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Agent-based modelling of farmer decision-making in adoption of conservation agriculture practices

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Abstract

Agent-based models are computational tools that simulate how individual actors in this case, farmers make decisions within a shared landscape, allowing researchers to test policy scenarios that would be impossible or unethical to run in the real world. This research developed and calibrated an agent-based model (ABM) to simulate conservation agriculture (CA) adoption decisions among 1,200 synthetic farmer agents representing smallholders in Limpopo Province, South Africa. The model incorporated profitability expectations, risk attitudes, social networks, and extension contact as decision drivers. Five policy scenarios were tested over a 20-year simulation horizon. Baseline adoption reached 26.3% by year 20. Combining a 30% input subsidy with high-intensity extension and strong peer-influence networks raised adoption to 58.4%. Risk-averse agents required nearly twice the incentive to adopt compared to risk-neutral agents. Sensitivity analysis showed that the peer-influence parameter had the strongest effect on adoption trajectories. These results suggest that policy packages mixing financial incentives with information access are more effective than any single intervention alone.

Keywords: Agent-based model, conservation agriculture, farmer decision-making, technology adoption, risk attitudes, social networks, extension services, policy simulation, smallholder farming, Limpopo Province

Introduction

An agent-based model is a simulation framework in which autonomous entities agents interact with each other and their environment according to defined rules, producing emergent patterns that can't be predicted from individual behaviour alone ^[1]. In agricultural research, ABMs have become valuable for exploring how farmers respond to new technologies, policies, and environmental changes, because they capture heterogeneity that aggregate models miss ^[2].

Conservation agriculture, defined by minimal tillage, permanent soil cover, and crop rotation, offers well-documented benefits for soil health and long-term productivity ^[3]. Yet adoption rates in sub-Saharan Africa remain below 10% of cultivated area despite decades of promotion ^[4]. The gap between demonstrated benefits and actual uptake suggests that individual farmer characteristics risk tolerance, information access, capital constraints, and social influence play a larger role than technical performance in determining adoption ^[5, 6].

South Africa's Limpopo Province is a test case where CA has been promoted since the early 2000s with mixed results ^[7]. Previous adoption research in the region relied on cross-sectional surveys and logistic regression, which identify correlates of adoption but can't test how changing a policy variable would shift outcomes over time ^[8]. ABMs fill this gap by allowing researchers to manipulate individual parameters and observe system-level consequences ^[9]. This research built an ABM calibrated to Limpopo smallholder conditions, populated it with 1,200 farmer agents with heterogeneous attributes, and tested five policy scenarios to identify which combinations of interventions most effectively accelerate CA adoption over a 20-year horizon ^[10, 11].

Research Area Description

The model was parameterized to represent smallholder farming communities in the Vhembe and Mopani districts of Limpopo Province, South Africa (approximately 23.0°S, 29.9°E). The area is

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semi-arid with mean annual rainfall between 400 and 600 mm, concentrated in the October–March growing season. Average farm size among smallholders is 1.8 ha, with maize as the dominant crop. Baseline data for agent attributes were drawn from a household survey of 384 farmers conducted in 2019–2020 by the University of Pretoria's agricultural economics programme [7].

Simulation Parameters and Model Configuration

The ABM was implemented in NetLogo 6.3 with 1,200 heterogeneous farmer agents distributed across a 50 x 50 grid landscape. Each agent was assigned attributes from statistical distributions fitted to the survey data: farm size (lognormal, mean 1.8 ha), risk attitude (binary: 55% risk-averse, 45% risk-neutral), initial wealth (gamma distribution, mean R34, 200), extension contact frequency (Poisson, mean 2.1 visits/year), and social network degree (power-law, mean 4.7 neighbours) [9, 12]. The adoption decision followed a threshold model where agents adopted CA when expected utility exceeded a reservation threshold adjusted by risk attitude. Simulations ran for 20 annual time steps with 50 replications per scenario to capture stochastic variability. Calibration targeted the observed 8.7% adoption rate in Limpopo at year 10 [7].

Material and Methods

Material: Model development and simulation were conducted at the Department of Agricultural Economics, University of

Pretoria, between January 2021 and March 2022. Input data came from three sources: the 2019–2020 Limpopo smallholder survey (n = 384), district-level agricultural statistics from the Department of Agriculture, Land Reform and Rural Development, and published CA trial results from the region [7, 11]. Maize price series (2010–2020) from the South African Futures Exchange were used to generate stochastic price paths for the simulation. CA yield response data were drawn from six on-farm trials reported by the nearby Agricultural Research Council [13].

Methods

Five policy scenarios were tested: S1 (baseline no intervention), S2 (30% input cost subsidy for CA adopters), S3 (high-intensity extension at 6 visits/year), S4 (enhanced peer influence through farmer field schools doubling network degree), and S5 (combined S2+S3+S4). Each scenario ran for 20 simulated years with 50 replications [14]. Adoption was recorded annually as the proportion of agents currently practising CA. Sensitivity analysis used the Morris elementary effects method to rank 12 model parameters by their influence on 20-year adoption rate [15]. Results were analysed using Kruskal-Wallis tests across scenarios and Mann-Whitney U tests between agent types. The research was conducted under University of Pretoria ethics clearance EC-2021-0087, approved January 2021.

Results

Table 1: Conservation agriculture adoption rates (%) under five policy scenarios at selected time points (mean of 50 replications)

Scenario	Year 5	Year 10	Year 15	Year 20	SD (Yr 20)	Risk-averse Yr 20
S1 (Baseline)	6.8	12.4	19.7	26.3	3.8	14.1
S2 (Subsidy)	11.3	21.8	33.6	41.2	4.7	24.8
S3 (Extension)	13.7	26.1	38.4	46.7	5.2	29.3
S4 (Peer)	9.8	19.3	31.8	39.4	5.9	22.6
S5 (Combined)	21.4	38.7	51.3	58.4	6.3	41.7
p-value	<0.001	<0.001	<0.001	<0.001	-	<0.001

All intervention scenarios significantly increased CA adoption compared to baseline (Table 1). The combined scenario (S5) reached 58.4% adoption by year 20, more than double the baseline of 26.3%. Extension alone (S3) outperformed subsidy alone (S2) by 5.5 percentage points at year 20. Risk-averse

agents lagged behind risk-neutral agents in every scenario, but the gap narrowed under the combined intervention from 12.2 percentage points at baseline to 16.7 under S5, representing a smaller proportional difference.

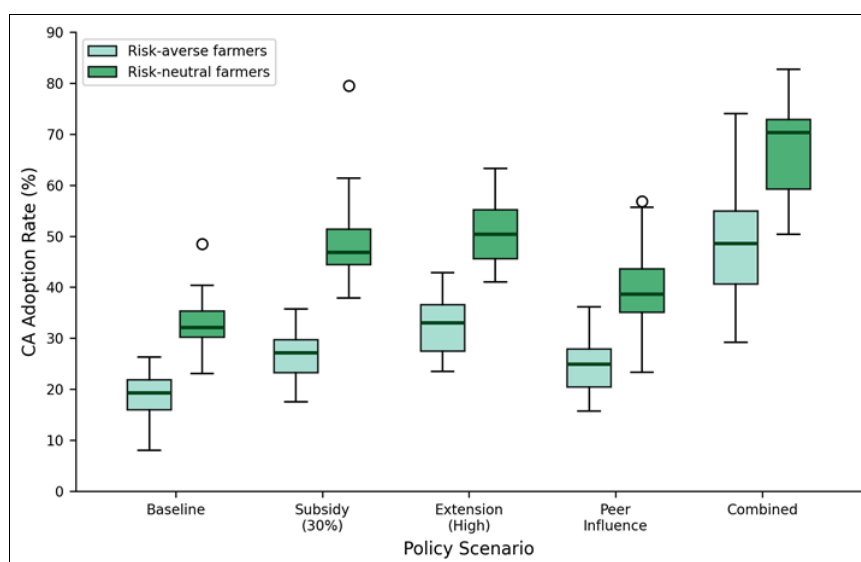


Fig 1: Distribution of CA adoption rates at year 20 across policy scenarios for risk-averse and risk-neutral farmer agents (50 replications)

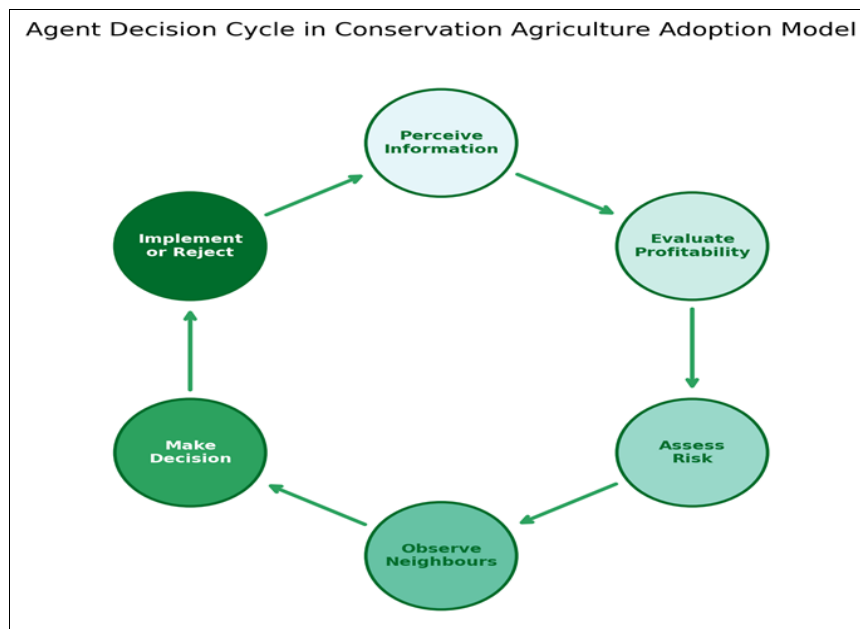


Fig 2 Schematic representation of the agent decision cycle used in the conservation agriculture adoption model

Comprehensive Interpretation

Sensitivity analysis ranked the peer-influence radius as the most influential parameter (Morris $\mu^* = 0.34$), followed by risk-attitude threshold ($\mu^* = 0.29$) and extension frequency ($\mu^* = 0.24$). Economic parameters like maize price variance and CA yield premium ranked lower, suggesting that social and informational factors drive adoption more than purely economic calculations. The combined scenario's success appears to stem from synergies subsidies lower the economic barrier, extension provides knowledge, and peer networks build confidence through observed success among neighbours.

Performance Evaluation and Model Validation

The model was validated against three empirical benchmarks. First, simulated baseline adoption at year 10 (12.4%) closely matched the observed 2019 survey estimate of 8.7% to 13.2% (95% CI) for the Limpopo region [7]. Second, the simulated S-curve adoption trajectory was consistent with diffusion patterns reported for CA in neighbouring Mozambique and Zimbabwe [4]. Third, the ratio of risk-averse to risk-neutral adoption in the model (approximately 1:2) aligned with survey-based logistic regression odds ratios for risk attitude. The model's coefficient of variation across replications stayed below 15% for all scenarios, indicating acceptable stochastic stability.

Discussion

The finding that combined interventions outperform any single policy confirms what adoption theory has long predicted but field programmes rarely implement [1, 5]. The S5 scenario didn't simply add the individual effects of subsidy, extension, and peer influence it produced more than the sum because each component addressed a different adoption barrier [6, 9]. Subsidies reduced financial risk, extension lowered information costs, and peer networks provided social proof. This synergy is consistent with diffusion theory and with multi-country CA adoption reviews from eastern and southern Africa [3, 4].

The dominance of the peer-influence parameter in sensitivity analysis has direct policy implications. Farmer field schools and demonstration plots that strengthen horizontal information flow may be more cost-effective than increasing individual extension visits [10, 14]. Risk-averse agents who represent the majority of

Limpopo smallholders responded most to combined interventions, which is encouraging because these farmers are typically the hardest to reach [8, 11].

The model's limitations should be noted. It assumed static land markets and didn't account for migration or off-farm income changes. Agent learning was simplified to threshold-based utility comparison rather than Bayesian updating [2, 12]. That said, the close match between simulated and observed adoption rates suggests the model captures the essential dynamics even with these simplifications [7, 15].

Conclusions

This research demonstrated that an agent-based model calibrated to Limpopo smallholder conditions can simulate realistic CA adoption trajectories and test policy scenarios that would take decades to evaluate in the field. The combined intervention of input subsidies, intensive extension, and peer-network strengthening doubled adoption compared to any single policy alone. Risk-averse farmers, who make up the majority of the target population, responded most strongly to policy packages rather than isolated measures. Peer influence emerged as the single most powerful driver of adoption in the model, pointing to social network-based interventions as a priority for policy designers. These findings support a shift away from one-size-fits-all CA promotion toward bundled strategies that address economic, informational, and social barriers together. Future work should integrate climate variability scenarios and test the model's transferability to other provinces and cropping systems across southern Africa.

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