



Participation is not enough: innovation adoption and the performance of maize farms in the Kikwit hinterland (Democratic Republic of the Congo)

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Abstract: For a quarter of a century, maize yields in the Democratic Republic of the Congo (DRC) have stagnated at around 770 kg per hectare while those of neighbouring countries have risen. Drawing on a survey of 158 farm households, including 110 maize producers, in the Kikwit hinterland (Kwilu Province), this paper examines the results chain linking participation in the National Agricultural Development Programme (PNDA), effective adoption of the innovations it promotes, and the productive performance of family farms. The approach combines descriptive statistics and a FAOSTAT benchmark, a Cobb-Douglas production function estimated by ordinary least squares with HC3 robust standard errors, propensity score matching, and a within-beneficiaries comparison. Three quarters of the surveyed farms (75.2%) fall below a national average yield that has itself declined by 3.8% since 2000. The average effect of participation is statistically indistinguishable from zero, whether estimated by matching (+12% to +18%) or by regression (+12.2%). By contrast, the adoption of new crop management practices is associated with a 34% increase in output over the full sample ($p < 0.05$) and 50.7% within beneficiaries (95% CI: [13.5, 100.0]). The participation-to-adoption conversion corridor is incomplete: only 68.7% of beneficiaries adopted the decisive crop management practices, 51.8% adopted the full package, and maize-mucuna intercropping stalls at 9.6%. Programme effects therefore operate mainly through the effective appropriation of innovations, which calls for systematic adoption indicators and post-diffusion monitoring in PNDA evaluation.

Keywords: agricultural programmes 1; extension services 2; propensity score matching 3; results chain 4; sub-Saharan Africa 5; technology diffusion 6

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1 Introduction

Improving agricultural productivity remains one of the major challenges of rural development in sub-Saharan Africa, where the performance of family farms falls far short of its agronomic potential (Jayne et al., 2019; van Ittersum et al., 2016). The Democratic Republic of the Congo (DRC) illustrates this with particular acuity: maize, the country's leading cereal by volume, was grown on about 3.1 million hectares in 2024 for an output of roughly 2.4 million tonnes, i.e. an average yield of 770 kg per hectare that has remained practically unchanged since 2000 (FAO, 2025). Over the same period, Angola more than doubled its maize yields (+107%) and Zambia raised them above 2,300 kg per hectare, nearly three times the Congolese level. With rapid demographic growth and mounting food demand, this prolonged stagnation makes the effectiveness of innovation-diffusion policies a central food security issue (FAO, 2024; OECD and FAO, 2025).

To address such constraints, several African countries have implemented programmes to promote agricultural innovations through the diffusion of improved technologies, farmer training and stronger support services, in the expectation that the adoption of new practices will durably raise the productivity and incomes of family farms (Klerkx and Begemann, 2020; Pretty et al., 2011). Evaluation evidence remains mixed, however, with gains often constrained by local adoption conditions, the economic circumstances of producers and the quality of technical support (Abate et al., 2018; Rurii and Nzengya, 2026). The recent literature accordingly stresses that programme evaluation should go beyond beneficiary status and distinguish participation from the effective adoption of the innovations promoted (Klerkx and Rose, 2020; Takahashi et al., 2020). Not all beneficiaries adopt the technologies on offer with the same intensity, while some non-beneficiary farmers gain access through local networks, agricultural services or peer exchanges; observed productivity differences may therefore depend more on changes in practices than on participation in the programme itself (Wossen et al., 2017).

This question is especially pertinent in the DRC, where the National Agricultural Development Programme (PNDA), supported by the World Bank and approved in June 2021, seeks to modernise family farms through the diffusion of innovations, training and technical support (World Bank, 2021). Across the country, including provinces far from investment corridors, such programmes face severe logistical, institutional and informational constraints characteristic of fragile states (Mellor, 2017). Yet the mechanisms through which these interventions actually influence productive performance remain poorly documented: the available quantitative micro-data concern mainly the seed systems of Katanga (Balasha et al., 2025), and no empirical evaluation, even a descriptive one, has been published on the effects of the PNDA in Kwilu Province, one of the country's principal food-crop areas in the west.

This study focuses on the maize farms of the Kikwit hinterland and assesses the results chain linking participation in the PNDA, effective adoption of agricultural innovations and productive performance. Specifically, it seeks to (i) identify the main determinants of maize output; (ii) measure the specific effect of PNDA beneficiary status; (iii) assess the contribution of the innovations actually adopted; and (iv) situate the observed performance within the national and regional dynamics of yields. Three hypotheses structure the analysis: output is driven primarily by the conventional factors of land, labour and experience, in a still extensive production logic (H1); participation in the PNDA, taken on its own, is not associated with higher output holding characteristics constant (H2); and the effective adoption of innovations, in particular crop management practices, is associated with higher performance, the programme effect operating mainly through this adoption (H3).

Relative to the existing literature, the paper makes three contributions. The first is analytical: it articulates the participation, adoption and performance links in a results-chain reading of diffusion programmes, enriched by three devices rarely combined in adoption studies in sub-Saharan Africa — the incremental explanatory power of the innovation block relative to beneficiary status, a participation-to-adoption conversion corridor measured directly by crossing status with adoption, and a propensity score matching estimate complemented by a comparison internal to beneficiaries. The second is contextual: the study provides the first quantitative micro-evidence on the effects of the PNDA in Kwilu, helping to document a category of territories (agricultural hinterlands in fragile-state settings) that has remained at the margin of the evaluation literature. The third is factual: anchoring the survey results in the FAOSTAT series for 2000-2024, it shows that the performance of the Kikwit hinterland farms (664 kg per hectare on average) stands 14% below a stagnant national average, with 75.2% of the surveyed farms below that level. The remainder of the article is organised as follows: Section 2 presents the context and the literature

review, Section 3 the conceptual framework, Section 4 the methods, Section 5 the results and Section 6 the discussion, before the conclusions and policy implications in Section 7.

2 Context and literature review

2.1 Innovation adoption and productivity in smallholder farms

The economics of agricultural technology adoption, building on the seminal work of Foster and Rosenzweig (2010), stresses that the decision to adopt results from cost-benefit trade-offs conditioned by information, human capital, credit constraints and risk. In sub-Saharan Africa, the persistence of wide yield gaps between farms and relative to agronomic potential is increasingly explained by differences in access to knowledge, innovations and agricultural services rather than by factor endowments alone (Lowder et al., 2021; Suri and Udry, 2022). For maize, productive performance depends notably on the quality of crop management practices, the use of improved seed, soil fertility management and the technical support provided to producers (van Ittersum et al., 2016).

A recurrent lesson of the empirical literature concerns the heterogeneity of innovation effects and the complementarity of practices. Studies of the simultaneous adoption of several technologies show that productivity gains depend less on the adoption of an isolated technology than on coherent combinations of practices, whose effect is conditioned by agro-ecological conditions and by the farm's management capacity (Khonje et al., 2018; Teklewold et al., 2013). Recent reviews of sustainable intensification (Pretty et al., 2011) and climate-smart agriculture (Rurii and Nzungu, 2026) confirm that adoption rates remain heterogeneous across practices, available resources and the capacity of producers to embed these changes durably in their production systems (Ayim et al., 2022). Moreover, adoption determinants are not confined to individual characteristics: membership of farmer organisations and social networks accelerate diffusion (Manda et al., 2020), while human-capital attributes, notably experience, shape the capacity to mobilise resources effectively (Marenja and Barrett, 2007).

More recently, attention has shifted to the adoption processes themselves. Drawing on an in-depth qualitative study in Ethiopia, Abetu et al. (2026) show that adoption is neither binary nor immediate: it follows heterogeneous and often interrupted pathways, in which the modes of diffusion and support matter as much as the attributes of the technology. This processual reading justifies distinguishing analytically between exposure to a programme (participation) and the effective appropriation of practices (adoption), and treating productive performance as the outcome of this results chain rather than as the direct effect of an administrative status.

2.2 Programme participation and effective adoption: lessons from evaluations

Agricultural development programmes are one of the main mechanisms of innovation diffusion in Africa, operating through farmer training, extension services, access to inputs and technical support; producers covered by these schemes generally display higher adoption levels than others (Klerkx and Rose, 2020; Ragasa and Mazunda, 2018). Impact evaluations, including experimental ones, nuance this picture: the randomised trial of Abate et al. (2018) in Ethiopia shows that the yield gains associated with the promoted technology packages depend strongly on the actual use of their components, while Wossen et al. (2017) establish that access to extension influences adoption first and, through it, household welfare. The review by Takahashi et al. (2020) synthesises this result: the effect of programmes on productivity operates essentially through adoption, whose level remains decisive but highly variable across beneficiaries.

Two methodological implications follow. First, participation in a programme does not automatically translate into higher productivity: observed effects depend on the quality of support, the intensity of interventions and the effective adoption of the innovations on offer (Schut et al., 2016); not all beneficiaries take up technologies with the same intensity, while some non-beneficiary producers can access them through local exchange networks or agricultural services (Klerkx and Begemann, 2020). Second, studies restricted to beneficiary status may overstate the programme's own role, since it is only an institutional device facilitating access to innovations. Adams and Jumpah (2021) illustrate this in northern Ghana: technology adoption affects welfare, but the effect remains modest and non-significant for some dimensions, pointing to the quality of appropriation rather than to access itself. This distinction is now central to the evaluation of agricultural policies, yet few studies have tested it in the Democratic Republic of the Congo.

2.3 Maize in western DRC and the PNDA

Congolese agriculture rests overwhelmingly on family farms, which dominate rural employment and urban food supply (Lowder et al., 2021). In the south-west, maize is one of the main food crops alongside cassava and groundnut, and Kwilu Province, whose main urban hub is Kikwit, serves as a food basket for urban centres (FAO, 2024). Production systems remain extensive, with yields below regional averages, limited use of modern inputs and marked land and logistical constraints; the recent literature on Central Africa nevertheless recalls that the apparent abundance of land masks strong differences in accessibility and quality across areas (Chamberlin et al., 2014). The barriers to the adoption of improved seed documented in the neighbouring Katanga — information, availability, fit with local preferences — are likely to apply, *mutatis mutandis*, in the west of the country (Balasha et al., 2025).

It is in this context that the PNDA operates, a national programme supported by the World Bank and approved in June 2021, whose development objective is to improve agricultural productivity and producers' access to markets, notably through activities in production development, commercialisation and institutional strengthening (World Bank, 2021). The programme embodies a transformational conception of family farming in which productivity growth is the condition for durable poverty reduction (Mellor, 2017). The innovations promoted in the study area — row planting, improved seed, new crop management practices and maize–mucuna intercropping — reflect this technological diffusion logic. The empirical evaluation of the conversion of these interventions into changes in practices, and then into production gains, nonetheless remains to be built: this is the object of the present contribution.

2.4. Identified gaps and hypotheses

Three gaps emerge from this review. First, the literature distinguishes conceptually between programme participation and the effective adoption of innovations, but empirical applications explicitly articulating the three links — participation, adoption, performance — remain rare in sub-Saharan Africa and non-existent for the DRC. Second, the agricultural hinterlands of fragile states, though numerous, are very unevenly represented in adoption studies, which limits the external validity of conclusions drawn from Ethiopia, Zambia or Ghana. Third, few studies situate their survey results in the long-term dynamics of national and regional yields, even though this benchmarking conditions the interpretation of observed gaps. To address these gaps, the paper tests the hypotheses H1 to H3 stated in the introduction, using the conceptual framework presented in the next section.

3. Conceptual framework and hypotheses

The analysis rests on the theory of agricultural production, whereby output results from the combination of four main factors: land, labour, capital and technology (Coelli et al., 2005; Hayami and Ruttan, 1985). In the family farms studied, the agricultural innovations promoted by the PNDA (improved seed, row planting, maize–mucuna intercropping and new crop management practices) form a component of the technology factor, while producers' experience and education influence their capacity to adopt and use these innovations efficiently. The PNDA is not treated as a direct production factor but as an institutional device facilitating access to innovations, training and support services (World Bank, 2021; Klerkx and Begemann, 2020). Its expected effect on output is therefore indirect and depends on the effective adoption of the innovations by producers.

Figure 1 formalises this results-chain reading. The first link (participation) denotes the farm's exposure to programme interventions: beneficiary status, training, support and inputs. The second link (effective adoption) captures the concrete appropriation of the innovations by the producer, measured by the practices declared in use at the survey. The third link (productive performance) corresponds to farm outcomes, measured by total output and yield. The direct path from participation to performance (H2) expresses the hypothesis of a specific effect of status — for instance through confidence, market access or network effects — independently of changes in practices. The mediated path (H3) expresses, by contrast, that participation converts into performance only through adoption. The conditional factors (production factors, human capital, institutional environment) control for structural differences between farms (H1). This architecture, inspired by agricultural innovation systems

approaches (Klerkx and Begemann, 2020; Schut et al., 2016), guides the simultaneous and then alternating introduction of variables in the empirical model, the direct measurement of the conversion corridor, the propensity score matching and the decompositions presented in Sections 4.4, 5.2 and 5.4 to 5.6.

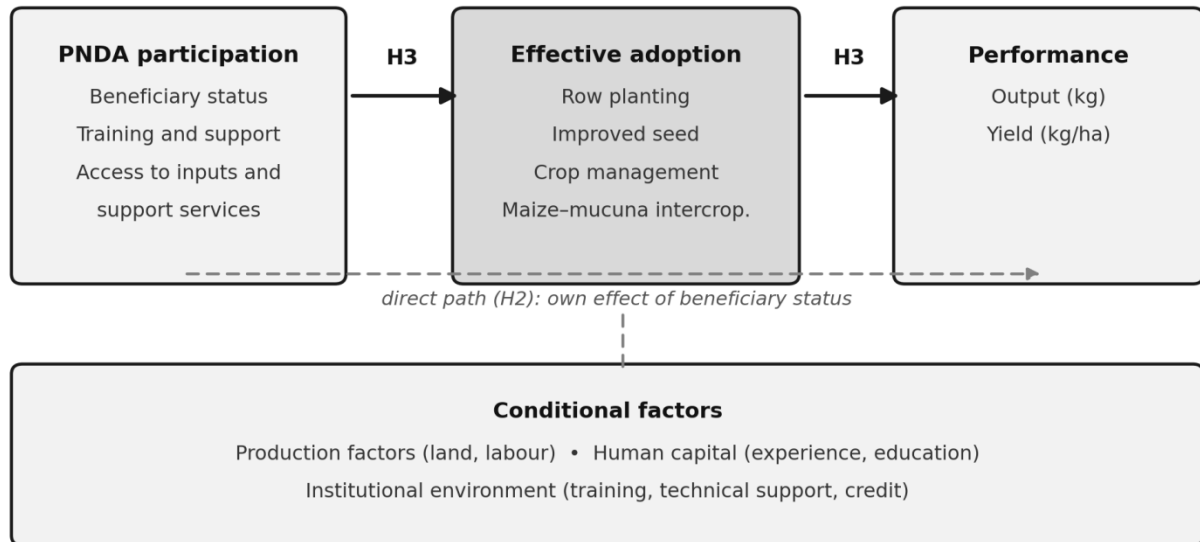


Figure 1. Conceptual framework: participation-adoption-performance results chain and associated hypotheses (H1-H3). Source: authors' elaboration.

4. Materials and methods

4.1. Study area

The study was carried out in the hinterland of Kikwit, in Kwilu Province, south-western Democratic Republic of the Congo. This area is one of the main supply basins of the city of Kikwit in food crops and is characterised by the predominance of family farming. The main crops grown are cassava, maize, groundnut and legumes, destined for self-consumption and for sale. The survey was conducted in the sectors of Kwenge, Imbongo and Kipuka, selected for their importance in maize production and their coverage by the PNDA. The simultaneous presence of beneficiary and non-beneficiary producers in these sectors provides a suitable setting for analysing the relationships between programme participation, innovation adoption and productive performance.

4.2. Data collection and sampling

The data come from a survey of 158 farm households conducted with a structured questionnaire administered on the KoBoCollect platform, covering the socio-economic characteristics of producers, the productive resources mobilised, access to agricultural services, the innovations adopted and farm performance. The sample was built purposively in line with the study objectives: PNDA beneficiaries were selected from the lists of local support structures, while non-beneficiaries were chosen in the same villages in order to limit differences linked to agro-ecological and socio-economic conditions. The higher proportion of beneficiaries reflects a methodological choice aimed at better documenting the innovations disseminated by the programme; the study therefore does not seek to estimate an average impact representative of the PNDA, but to analyse the relationships between programme participation, innovation adoption and farm output. The econometric analyses were restricted to farms for which maize was the main crop, which yielded a homogeneous subsample of 110 producers (69.6% of the initial sample);

the loss of one observation on the number of workers reduces the regression base to 109. The survey involved adult farmers who participated voluntarily with the support of local PNDA structures; responses were recorded anonymously and are reported in aggregate or anonymised form.

4.3. Study variables

The dependent variable is total maize output, expressed in kilograms. In line with the conceptual framework, the explanatory variables are grouped into four categories: production factors (area cultivated with maize in hectares and labour, measured by the number of workers), human capital (farming experience in years and education), the institutional environment (PNDA participation, access to training, technical support and access to agricultural credit) and the agricultural innovations, comprising four declared practices: improved seed, row planting, the new crop management practices recommended by the PNDA, and maize–mucuna intercropping. Table S1 in the supplementary material presents the definition, measurement, expected sign and associated hypothesis for each variable.

4.4. Analytical strategy

The analysis proceeds in five steps corresponding to the links of the results chain. The first step characterises the farms and situates their performance in the national and regional context: descriptive statistics are complemented by a comparison with maize yields from the FAOSTAT database (FAO, 2025), using three-year averages for 2022–2024 for the DRC and neighbouring countries (Angola, Congo, Cameroon, Zambia, Central African Republic), together with the 2000–2024 evolution. This benchmarking provides the external yardstick against which the performance of the sample is assessed.

The second step analyses the adoption gradient of the innovations and, above all, quantifies the first conversion link of the chain: the proportion of PNDA beneficiaries who have actually adopted each innovation. The micro-data allow a direct crossing of beneficiary status with declared adoption, without recourse to compatibility bounds: the participation-to-adoption conversion rate is computed for each of the four promoted practices, together with joint adoption of the central practices (the full package and adoption of at least two of the three central practices) and adoption intensity, defined as the number of practices adopted (0 to 4). Non-beneficiaries were also asked about their use of improved crop management practices outside the programme, which documents spontaneous diffusion.

The third step estimates the determinants of output using a Cobb-Douglas production function, widely used in agricultural productivity analyses (Coelli et al., 2005; Takahashi et al., 2020). The estimated form is as follows:

$$\ln(Y_i) = \beta_0 + \beta_1 \ln(\text{SUP}_i) + \beta_2 \ln(\text{MO}_i + 1) + \beta_3 \text{EXP}_i + \gamma'Z_i + \delta'X_i + \varepsilon_i \quad (1)$$

where Y denotes the total maize output of farm i , SUP the cultivated area, MO labour, EXP farming experience, Z the vector of institutional variables (PNDA beneficiary status, training, support, credit) and X the vector of innovations (improved seed, row planting, crop management practices, maize–mucuna intercropping); ε is a random error term. The model is estimated by ordinary least squares with HC3 robust standard errors. Two alternating specifications are estimated: Model 1 introduces beneficiary status alone, and Model 2 replaces it with the four innovations, in order to circumvent the strong multicollinearity between the programme and the technologies it disseminates. For non-beneficiaries, adoption of the promoted innovations is coded 0, exposure to the programme being the condition of their diffusion. This specification does not aim to estimate a global causal effect of the PNDA, but to determine whether participation retains an effect of its own once the innovations actually adopted are taken into account.

The fourth step evaluates the participation effect by propensity score matching (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008), in order to confront the regression results with a quasi-experimental estimate based on observables. A logit of PNDA participation is first estimated on characteristics presumed to predate the programme: cultivated area, labour, experience, age, sex, education, household size and sectors; the propensity score is derived from it. The average treatment effect on the treated (ATT) is then estimated by nearest-neighbour matching (one treated unit to at most four controls, with a caliper of 0.2 standard deviations of the score logit) and

by Gaussian kernel matching (bandwidth 0.05) on common support; standard errors are obtained by a non-parametric bootstrap with 1,000 replications, re-estimating the score at each draw (Smith and Todd, 2005). Matching quality is assessed by standardised biases before and after matching and by the overall logit test. Total output and yield are used successively as outcome variables.

The fifth step isolates the adoption channel through an analysis internal to beneficiaries, which by construction neutralises selection related to participation: among the 83 PNDA beneficiary maize producers, output is regressed, given characteristics (cultivated area, labour, experience, sectors; HC3), on the declared adoption of each practice tested in a separate model, and then on adoption intensity (the number of practices adopted). The resulting adoption premiums are converted into percentages via $\exp(\beta) - 1$. Finally, three indicators derived from the previous specifications complete the decomposition of the results chain: returns to scale (the sum of land and labour elasticities), the incremental explanatory power of the innovation block (the difference in R^2 between Models 2 and 1), and the confrontation of the adoption premiums with the participation effects estimated by regression and by matching. This architecture shows to what extent the effect associated with the programme operates through changes in practices, in line with hypothesis H3.

4.5. Identification considerations and diagnostics

As the data used are observational and cross-sectional, neither PNDA participation nor innovation adoption results from random assignment. Matching estimates rest on the conditional independence assumption: conditional on observed characteristics, the potential outcome in the absence of the programme would be identical for beneficiaries and non-beneficiaries; this assumption remains unverifiable for unobserved characteristics. The overall logit test of participation ($p = 0.41$) and the balance of covariates across groups suggest, however, that participation is only weakly related to observables, which makes matching credible in this application. Moreover, the analysis internal to beneficiaries neutralises status-related selection but remains exposed to the selection of the most productive farmers into adoption. Estimation quality was checked through several diagnostics: multicollinearity assessed by variance inflation factors (VIF), heteroscedasticity by the Breusch-Pagan test, normality of residuals by the Jarque-Bera test, and systematic use of HC3 robust standard errors; results are assessed on both total output and yield (kg/ha).

4.6. Limitations of the study

The results must be interpreted in the light of three limitations. First, the cross-sectional nature of the data does not allow definitive causal relationships to be established: propensity score matching corrects for differences in observed characteristics but remains exposed to unobserved factors (plot quality, motivation, market access), and the comparison internal to beneficiaries is still subject to the selection of the most productive farmers into adoption. Second, the agricultural innovations are measured from producers' declarations, which may introduce reporting bias, especially when the innovations are associated with a programme under evaluation. Third, the purposive sampling, the small size of the control group (27 non-beneficiaries) and the focus on maize producers of the Kikwit hinterland limit the external validity of the conclusions; these must not be generalised to the whole PNDA or to other provinces without caution. These limitations, common to adoption studies in rural Congo, are mitigated by the convergence of the three approaches — regressions, matching and internal comparison — presented in Sections 5.3 to 5.5.

5. Results

5.1. Farm performance in its national and regional context

The sample comprises 158 farm households spread across the sectors of Kwenge, Imbongo and Kipuka, of which 110 producers (69.6%) declare maize as their main crop; 74.7% of the surveyed households (75.5% of the maize

subsample) benefited from PNDA support. Table 1 presents the characteristics of the subsample. Average maize output stands at 515 kg per farm for an average cultivated area of 0.95 ha, confirming the predominance of small family farms. The recomputed yield averages 664 kg per hectare but with considerable dispersion (standard deviation of 948 kg/ha) and a median of 600 kg/ha, a sign of marked asymmetry: half of the farms remain at an already low level, while a few units, pulling the mean upwards, reach 10,000 kg/ha. Producers have on average 17 years of farming experience and mobilise about four workers.

Table 1. Characteristics of the surveyed maize farms in the Kikwit hinterland (n = 110).

Variable	N	Mean	Standard deviation	Minimum	Median	Maximum
Total output (kg)	110	514.55	435.54	100	400	3,000
Cultivated area (ha)	110	0.95	0.67	0.05	1.00	4.00
Recomputed yield (kg/ha)	110	663.79	948.16	100	600	10,000
Number of workers	109	3.79	3.78	0	3	30
Farming experience (years)	110	17.05	11.73	1	15	50

Note: the recomputed yield is the ratio of output to cultivated area, per farm.

Source: survey data, 2026.

The comparison with the FAOSTAT series requalifies these levels (Table S2 and Figure 2). The average yield of the sample (664 kg/ha) lies 14% below the recent Congolese national average (770 kg/ha in 2022-2024) — a gap consistent with the hinterland position, further removed from input and marketing corridors — and the distribution is massively pulled downwards: 75.2% of farms (82 out of 110) lie below this national average, and 99.1% below the Zambian level (2,311 kg/ha). Above all, Figure 2 shows that this national average is itself stagnant: from 799 kg/ha in 2000 it has fallen by 3.8% over a quarter of a century, whereas Angola (+107%) and, to a lesser extent, Zambia (+24.6%) and Congo (+25%) have progressed; Zambia now reaches 2,311 kg/ha, 3.5 times the sample level. The productivity deficit of the Kikwit hinterland is thus embedded in a prolonged national stagnation rather than in a conjunctural gap: it is this double gap — downwards relative to neighbours, upwards relative to agronomic potential — that any diffusion policy must reduce.

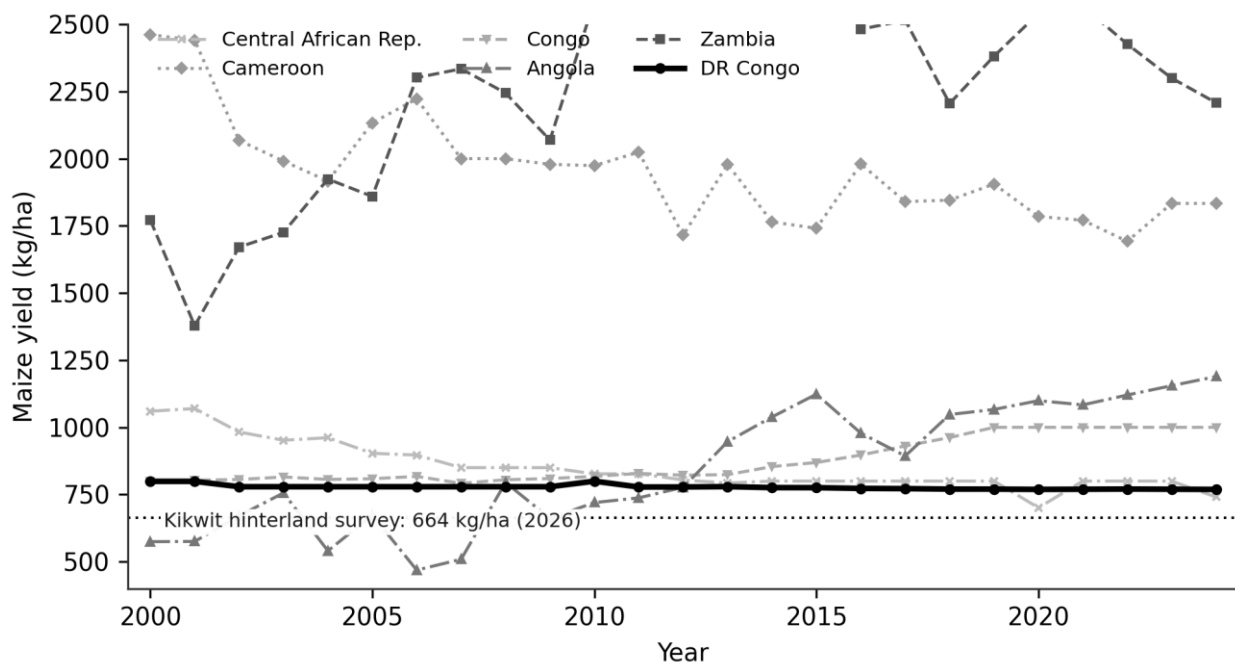


Figure 2. Evolution of average maize yields in the DRC and neighbouring countries, 2000-2024, and position of the mean yield of the survey sample. Source: FAO (2025), authors' calculations.

5.2. Participation in the PNDA and the innovation adoption gradient

The descriptive statistics attest to a strong penetration of the PNDA in the study area: 75.5% of maize producers declare having benefited from programme support. However, the adoption rate varies strongly across innovations (Table 2 and Figure 3). Row planting is the most widespread practice (71.8%), followed by improved seed (60.0%) and the recommended new crop management practices (51.8%); maize–mucuna intercropping remains marginal (7.3%), probably because of its technical demands, the extra labour it entails or still limited awareness of its benefits. On average, one innovation out of the four promoted is adopted by 47.7% of producers, sketching a clearly decreasing adoption gradient as the complexity of practices increases.

The direct crossing of beneficiary status with declared adoption now measures the participation-to-adoption conversion corridor without uncertainty (Table 2 and Figure 3). Among the 83 PNDA beneficiaries, 95.2% practise row planting and 79.5% use improved seed; the conversion rate falls to 68.7% for the recommended crop management practices — the very ones that prove decisive for output — and to 9.6% for maize–mucuna intercropping. Joint adoption confirms this hierarchy: 91.6% of beneficiaries combine at least two of the three central practices, but only 51.8% adopt the full package (improved seed, row planting and crop management practices), and no beneficiary remains outside all promoted practices. Finally, 40.0% of non-beneficiaries declare resorting of their own accord to improved crop management practices, a sign of substantial spontaneous diffusion outside the programme. The participation-adoption link is thus structurally incomplete: programme diffusion guarantees neither the universality nor the intensity of appropriation, and it is precisely on the most productive practice that the relay is lost.

Table 2. Adoption of the innovations promoted by the PNDA and observed participation-to-adoption conversion corridor (n = 110).

Innovation	Frequency	Share of maize producers (%)	Conversion among beneficiaries (% of 83)
PNDA support (beneficiary status)	83	75.5	—
Row planting	79	71.8	95.2
Improved seed	66	60.0	79.5
Recommended new crop management practices	57	51.8	68.7
Maize–mucuna intercropping	8	7.3	9.6
Full package (improved seed + row planting + crop management)	43	39.1	51.8
At least two of the three central practices	76	69.1	91.6
None of the four promoted practices	0	0.0	0.0

Note: conversion is measured directly by crossing beneficiary status with declared adoption; adoption is observed only for programme beneficiaries. In addition, 40.0% of non-beneficiaries (16 out of 40) declare resorting to improved crop management practices outside the programme.

Source: survey data, 2026, authors' calculations.

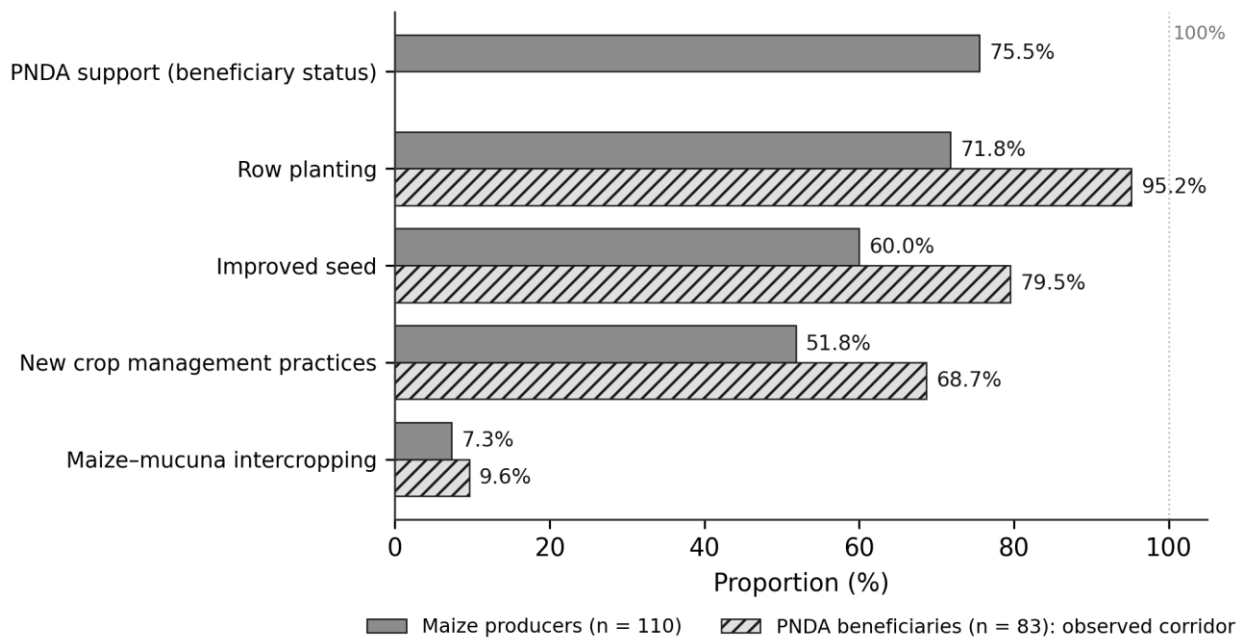


Figure 3. Adoption profile of the innovations promoted by the PNDA: share of maize producers (n = 110) and observed conversion corridor among beneficiaries (n = 83). Source: survey data, 2026, authors' calculations.

5.3. Determinants of maize output

Table 3 presents the two OLS specifications estimated with HC3 robust standard errors; the coefficient plot in Figure S1 (supplementary material) provides a graphical reading. In both models, cultivated area is positively and significantly associated with output: a 1% increase in area is associated with an increase of about 0.56 to 0.57% in output, underlining the weight of the land factor. Farming experience also displays a positive and significant association: each additional year of experience is associated with an increase of about 1.2 to 1.3% in output, suggesting that the most experienced producers mobilise the available resources more effectively (H1 confirmed). By contrast, labour is not significant, at the given power, in any specification.

The contrast between beneficiary status and effective adoption is at the heart of the results (H2 and H3). In Model 1, the coefficient on PNDA beneficiary status corresponds to an average premium of +12.2% in output, but it is not statistically significant ($p = 0.422$). In Model 2, among the four innovations, only the new crop management practices display a positive and significant association with output: all else equal, farms having adopted them produce on average 34% more than the others ($\beta = 0.292$; $p = 0.042$). Improved seed (+8.3%, $p = 0.638$), row planting (-15.8%, $p = 0.353$) and maize–mucuna intercropping (-18.0%, $p = 0.397$) show no significant association. These coefficients are not interpreted as causal effects, but the gap in significance between administrative status and actual change of practice is robust to the alternation of specifications.

Table 3. Determinants of maize output: OLS estimation with robust standard errors (HC3).

Variable	Model 1	p	Model 2	p	Average premium (Model 2)
Constant	5.629***	0.000	5.722***	0.000	—
ln(Cultivated area)	0.572***	0.001	0.561***	0.001	—
ln(Labour + 1)	0.138	0.123	0.100	0.291	—
Farming experience	0.013**	0.011	0.012**	0.020	—
PNDA support	0.115	0.422	—	—	+12.2% (ns)
Improved seed	—	—	0.080	0.638	+8.3% (ns)
Row planting	—	—	-0.172	0.353	-15.8% (ns)

Variable	Model 1	p	Model 2	p	Average premium (Model 2)
Maize–mucuna intercropping	—	—	-0.199	0.397	-18.0% (ns)
New crop management practices	—	—	0.292**	0.042	+33.9% (p < 0.05)
R ²	0.393		0.424		—
Adjusted R ²	0.370		0.384		—
Observations	109		109		—

Note: ***, ** and * denote significance at the 1%, 5% and 10% levels. The average premium converts the coefficient of the binary variables into a percentage effect: $\exp(\beta) - 1$; 'ns' = not significant. Model 1 assesses the association of beneficiary status; Model 2 replaces this status with the adopted innovations; for non-beneficiaries, adoption of the promoted innovations is coded 0, exposure to the programme being the condition of their diffusion (see Section 4.4).

Source: authors' calculations from the survey data, 2026.

5.4.The effect of participation: propensity score matching

The matching estimation confirms and strengthens the regression result (Table 4 and Figure 4). The participation logit explains only a marginal fraction of the variance of beneficiary status (pseudo-R² = 0.076; likelihood-ratio test p = 0.41): given observed characteristics, being a PNDA beneficiary is almost a matter of chance in the study area, which lends credibility to the conditional independence assumption. Common support is wide ([0.418, 0.942]): only 5 of the 82 beneficiary farms remain unmatched within the caliper, each treated unit mobilising on average 2.6 controls; the average standardised bias falls from 11.3% before matching to 9.5% after. The average treatment effect on the treated stands at +17.8% of output under nearest-neighbour matching (95% CI: [-30.6, +78.0]; p ≈ 0.49), at +12.0% under kernel matching, and at +11.2% to +15.0% on yield depending on the specification: all confidence intervals comfortably include zero. Participation in the programme, at the time of the survey and given observables, is thus not accompanied by a statistically discernible performance gain — converging with the non-significance of status in Model 1 (H2 corroborated by a second estimation route).

Table 4. Effect of participation in the PNDA: propensity score matching (n = 109; 82 matched beneficiaries).

Indicator	Value	Reading
Pseudo-R ² of the participation logit	0.076	Participation weakly related to observables (LR $\chi^2(9) = 9.32$; p = 0.41)
Common support (propensity score)	[0.418, 0.942]	5 treated units without a match within the caliper, not retained
Effective matches	198	2.6 controls per treated unit on average (1:4, caliper 0.2 σ of the score logit)
Average standardised bias (before → after)	11.3% → 9.5%	Satisfactory covariate balance after matching
ATT NN — output	+0.164	+17.8%; 95% CI: [-30.6, +78.0]; p ≈ 0.49
ATT kernel — output	+0.113	+12.0%; 95% CI: [-20.2, +76.8]; p ≈ 0.57
ATT NN — yield	+0.106	+11.2%; 95% CI: [-26.7, +67.2]; p ≈ 0.60
ATT kernel — yield	+0.140	+15.0%; 95% CI: [-11.7, +68.7]; p ≈ 0.40

Note: ATT = average treatment effect on the treated, in log points (column 'Value') and in percentage (column 'Reading'). Nearest-neighbour (NN) matching (1:4 with replacement, caliper of 0.2 standard deviations of the score logit) and Gaussian kernel matching (bandwidth 0.05) on common support; confidence intervals from a non-parametric bootstrap with 1,000 replications re-estimating the score at each draw. Score variables: cultivated area, labour, experience, age, sex, education, household size and sectors.

Source: authors' calculations from the survey data, 2026.

5.5. The adoption channel: premiums by practice and intensity among beneficiaries

The analysis internal to the 83 beneficiaries neutralises status-related selection and measures the second link of the chain directly (Table 5). Among the promoted practices, only the adoption of the new crop management practices is associated with higher output: +50.7% on average all else equal (95% CI: [+13.5, +100.0]; $p = 0.005$), on a contrast of 56 adopters against 26 non-adopters; as an uncontrolled raw premium, the gap reaches +82.5% (575 vs 315 kg; $p < 0.001$). Improved seed (+6.8%; $p = 0.77$), row planting (-32.4%; $p = 0.36$) and maize–mucuna intercropping (-17.6%; $p = 0.35$) show no significant association — the estimates for row planting and mucuna being fragile given the contrasted counts (4 non-adopters and 8 adopters respectively). Adoption intensity does not discriminate performance: no beneficiary reports zero practices (7 adopt one, 30 two, 40 three and 5 four), and the estimated gradient (+12.2% per additional practice) is not significant ($p = 0.35$). The composition of the adopted package therefore matters more than its breadth: it is the adoption of the decisive practice — the crop management practices — that separates the better-performing farms within the very population of beneficiaries (H3 confirmed by a comparison with status selection neutralised). The non-significance of the seed premium is consistent with field reports of partial use of the distributed seed, some beneficiaries having mixed it with their own stocks (see Section 6.3).

Table 5. Adoption premiums internal to PNDA beneficiaries (dependent variable: $\ln(\text{output})$; HC3; $n = 82$).

Practice adopted	Coefficient β	p	Premium ($\exp(\beta)-1$)	95% CI of the premium	Adopters / non-adopters
New crop management practices	0.410**	0.005	+50.7%	[+13.5, +100.0]	56 / 26
Improved seed	0.066	0.769	+6.8%	[-31.1, +65.4]	65 / 17
Row planting	-0.392	0.364	-32.4%	[-71.0, +57.5]	78 / 4
Maize–mucuna intercropping	-0.194	0.350	-17.6%	[-45.2, +23.7]	8 / 74
Adoption intensity (number of practices, 0-4)	0.115	0.345	+12.2% per practice	[-11.7, +42.5]	distribution 0/7/30/40/5

*Note: each practice is tested in a separate model including the following controls: $\ln(\text{cultivated area})$, $\ln(\text{labour} + 1)$, farming experience and sectors; **: significant at 5%. Adoption intensity is the number of declared practices (0 to 4); its distribution among beneficiaries is given in the last column. As an uncontrolled raw premium, the output gap between adopters and non-adopters of the crop management practices reaches +82.5% (575 vs 315 kg; $p < 0.001$). The estimates for row planting and mucuna are fragile given the contrasted counts (4 non-adopters and 8 adopters respectively).*

Source: authors' calculations from the survey data, 2026.

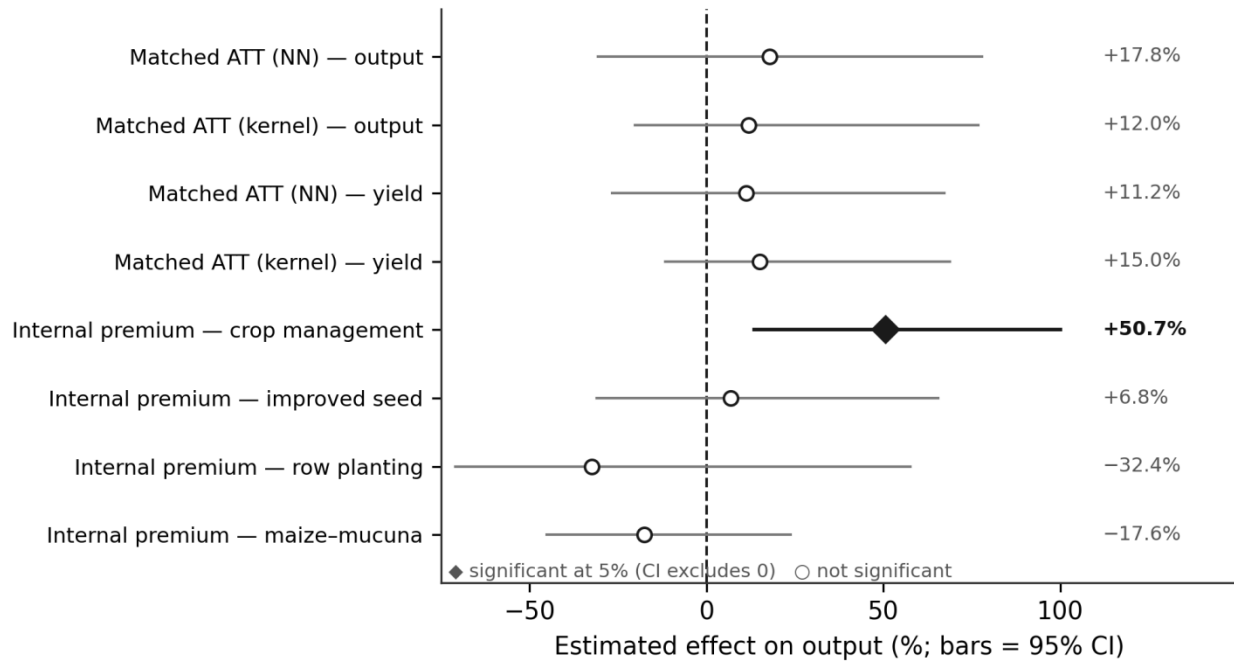


Figure 4. Estimated effects on output: matched ATTs of participation (NN and kernel) and adoption premiums internal to beneficiaries, with 95% confidence intervals. Source: authors' calculations from the survey data, 2026.

5.6.From participation to adoption: decomposition of the results chain

Table 6 brings together the indicators that illuminate the passage from participation to performance. First, the sum of the land and labour elasticities stands at 0.710 in Model 1 and 0.661 in Model 2: returns to scale are decreasing, the signature of a still extensive growth operating below optimal farm size, consistent with the absence of productivity gains at national level (Section 5.1). Second, the explanatory power of the model incorporating the innovations ($R^2 = 0.424$) exceeds that of the model based on beneficiary status ($R^2 = 0.393$) by 0.031 points, a relative gain of 7.9%: the direct measurement of the adopted practices captures more productive heterogeneity than administrative status. Third, the convergence of the three approaches orders the two links unambiguously: the participation effect is non-significant in the conditional regression (+12.2%), in the matched estimate (+11.2% to +17.8% depending on the specification) and, within beneficiaries themselves, the internal comparison locates the bulk of the performance differential in the adoption of the crop management practices (+50.7%); yet this decisive practice is adopted by only 68.7% of beneficiaries and the full package by 51.8%. The productive association concentrates where an actual change of practice is observed, and the incomplete conversion of the first link constitutes the main margin of improvement of the programme in the study area.

Table 6. Decomposition of the results chain: beneficiary status versus effective adoption.

Indicator	Value	Reading
Returns to scale (land + labour elasticities)	0.710 (Model 1); 0.661 (Model 2)	Extensive growth with decreasing returns to scale (H1)
R^2 (Model 1 → Model 2)	0.393 → 0.424	Incremental gain of +0.031 points (+7.9%) in favour of the innovation block
Beneficiary status premium (regression, Model 1)	+12.2% (ns)	No own effect of status (H2)
Participation ATT (matching, output)	+12.0% to +17.8% (CIs including 0)	Quasi-experimental confirmation of the absence of an own status effect (H2)
Adoption premium (crop management practices, full sample)	+33.9% ($p < 0.05$)	The productive association concentrates on effective adoption (H3)

Indicator	Value	Reading
Internal adoption premium (crop management practices, beneficiaries)	+50.7% (p < 0.01)	The adoption channel remains significant with status selection neutralised (H3)
Participation-to-adoption conversion (crop management practices)	68.7% (observed)	31.3% of beneficiaries have not adopted the decisive practice
Adoption of the full package (3 central practices)	51.8% (observed)	Nearly one beneficiary in two does not adopt the whole package

Note: indicators drawn from Tables 2 to 5; premiums computed as $\exp(\beta) - 1$; 'ns' = not significant; CI = 95% confidence interval (bootstrap with 1,000 replications for the ATT).

Source: authors' calculations from the survey data, 2026.

5.7. Econometric diagnostics and robustness

The econometric diagnostics, detailed in Table S3 (supplementary material), support the retained specifications. The two production models display a satisfactory explanatory power for farm survey data, and the model incorporating the innovations explains the observed variations slightly better. The Breusch-Pagan tests do not indicate significant heteroscedasticity (p = 0.330 and 0.548) and the Jarque-Bera tests do not reject the normality of the residuals (p = 0.702 and 0.830); the VIFs remain below the usual threshold of 10 (3.54 and 6.89), with HC3 robust standard errors throughout. The internal beneficiary model displays analogous diagnostics (Breusch-Pagan p = 0.200; Jarque-Bera p = 0.945; maximum VIF below 1.8; n = 82), and the yield-based estimation leads to the same qualitative hierarchies. By contrast, the full model including PNDA status and all the innovations exhibited strong multicollinearity (VIF of 32.34 for PNDA status and 21.30 for row planting), reflecting that several innovations are disseminated mainly by the programme; this motivates the alternating specifications and illustrates the institutional nature of the link between programme and adoption. Overall, the diagnostics confirm the robustness of the retained models.

6. Discussion

6.1. A still extensive growth with decreasing returns

Three lessons structure the discussion. The first concerns the nature of productive growth. The land elasticity (0.56-0.57), the non-significance of labour and, above all, the decreasing returns to scale (0.66-0.71) indicate that the growth of output still rests largely on the extension of cultivated areas rather than on intensification. This configuration is characteristic of many family farms in sub-Saharan Africa, where constraints on access to inputs, equipment and technologies limit productivity gains (Jayne et al., 2019); it also echoes the reminder that the apparent land abundance of Central Africa conceals strong accessibility and quality constraints (Chamberlin et al., 2014). The FAOSTAT benchmarking gives this finding its systemic dimension: the stagnation of Congolese yields since 2000, in contrast with Angola and Zambia, suggests that the Kikwit hinterland farms are not an isolated case but the microeconomic expression of a durable failure to convert public interventions into changes of practice (FAO, 2025; van Ittersum et al., 2016).

The positive effect of farming experience (about +1.3% of output per year) highlights the role of human capital in farm performance. The most experienced producers generally command a better mastery of crop management practices and a greater capacity to adapt to local constraints, which is consistent with the analyses of Marenja and Barrett (2007) in Kenya and, more recently, with the adoption-process model of Abetu et al. (2026): the accumulation of experience conditions the capacity to translate technical information into actual practice. In a diffusion programme such as the PNDA, this pre-existing human capital is therefore as much a lever as a filter for the effectiveness of training actions.

6.2. The programme as a facilitator: an innovation systems reading

The second lesson bears on the mechanism of programme action. The absence of a significant association between beneficiary status and output — +12.2%, not significant, in regression, and +12% to +18% in matching —

contrasted with the crop management adoption premium (+33.9% on the full sample; +50.7% within beneficiaries, $p < 0.01$) and the gain in explanatory power of the innovation block (+7.9% of R^2), does not mean that the PNDA is devoid of effect. It rather suggests that its influence operates mainly through the changes of practice it fosters: participation is a favourable condition of access to innovations, but the improvement of output depends on their effective appropriation. This interpretation is consistent with the agricultural innovation systems approaches, according to which development programmes play essentially a facilitating role by improving access to knowledge, technologies and support services, rather than acting directly on production (Klerkx and Begemann, 2020; Klerkx and Rose, 2020).

It also joins the corpus of available empirical evaluations: productivity gains depend on the actual use of the innovations rather than on their mere availability (Abate et al., 2018; Adams and Jumpah, 2021; Marennya and Barrett, 2007), and the diffusion channels — extension, farmer organisations, cooperatives — affect welfare only through the adoption they induce (Manda et al., 2020; Ragasa and Mazunda, 2018; Wossen et al., 2017). The specific contribution of the present study to this corpus is to quantify the incompleteness of the relay between the first two links on observed data: only 68.7% of beneficiaries adopted the decisive crop management practices, 51.8% the full package, and maize–mucuna intercropping stalls at 9.6% — a massive conversion loss between exposure to the programme and change of practice, in a fragile-state context where proximity support capacities are severely constrained. The fact that 40% of non-beneficiaries declare resorting of their own accord to improved practices confirms, in the opposite direction, that access to the programme is neither necessary nor sufficient for a change of practice: what matters is appropriation.

6.3. The heterogeneity of innovations: why crop management practices and not seed?

The third lesson concerns the heterogeneity of effects across innovations, only the 'new crop management practices' component being associated with output. This result is interpreted in the light of three complementary mechanisms. The first is intensity of use: the crop management practices (row planting actually observed, recommended spacings, associated management) translate into a change in the conduct of the plot that engages the whole crop cycle, whereas the declared adoption of an input-type innovation, such as improved seed, can remain partial. The qualitative observations gathered during the survey corroborate this reading. Three beneficiaries reported that some farmers had not sown the full quantity of the improved seed they had received, fearing an unsatisfactory harvest, and had instead mixed the distributed seed with their own. Although not systematic, these accounts point to partial and precautionary patterns of input use and are consistent with the barriers documented in the neighbouring Katanga — information, availability, fit with local preferences — which help explain the gap between declared adoption and actual use (Balasha et al., 2025), as well as with the general warning against conflating exposure with appropriation (Abetu et al., 2026).

The second mechanism is the complementarity of practices: the literature on multiple adoption shows that the material gains of innovations materialise when practices are combined coherently with local conditions (Khonje et al., 2018; Teklewold et al., 2013). The analysis internal to beneficiaries refines this mechanism in an unexpected way: adoption intensity — the number of practices adopted — does not discriminate performance (gradient of +12.2% per practice, not significant), whereas the composition of the package matters in the first place (+50.7% for the crop management practices alone). Adopting much is not the same as adopting what counts. The very low adoption rate of maize–mucuna intercropping (9.6%) and its non-significant negative coefficient suggest that this component, demanding in labour and know-how, has not yet reached the critical mass of users needed for its valorisation; conversely, the near-universality of row planting among beneficiaries (95.2%) makes its econometric estimation unstable (only 4 non-adopters) and suggests that this relay is now secured. The third mechanism lies in time lags: the benefits of improved seed or of crop associations may materialise only after several cycles, whereas adjustments in crop management practices produce more immediate effects. These three mechanisms converge on the same operational implication: the evaluation of a diffusion programme must measure the quality and the permanence of use, not the mere declaration of adoption (Rurii and Nzenzengya, 2026; Takahashi et al., 2020).

6.4. Implications for the evaluation and monitoring of the PNDA

In terms of policy, these results call for an overhaul of the evaluation indicators of the PNDA and similar programmes. The conventional indicators — number of beneficiaries, training sessions delivered, volumes of inputs distributed — measure the first link of the chain, that of participation; they leave in the shadow the conversion into adoption that conditions performance. It is recommended to complement them systematically with indicators of effective adoption and maintenance of innovations (participation-to-adoption conversion rates by practice, persistence over several cycles, compliance with technical itineraries), measured through independent post-diffusion surveys. In the study area, the operational objective is quantified: 26 of the 83 beneficiaries (31.3%) have not adopted the decisive practice and 40 (48.2%) have not adopted the full package; bringing the conversion of the crop management practices up to the level already reached by row planting (95.2%) would represent, at a constant internal premium (+50.7%), a substantial potential output gain for these farms.

Operationally, the results underline the need for extension services, development organisations and PNDA implementation teams to support producers in the actual use of the innovations, beyond their mere diffusion: regular technical follow-up, demonstrations under real conditions, training tailored to producers' needs and feedback on the difficulties encountered would foster durable appropriation. Strengthening the quality of inputs — notably the provenance and local adaptation of the distributed seed — appears as a *sine qua non* condition of this appropriation, in line with the lessons of Congolese studies on seed systems (Balasha et al., 2025). Finally, producers could be further encouraged to share their experiences within farmer organisations, whose role as accelerators of diffusion is established (Manda et al., 2020; Schut et al., 2016).

6.5.Limitations and future research

These implications must be weighed against the limitations of the study. As the data are cross-sectional and observational, the associations evidenced — adoption premiums, R^2 gain, matched ATTs — are not interpreted causally: propensity score matching corrects for differences in observed characteristics but rests on the unverifiable conditional independence assumption, and the small size of the control group (27 non-beneficiaries) translates into wide confidence intervals around the participation effects; the comparison internal to beneficiaries, for its part, remains exposed to the selection of the most productive farmers into adoption. The convergence of the three approaches — conditional regression, matching and internal comparison — on the same hierarchy of links nevertheless constitutes an appreciable robustness argument. Future research should mobilise panel data or quasi-experimental designs to identify causal effects, document the temporal dynamics of adoption (disadoption, maintenance, intensification) and extend the analysis to the other value chains and provinces covered by the PNDA.

7.Conclusion and implications

This study analysed the results chain linking participation in the National Agricultural Development Programme, the adoption of agricultural innovations and the performance of the maize farms of the Kikwit hinterland. The results confirm the three hypotheses tested. Output remains driven first by the conventional factors — cultivated area and farming experience — in an extensive logic with decreasing returns to scale (H1). PNDA beneficiary status is associated with no higher output, whether in conditional regression (+12.2%, not significant) or in matched propensity score estimation (+12% to +18%, confidence intervals including zero) (H2). By contrast, the effective adoption of the new crop management practices is associated with a 34% increase in output over the full sample and 50.7% in the within-beneficiaries comparison ($p < 0.01$), and the innovation block captures 7.9% of additional explanatory power relative to simple beneficiary status (H3). The FAOSTAT benchmarking situates these performances within a national stagnation of maize yields (770 kg/ha in 2022-2024 against 799 kg/ha in 2000), below which the sample, at 664 kg/ha, still ranks, with 75.2% of the surveyed farms below that level.

The overall policy conclusion is direct: participating is not enough. The effectiveness of the PNDA, as observable in the study area, depends less on the volume of beneficiaries reached — programme penetration exceeds 75% — than on the conversion of this participation into actual practices, a conversion now measured and incomplete: 68.7% of beneficiaries adopt the decisive crop management practices, 51.8% the full package, and maize–mucuna intercropping stalls at 9.6%. Two main recommendations follow. For PNDA managers and public decision-

makers: complement monitoring indicators with measures of effective adoption and maintenance of the innovations, derived from systematic post-diffusion surveys, and target as a priority the 31.3% of beneficiaries who have not yet adopted the decisive practice. For extension services and support organisations: strengthen proximity support, post-training follow-up, the quality of the distributed inputs and demonstrations under real conditions, so as to tighten the participation-to-adoption conversion corridor. These measures, inexpensive relative to the diffusion investments already made, condition the capacity of the programme to transform the stagnation of Congolese yields observed for a quarter of a century.

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