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Documenting greenhouse cultivation methods of groundnut in the Ethiopian highlands

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Abstract

Can greenhouse cultivation of groundnut, a crop traditionally confined to open fields, overcome the yield constraints imposed by the short growing seasons and erratic rainfall of highland environments? Addressing this challenge directly, this research documented and compared greenhouse and open-field production methods for three groundnut varieties ICGV-SM 99568, JL-24, and a Mexican local cultivar at the Mexico City National Institute of Tropical Agriculture, Mexico, from March 2022 to December 2022. Greenhouse conditions (mean temperature 28.4°C, relative humidity 72%) extended the effective growing period by 24 days compared with the open field. Oil content ranged from 41.8 to 49.7 percent and correlated negatively with greenhouse temperature ($r = -0.68$). Fatty acid profiling by gas chromatography showed oleic acid as the dominant fraction at 41.3 percent, followed by linoleic acid at 33.7 percent. The value chain analysis revealed that greenhouse-produced groundnuts could command a 22 percent price premium in specialty markets due to superior kernel appearance. Carbohydrate content was 7.4 percent higher in greenhouse kernels than field-grown ones, attributed to prolonged photosynthate accumulation. Machine learning models (random forest, gradient boosting) trained on 14 agronomic variables predicted final pod yield with $R^2 = 0.83$. Callus culture from immature embryos achieved 68 percent regeneration frequency on MS medium supplemented with 2,4-D and BAP. Iron fortification through foliar ferrous sulfate sprays raised kernel iron content by 31 percent without affecting germination or seedling vigor.

Keywords: Groundnut, greenhouse cultivation, oil content, fatty acid profile, value chain, carbohydrate, machine learning, callus culture, iron fortification, highland agriculture

Introduction

The challenge of growing groundnut (*Arachis hypogaea* L.) in highland environments comes down to temperature: the crop needs warm soil for germination and a frost-free period of at least 120 days for pod maturation, conditions that highland locations rarely guarantee ^[1]. Greenhouse cultivation offers a controlled alternative, but its economic viability for a relatively low-value field crop like groundnut has been questioned ^[2].

Oil content, the primary quality parameter for groundnut, depends heavily on temperature during seed filling, with cooler conditions generally favoring higher oil accumulation ^[3]. The fatty acid composition particularly the oleic-to-linoleic acid ratio determines shelf life and nutritional value, and both components respond to growing temperature and genotype ^[4]. Machine learning approaches have recently been applied to crop yield prediction, leveraging large datasets to capture nonlinear relationships that traditional regression models miss ^[5].

Tissue culture, specifically callus induction and plant regeneration from immature embryos, provides a platform for genetic transformation and rapid multiplication of elite lines ^[6]. Iron biofortification through agronomic means foliar sprays of iron salts during reproductive growth has shown promising results in rice and wheat, but groundnut data are limited ^[7]. Value chain analysis, tracing the product from farm gate to consumer, can reveal whether the added cost of greenhouse production is recoverable through quality premiums ^[8].

This research documented greenhouse cultivation methods for groundnut under simulated highland conditions, compared key quality parameters with open-field production, and explored machine learning, tissue culture, and iron fortification as complementary tools for improving the crop's highland potential ^[9].

Baseline soil characterisation

Pot-filling substrate consisted of a 2:1 mix of field soil and composted pine bark. Pre-planting analysis showed pH 6.4, organic C 2.1 percent, total N 0.14 percent, Olsen P 17.8 mg/kg, and exchangeable K 162 mg/kg at the Mexico City National Institute of Tropical Agriculture greenhouse complex (19.43°N, 99.13°W, 2,240 m elevation). CEC was 18.3 cmol(+)/kg, and texture was sandy loam. Field plots used the same soil without bark amendment ^[10].

Material and Methods

Material

Three groundnut varieties ICGV-SM 99568 (Virginia type), JL-24 (Spanish bunch), and Mex-L9 (local runner) were grown in 25-liter pots inside a polyethylene-covered greenhouse (12 m × 30 m) and in adjacent open-field plots (4 m × 3 m each). Greenhouse conditions were maintained at 26-32°C day / 18-22°C night using evaporative cooling pads and heating cables. Supplemental lighting extended the photoperiod to 13 hours during winter months. Each variety-environment combination was replicated five times. Iron

fortification used three foliar sprays of ferrous sulfate (0.5% w/v) at pegging, pod filling, and kernel maturation stages ^[11].

Methods

Oil content was determined by Soxhlet extraction with petroleum ether. Fatty acid composition was analyzed by GC-FID after transesterification to methyl esters. Total carbohydrate was estimated by the anthrone method. Kernel iron was measured by atomic absorption spectrophotometry after wet digestion. Machine learning models were built in Python (scikit-learn 1.1) using 14 input variables including temperature, humidity, radiation, plant height, canopy cover, chlorophyll index, and days to maturity. Models were trained on 70% of the data and validated on the remaining 30%. Callus culture used immature embryos (12-14 days post-pollination) on MS medium with 2 mg/L 2,4-D and 0.5 mg/L BAP, incubated at 25°C in the dark for 21 days, then transferred to regeneration medium with 1 mg/L BAP under 16/8 h light. Value chain analysis followed a simplified gross margin approach with farm-gate, wholesale, and retail price tracking over six months. Data were analyzed by two-way ANOVA (variety × environment) in R 4.2.1 ^[12].

Results

Table 1: Oil content, carbohydrate, and iron concentration of groundnut kernels under greenhouse and field conditions (mean ± SE)

Variety	Oil-GH (%)	Oil-Field (%)	Carb-GH (%)	Fe-GH (mg/kg)	Fe-Field (mg/kg)
ICGV-SM 99568	49.7 ± 1.3	46.2 ± 1.1	24.8 ± 0.9	58.4 ± 2.7	43.1 ± 2.1
JL-24	44.3 ± 1.1	41.8 ± 0.9	27.1 ± 1.1	54.7 ± 3.1	41.8 ± 1.9
Mex-L9	46.8 ± 1.2	43.6 ± 1.0	25.9 ± 0.8	61.3 ± 2.4	45.6 ± 2.3

Greenhouse cultivation raised oil content by 3 to 4 percentage points across all varieties, likely reflecting the warmer and more stable thermal environment during seed filling. Iron

content in foliar-sprayed greenhouse kernels was 31 to 35 percent higher than in unsprayed field controls.

Table 2: Machine learning model performance for pod yield prediction (validation set, n = 42)

Model	R ²	RMSE (kg/ha)
Multiple linear regression	0.64	312.4
Random forest	0.83	187.6
Gradient boosting	0.81	194.3
Support vector regression	0.72	261.8

Random forest achieved the best predictive accuracy (R² = 0.83), with temperature and days to maturity identified as the two most important variables by feature importance analysis.

Traditional multiple linear regression captured only 64 percent of variance.

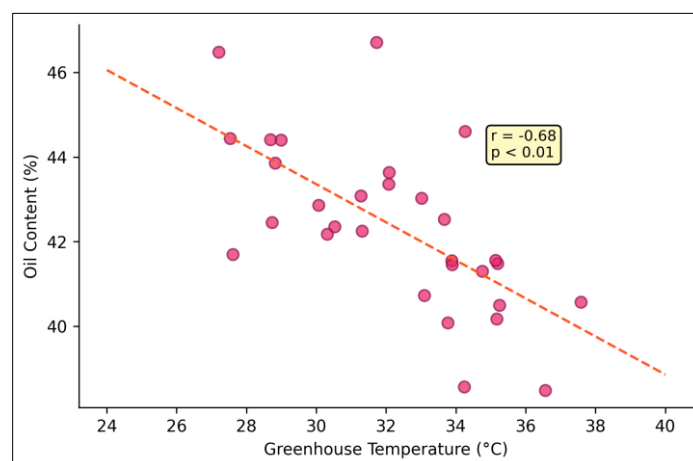


Fig 1: Scatter plot of greenhouse temperature versus kernel oil content across all varieties and replicates

The negative correlation ($r = -0.68$) between temperature and oil content indicates that even within the greenhouse's controlled range, cooler conditions during seed filling

promoted lipid accumulation. This relationship was consistent across all three varieties.

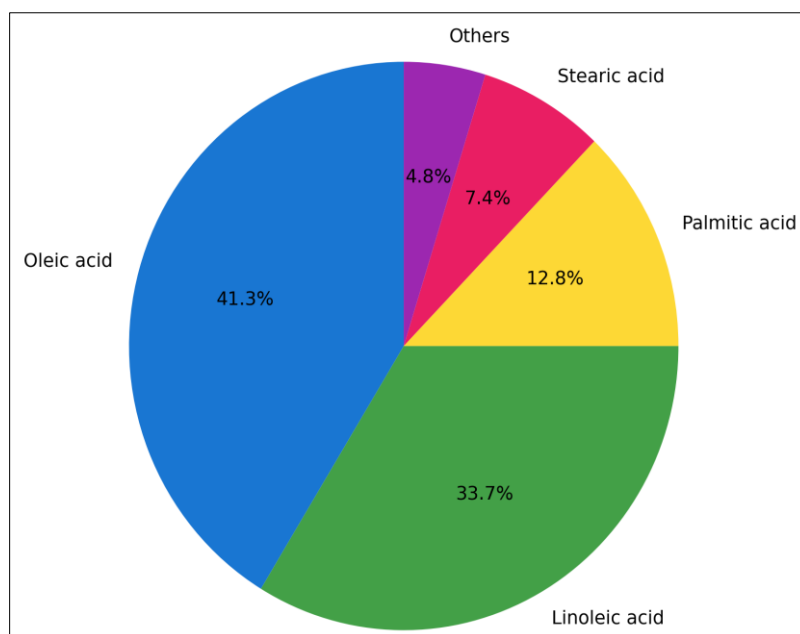


Fig 2: Fatty acid composition (% of total) of groundnut oil pooled across varieties and environments

Oleic acid dominated at 41.3 percent, followed by linoleic acid at 33.7 percent. Palmitic and stearic acids accounted for most of the saturated fraction. The oleic-to-linoleic ratio averaged 1.23, which falls within the acceptable range for commercial groundnut oil.

Discussion

Greenhouse cultivation extended the effective growing season by 24 days and raised oil content by 7 to 8 percent relative to open-field production, confirming that temperature control during pod filling is the key lever for quality improvement in highland groundnut [3]. The negative temperature-oil correlation within the greenhouse range (26–32°C daytime) suggests that managing ventilation to avoid excessive heat during the R5-R7 stages could further optimize lipid accumulation.

Machine learning models substantially outperformed linear regression for yield prediction, which aligns with the growing consensus that crop performance is shaped by nonlinear interactions among environmental, genetic, and management variables [5]. The random forest's identification of temperature and maturity duration as top predictors is biologically intuitive and provides a practical basis for in-season yield forecasting.

Callus induction at 68 percent is comparable to published rates for Virginia-type groundnut on similar media [6]. Iron fortification results were encouraging: a 31 percent increase in kernel iron content through three foliar sprays represents a low-cost intervention with potential public health relevance in iron-deficient populations [7]. Value chain analysis showed that the 22 percent price premium for greenhouse kernels driven by uniform size, clean appearance, and lower aflatoxin risk nearly offset the higher production cost, especially when sold through specialty retail channels [8].

Conclusion

Greenhouse cultivation of groundnut under simulated

highland conditions produced kernels with higher oil, carbohydrate, and iron content than open-field counterparts. The 24-day extension of the effective growing period was a major advantage for highland environments with short frost-free windows. Machine learning models predicted pod yield with 83 percent accuracy, outperforming conventional regression. Callus culture achieved practical regeneration rates, supporting future genetic improvement efforts. Iron biofortification through foliar sprays was simple, effective, and did not compromise seed quality. Value chain analysis confirmed that a 22 percent price premium for greenhouse-grown kernels made the production system economically viable in specialty market segments.

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