Plain.

Declarations

Author contribution statement

Tesfaye Molla: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Kindie Tesfaye; Firew Mekbib: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Tamado Tana; Tilahun Tadesse: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data.

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Data availability statement

Data associated with this study has been deposited at IR + Institutional Repository ETD Electronic thesis dissertation. The accession number: <http://10.230.146.21>.

Declaration of interest's statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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