

# Financing and Training to Address the Gender Gap in Agriculture in Peru



A supervised learning, random forest prediction model  
Jose Carlo Burga





**Abstract**

**Audience / Benefits / Call to Action**

**Next Steps**

## Financing and Training to Address the Gender Gap in Agriculture in Peru

**A supervised learning model trained to predict locations where the gender gap more pronounced within the agricultural sector in Peru**

**LaGuardia Community College**  
**Continuing Education Program**  
**Data Analytics Program**  
Python for Data Analytics

Jose Carlo Burga

### Abstract

This project addresses the gender gap in agriculture in Peru by focusing on financing and training. It explores the disparities faced by women in accessing agricultural resources and the impact of targeted financial support and training programs. Using a combination of statistical analysis and machine learning models, the research highlights significant barriers women encounter, such as high interest rates, lack of collateral, and red tape. The findings suggest that improving financial inclusion and providing tailored training can enhance women's productivity and economic empowerment in the agricultural sector.

The machine learning model, specifically a Random Forest model, is trained to predict locations where the gender gap is most pronounced. This prediction is based on various features such as socio-economic indicators, agricultural productivity, access to financial services, and availability of training programs. The model's predictions are based on public data from Peru's National Agrarian Census of 2012, and the strategy will be adjusted as necessary based on new data, model feedback, and results.

This approach combines data-driven insights with practical interventions, providing a powerful tool for tackling gender inequality in agriculture. By accurately predicting the locations where the gender gap is most severe initially to the region level, for resources can be allocated more effectively, thus leading to greater impact.

[GitHub Repository](#)

#Peru #Agriculture #Gender\_Gap #Financing\_Access #Training\_Access #Machine\_Learning #Supervised\_Learning  
#Regression #Random\_Forest #Scikit\_Learn #Pandas #Jupyter\_Notebooks #Studio\_Visual\_Code #Python

### Audience: Stakeholders in the agricultural sector

- Bilateral and multilateral organizations focused on sustainable agriculture
- Financial institutions involved in sustainable investments in agriculture
- Private sector entities in agriculture
- Policy makers
- Researchers
- People, especially women, in agriculture

### Benefits: Generate significant improvements in:

- Agricultural productivity
- Economic growth
- Social equality

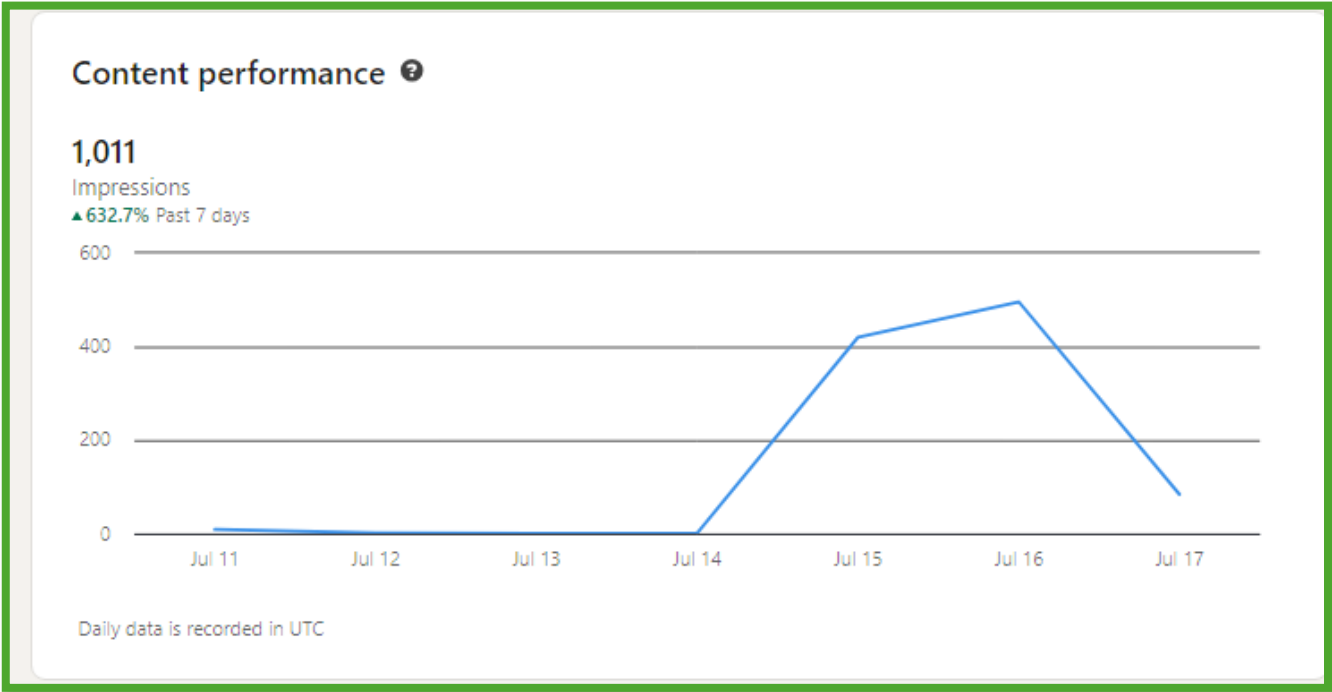
### Call to Action:

- To deliver financing and training for women in agriculture
- To further research in this area
- To reduce barriers for women in agriculture
- To validate and expand upon this research findings
- To developing financial products accessible and beneficial to women in agriculture.

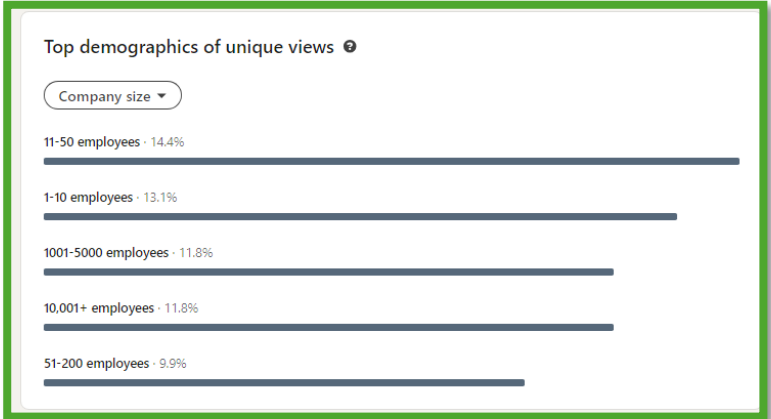
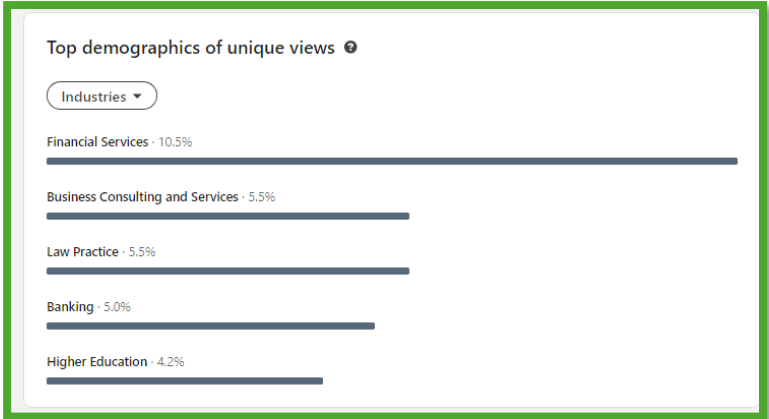
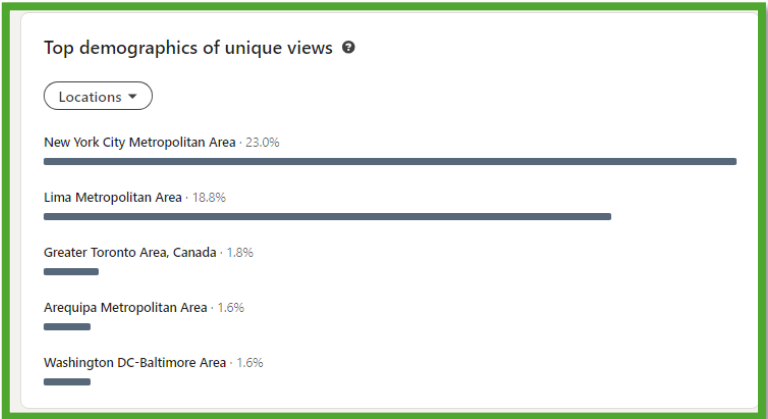
### Next Steps

- Historical Depth of the data: The data considered for this model covers the year 2012 only.
  - I have acquired, and prepared tabular appends with annual datasets covering the period 2014 – 2022
- The current analysis is based in gender gap calculation only
  - Is necessary to build a SQL database to strengthen the relations between gender gap, statistical, and ratio analyses, to create more complex and advanced features to be feed to the model.
- There is no precedent for the comprehensive objective of this project: “predict (through supervised learning) the location where the gender gap in agriculture is more pronounced in Peru, to tackle gender inequality through impact financing and training

## Audience (LinkedIn statistics)



## Audience (Top performing post statistics)





A collection of colorful wooden Tetris blocks, including I, O, T, L, and Z shapes, scattered on a wooden surface. The blocks are in various colors like purple, blue, green, orange, red, pink, yellow, and grey. The text "Supervised Learning Model" is overlaid in the center.

# Supervised Learning Model



# Datasets

Agriculture: Producer Profile

#	Column	Non-Null Count	Dtype
0	index	52 non-null	int64
1	year	52 non-null	int64
2	region_id	52 non-null	int64
3	region	52 non-null	object
4	gender_id	52 non-null	int64
5	gender	52 non-null	object
6	producers_thousands	52 non-null	float64
7	granted_loans_thousands	52 non-null	float64
8	illiteracy_percent	52 non-null	float64
9	postgraduate_percent	52 non-null	float64
10	primary_percent	52 non-null	float64
11	secondary_percent	52 non-null	float64
12	dont_need_loans_percent	52 non-null	float64
13	high_interest_percent	52 non-null	float64
14	no_collateral_percent	52 non-null	float64
15	or_reasons_percent	52 non-null	float64
16	red_tape_percent	52 non-null	float64
17	will_not_get_it_percent	52 non-null	float64
18	affiliation_percent	52 non-null	float64
19	Spanish	52 non-null	float64
20	Quechua	52 non-null	float64
21	Aymara	52 non-null	float64
22	Amazonia	52 non-null	float64
23	requested_loans_percent	52 non-null	float64
24	trained_thousands	52 non-null	float64
25	purpose_sales	52 non-null	float64
26	purpose_self_consumption	52 non-null	float64
27	purpose_self_provision	52 non-null	float64
28	purpose_animal_food	52 non-null	float64

Agriculture: Employment

#	Column	Non-Null Count	Dtype
0	index	7140 non-null	int64
1	year	7140 non-null	int64
2	region_id	7140 non-null	float64
3	region	7140 non-null	object
4	sector_id	7140 non-null	int64
5	sector	7140 non-null	object
6	gender_id	7140 non-null	int64
7	gender	7140 non-null	object
8	agriculture_employment	7140 non-null	float64

Agriculture: Main Indicators

#	Column	Non-Null Count	Dtype
0	index	29 non-null	int64
1	year	29 non-null	int64
2	region_id	29 non-null	int64
3	region	29 non-null	object
4	revenue_pen_2007	29 non-null	float64
5	gdp_percent	29 non-null	float64
6	added_value_PEN07	29 non-null	int64
7	harvested_mill_ha	29 non-null	float64
8	crops_mill_ha	29 non-null	float64

Agriculture: Natural Disasters

#	Column	Non-Null Count	Dtype
0	index	470 non-null	int64
1	year	470 non-null	int64
2	region_id	470 non-null	int64
3	region	470 non-null	object
4	crops_affected_by_disasters	470 non-null	float64

# Dataframes

Data source: Peru National Agricultural Census 2012

## Common Category Columns

#	Column	Non-Null Count	Dtype
0	index	52 non-null	int64
1	year	52 non-null	int64
2	region_id	52 non-null	int64
3	region	52 non-null	object
4	gender_id	52 non-null	int64
5	gender	52 non-null	object

Drop

4	sector_id	7140 non-null	int64
5	sector	7140 non-null	object

#	Column	Non-Null Count	Dtype
0	index	7140 non-null	int64
1	year	7140 non-null	int64
2	region_id	7140 non-null	float64
3	region	7140 non-null	object
6	gender_id	7140 non-null	int64
7	gender	7140 non-null	object

## Relevant Feature Columns

6	producers_thousands	52 non-null	float64
7	granted_loans_thousands	52 non-null	float64
8	illiteracy_percent	52 non-null	float64
9	postgraduate_percent	52 non-null	float64
10	primary_percent	52 non-null	float64
11	secondary_percent	52 non-null	float64
12	dont_need_loans_percent	52 non-null	float64
13	high_interest_percent	52 non-null	float64
14	no_collateral_percent	52 non-null	float64
15	or_reasons_percent	52 non-null	float64
16	red_tape_percent	52 non-null	float64
17	will_not_get_it_percent	52 non-null	float64
18	affiliation_percent	52 non-null	float64
19	Spanish	52 non-null	float64
20	Quechua	52 non-null	float64
21	Aymara	52 non-null	float64
22	Amazonia	52 non-null	float64
23	requested_loans_percent	52 non-null	float64
24	trained_thousands	52 non-null	float64
25	purpose_sales	52 non-null	float64
26	purpose_self_consumption	52 non-null	float64
27	purpose_self_provision	52 non-null	float64
28	purpose_animal_food	52 non-null	float64

# Features

## Concatenation / Final Columns

#	Column	Non-Null Count	Dtype
0	index	52 non-null	int64
1	year	52 non-null	int64
2	region_id	52 non-null	int64
3	region	52 non-null	object
4	gender_id	52 non-null	int64
5	gender	52 non-null	object
6	producers_thousands	52 non-null	float64
7	granted_loans_thousands	52 non-null	float64
8	illiteracy_percent	52 non-null	float64
9	postgraduate_percent	52 non-null	float64
10	primary_percent	52 non-null	float64
11	secondary_percent	52 non-null	float64
12	dont_need_loans_percent	52 non-null	float64
13	high_interest_percent	52 non-null	float64
14	no_collateral_percent	52 non-null	float64
15	or_reasons_percent	52 non-null	float64
16	red_tape_percent	52 non-null	float64
17	will_not_get_it_percent	52 non-null	float64
18	affiliation_percent	52 non-null	float64
19	Spanish	52 non-null	float64
20	Quechua	52 non-null	float64
21	Aymara	52 non-null	float64
22	Amazonia	52 non-null	float64
23	requested_loans_thousands	52 non-null	float64
24	trained_thousands	52 non-null	float64
25	purpose_sales	52 non-null	float64
26	purpose_self_consumption	52 non-null	float64
27	purpose_self_provision	52 non-null	float64
28	purpose_animal_food	52 non-null	float64
29	agriculture_employment	7140 non-null	float64

8	agriculture_employment	7140 non-null	float64
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4	revenue_pen_2007	29 non-null	float64
5	gdp_percent	29 non-null	float64
6	added_value_PEN07	29 non-null	int64
7	harvested_mill_ha	29 non-null	float64
8	crops_mill_ha	29 non-null	float64

#	Column	Non-Null Count	Dtype
0	index	29 non-null	int64
1	year	29 non-null	int64
2	region_id	29 non-null	int64
3	region	29 non-null	object
4	revenue_pen_2007	29 non-null	float64
5	gdp_percent	29 non-null	float64
6	added_value_PEN07	29 non-null	int64
7	harvested_mill_ha	29 non-null	float64
8	crops_mill_ha	29 non-null	float64

4	crops_affected_by_disasters	470 non-null	float64
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#	Column	Non-Null Count	Dtype
0	index	470 non-null	int64
1	year	470 non-null	int64
2	region_id	470 non-null	int64
3	region	470 non-null	object

Model Development Step by Step: Full Code \*

Statistical Analysis

mean	std	minimum	25% Q	50% Q	75% Q	maximum
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Methodology

Method	Supervised Learning	A type of machine learning where the model is trained on a labeled dataset to make predictions.
Technique	Random Forest	An ensemble learning method that operates by constructing multiple decision trees during training and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.
Model	Trained Random Forest Model	A model that has been trained using the Random Forest technique on a specific dataset.
Tool	Scikit-learn	A Python library that provides simple and efficient tools for predictive data analysis, equipped to work with numerical tables or data frames.

Model Implementation

The main objective of the Random Forest model is to improve prediction accuracy by reducing overfitting of the model and handling large data with higher dimensionality. It does this by creating multiple decision trees and merging them together.

Formula

There isn't a specific formula for Random Forest like there is for some other models. Instead, it's a collection of decision trees, each created from a different subset of your data. The final prediction is made by averaging the predictions of each tree if it's a regression problem, or by majority voting if it's a classification problem.

Steps

**Bootstrap the data:** Create multiple subsets of the original dataset, selecting observations with replacement.

**Create the Random Forest:** For each new data subset, create a decision tree. The optimal split at each node is found from a random subset of features.

**Make a prediction:** Each individual tree in the Random Forest spits out a class prediction and the class with the most votes becomes the model's prediction.

\* Model Development Step by Step

1. Data Preparation for Random Forest Model
2. Data Pre-Processing for Random Forest Model (new file)
3. Feature Selection & Importance
4. Model Training
5. Printing the Decision Tree
6. Performing a Prediction
7. Model Evaluation

Category vs Features

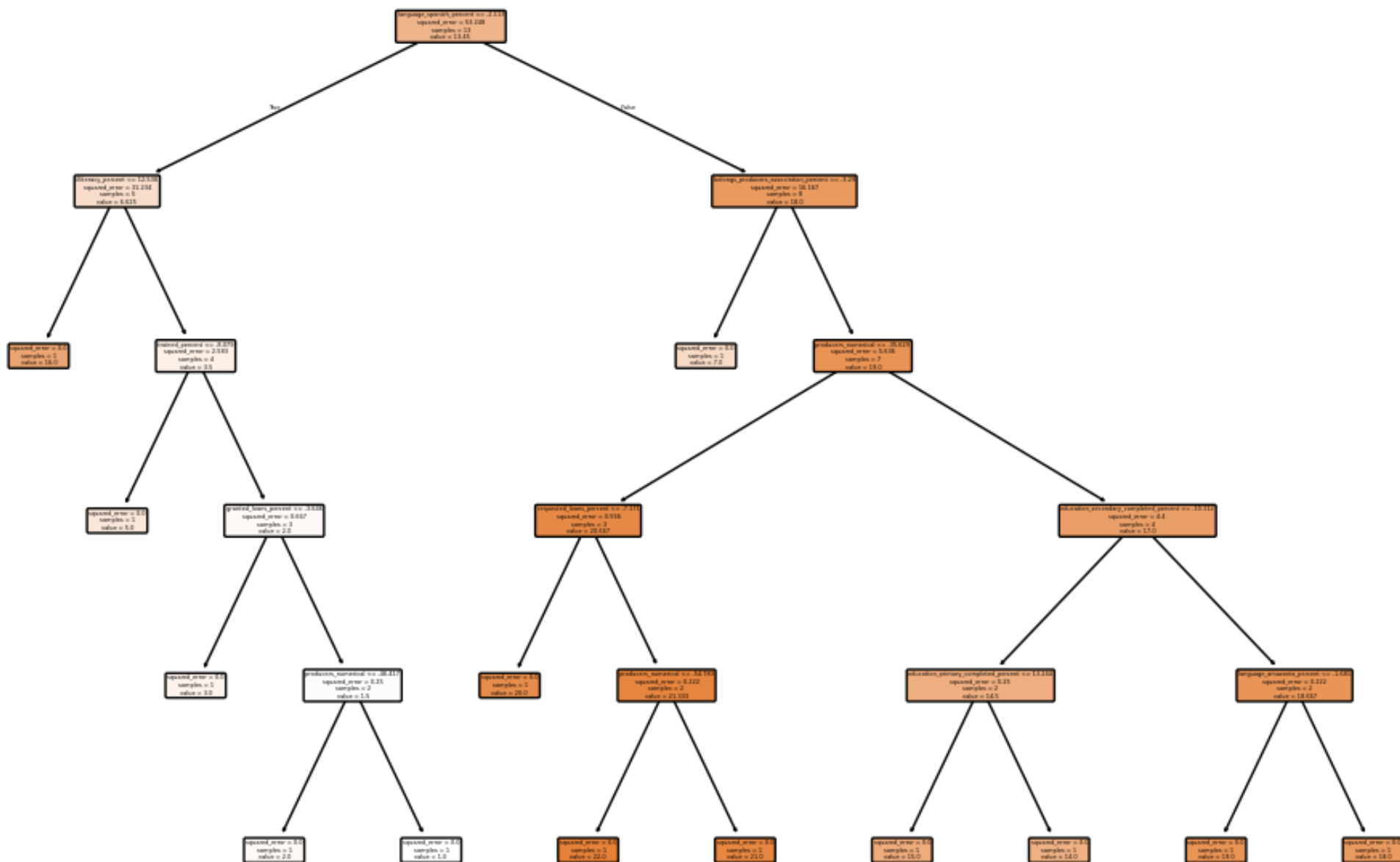
#	Column	Non-Null Count	Dtype	Final Feature
0	index	52 non-null	int64	category_index
1	year	52 non-null	int64	category_year
2	region_id	52 non-null	int64	category_region_id
3	region	52 non-null	object	category_region
4	gender_id	52 non-null	int64	category_gender_id
5	gender	52 non-null	object	category_gender
6	producers_thousands	52 non-null	float64	producers_numerical
7	granted_loans_percent	52 non-null	float64	granted_loans_percent
8	illiteracy_percent	52 non-null	float64	illiteracy_percent
9	postgraduate_percent	52 non-null	float64	education_postgraduate_completed_percent
10	primary_percent	52 non-null	float64	education_primary_completed_percent
11	secondary_percent	52 non-null	float64	education_secondary_completed_percent
12	dont_need_loans_percent	52 non-null	float64	don't_need_loans_percent
13	high_interest_percent	52 non-null	float64	high_interests_percent
14	other_reasons_percent	52 non-null	float64	other_reasons_percent
15	no_collateral_percent	52 non-null	float64	no_collateral_percent
16	red_tape_percent	52 non-null	float64	red_tape_percent
17	will_not_get_it_percent	52 non-null	float64	will_not_get_it_percent
18	affiliation_percent	52 non-null	float64	belongs_producers_association_percent
19	Spanish	52 non-null	float64	language_spanish_percent
20	Quechua	52 non-null	float64	language_quechua_percent
21	Aymara	52 non-null	float64	language_aymara_percent
22	Amazonia	52 non-null	float64	language_amazonia_percent
23	requested_loans_thousands	52 non-null	float64	requested_loans_percent
24	trained_thousands	52 non-null	float64	trained_percent
25	purpose_sales	52 non-null	float64	purpose_sales_percent
26	purpose_self_consumption	52 non-null	float64	purpose_self_consumption_percent
27	purpose_self_provision	52 non-null	float64	purpose_self_provision_percent
28	purpose_animal_food	52 non-null	float64	purpose_animal_food_percent
29	employment_agriculture_percent	7140 non-null	float64	employment_agriculture_percent

Feature Selection & Importance \*\*

category_region_id
producers_numerical
granted_loans_percent
requested_loans_percent
trained_percent
belongs_producers_association_percent
illiteracy_percent
education_primary_completed_percent
education_secondary_completed_percent
employment_agriculture_percent
language_spanish_percent
language_quechua_percent
language_aymara_percent
language_amazonia_percent

\*\* Although the analysis includes numerical versions of this features, numerical columns have been excluded from this model

## Decision Tree



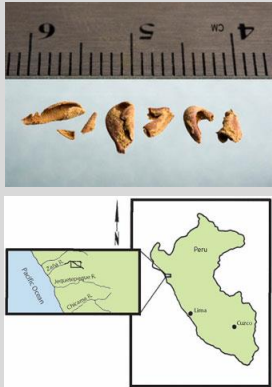


A collection of colorful wooden blocks in various shapes (crosses, L-shapes, rectangles) scattered on a wooden surface. The blocks are in shades of purple, blue, green, orange, red, pink, grey, brown, and yellow. The text "Supporting Research" is overlaid in the center in a white, bold, sans-serif font.

# Supporting Research

## Agriculture in Peru

- **Timeline:** 10 millennia of agricultural development in Peru
- **Demographics:** 25% of the population is dedicated to agriculture as of 2022



### Agriculture in Peru: 9,240 – 5,500 years ago Preceramic Adoption of Peanut, Squash, and Cotton in Northern Peru Tom D. Dillehay, Jack Rossen, Thomas C. Andres, And David E. Williams

The early development of agriculture in the New World has been assumed to involve early farming in settlements in the Andes, but the record has been sparse. Peanut (*Arachis* sp.), squash (*Cucurbita moschata*), and cotton (*Gossypium barbadense*) macrofossils were excavated from archaeological sites on the western slopes of the northern Peruvian Andes. Direct radiocarbon dating indicated that these plants grew between 9240 and 5500 14C years before the present. These and other plants were recovered from multiple locations in a tropical dry forest valley, including household clusters, permanent architectural structures, garden plots, irrigation canals, hoes, and storage structures. These data provide evidence for early use of peanut and squash in the human diet and of cotton for industrial purposes and indicate that horticultural economies in parts of the Andes took root by about 10,000 years ago.

## Gender Gap in Agriculture: Python Data Analysis: Jupyter Notebooks via GitHub Repositories

- Women in agriculture have limited access to training and financing
- Women in agriculture have a limited participation in producer associations

### Agriculture in Peru (2,000 BCE – 1,400 CE): Irrigation and Land Use on the Arid North Coast of Peru: Assessing Ancient Agricultural Systems Through Drone Photography, Soil Analysis, and Local Knowledge Authors: C. Prado, J. Eerkens, R. Beresford-Jones, and E. Van Valkenburgh

This paper explores the historical development of agriculture along Peru's arid north coast, focusing on the prehispanic timeline and agricultural products of different cultures. Intensive irrigation-based farming began in the second millennium BCE, featuring early canals and check dams. Early Andean cultures grew crops like squash, beans, and cotton. From the first millennium BCE to the first millennium CE, advanced water management techniques were developed, crucial for handling the El Niño Southern Oscillation (ENSO). Key crops included maize, beans, and manioc. Significant hydraulic engineering advancements and irrigation network expansions occurred from the first millennium CE to the 15th century. The Moche civilization (100-800 CE) built extensive canal systems, cultivating maize, beans, squash, and peanuts. The Chimú civilization (11th-15th century) further developed these systems, creating interconnected canals for diverse crops such as maize, cotton, and quinoa. These innovations supported large populations and complex societies. The paper concludes that the prehispanic agricultural timeline in Peru showcases a continuous evolution of water management and farming practices. By examining the specific crops and techniques used by different cultures, we gain insights into the adaptability and resilience of ancient agricultural systems. These historical practices offer valuable lessons for sustainable agriculture in arid regions globally, demonstrating effective responses to environmental challenges.

### Agriculture during the Colony (1681 – 1800 CE)

**Title:** Crecimiento Económico en el Espacio Peruano

**Carlos Newland, Universidad Argentina de la Empresa**

**John Coatsworth, Rockefeller Center for Latin American Studies, Harvard University**

In-depth analysis of the evolution of agriculture in Peru from 1681 to 1800. The authors highlight a period of economic crisis and agricultural decline from 1681 to 1750. This was followed by an improvement and overall growth in agriculture from 1750 to 1800. In conclusion, despite the initial collapse, there was a subsequent expansion of agricultural production in the 18th century. This expansion was not homogeneous across regions, with Lima experiencing a decline. However, the overall trend suggests stability or improvement in per capita agricultural production and likely increases in real wages for the region, except in Lima.

### Agriculture during the Republic (1,875 – 1,933)

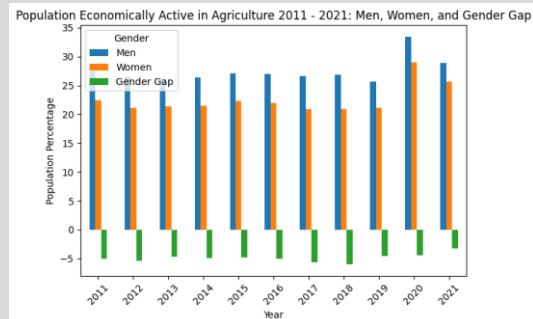
**Title:** Plantation Agriculture and Social Control in Northern Peru, 1875–1933

**Author:** Michael J. Gonzales

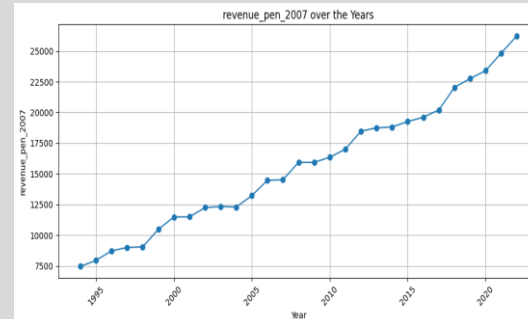
The author explores the development of plantation agriculture in Northern Peru from 1875 to 1933. Beginning with the economic and political transformation during the 1860s and 1870s, marked by the decline of the guano boom and the rise of coastal agriculture. By the late 19th century, sugarcane plantations had become significant economic entities, driven by technological advancements and the influx of capital from former guano traders.

In the early 20th century, the sugar industry continued to expand, with plantations adopting modern agricultural practices and machinery. Author concludes with the impact of the War of the Pacific and the subsequent recovery of Peru's agricultural sector, as well as the transition from traditional to modern practices, reflecting broader economic and social changes in Northern Peru.

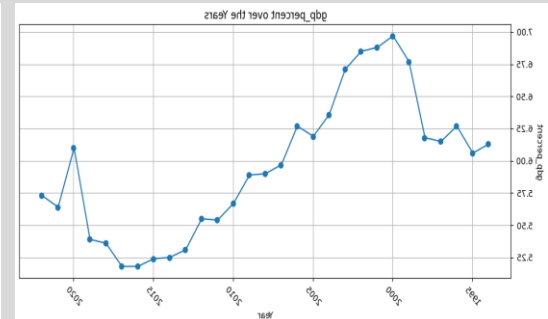
#### Total Population Dedicated to Agriculture



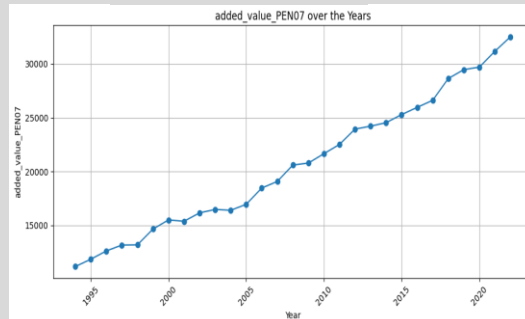
#### Total Agricultural Revenue



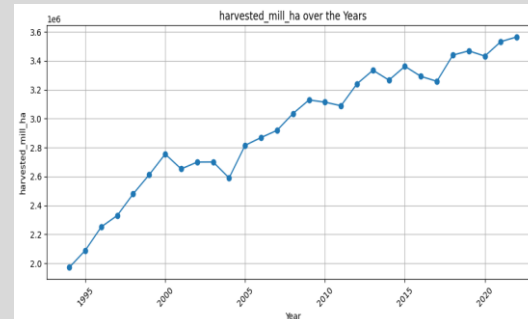
#### Agricultural GDP



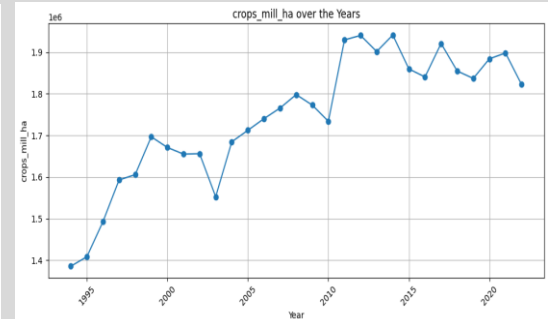
#### Agricultural Added Value



#### Harvest



#### Crops



Referential Research: Finance and Training in Peru

	Access to Credit and Credit Risk	Financial Inclusion (Services & Literacy)	Training in Agriculture in Peru
	Study on Peruvian Microfinance Institution	Financial Inclusion in Peru	Gender Equality in Peru: Unleashing the Potential of Women (2022)
Summary	This study was conducted at a Peruvian microfinance institution specializing in rural microcredits. The authors proposed a model for assessing microcredit applications using machine learning techniques. The goal was to improve the <u>assertiveness of the credit granting process</u> and <u>reduce the default rate</u> .	This paper by Rocío Maehara et al. explores the application of machine learning (ML) methods to assess <b>financial inclusion in Peru</b> . The study uses data from the National Survey of Demand for <b>Financial Services</b> and <b>Financial Literacy</b> 2019, covering a sample of 1205 Peruvian citizens.	This OECD’s report outlines significant data on women's access to training in the agricultural sector. The report highlights that women in Peru's agricultural sector face substantial barriers to accessing training, which impacts their productivity and economic opportunities.
Methods	Data Pre-processing, Cross-validation, Supervised Learning	Data Pre-processing, Grid Search Procedure, Supervised Learning	Surveys and Questionnaires, Statistical Analysis, Regression Models, Qualitative Interviews, Focus Groups.
Techniques	Handling missing data, Normalizing variables, One Hot coding	10-fold cross-validation	n/a
Models	Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree (dTree), k-Nearest Neighbors (kNN)	Logistic Regression (LR), Artificial Neural Networks (ANNs), Decision Trees (DTs), Random Forest (RF), XGBoost, Support Vector Machine with RBF kernel (SVC RBF)	n/a
Tools	Scikit Learn, Keras, Pandas, Numpy, Matplotlib	Not explicitly mentioned	n/a



# Supervised Learning (Random Forest) Predictive Model

8	Description	Code
1	Data Collection	<a href="https://github.com/jcburga/python_final_research/blob/main/concatenate_clean_agriculture_producer_employment.csv">https://github.com/jcburga/python_final_research/blob/main/concatenate_clean_agriculture_producer_employment.csv</a>
	Data Collection	<a href="https://github.com/jcburga/python_final_research/blob/main/ml_producer_profile_selected_features.csv">https://github.com/jcburga/python_final_research/blob/main/ml_producer_profile_selected_features.csv</a>
	Statistical Analysis	<a href="https://github.com/jcburga/python_final_research/blob/main/%231_ml_producer_statistical.ipynb">https://github.com/jcburga/python_final_research/blob/main/%231_ml_producer_statistical.ipynb</a>
2	Data Exploration:	<a href="https://github.com/jcburga/python_final_research/blob/main/%232A_ml_producer_exploration.ipynb">https://github.com/jcburga/python_final_research/blob/main/%232A_ml_producer_exploration.ipynb</a>
	Data Preparation:	<a href="https://github.com/jcburga/python_final_research/blob/main/%232B_ml_producer_preparation.ipynb">https://github.com/jcburga/python_final_research/blob/main/%232B_ml_producer_preparation.ipynb</a>
3	Feature Selection & Importance	<a href="https://github.com/jcburga/python_final_research/blob/main/%233B_ml_producer_feature_selection_importance.ipynb">https://github.com/jcburga/python_final_research/blob/main/%233B_ml_producer_feature_selection_importance.ipynb</a>
	Data Pre-Processing:	<a href="https://github.com/jcburga/python_final_research/blob/main/%234_ml_producer_pre_processing.ipynb">https://github.com/jcburga/python_final_research/blob/main/%234_ml_producer_pre_processing.ipynb</a>
4	Model Training: Split,	
5	Prediction:	<a href="https://github.com/jcburga/python_final_research/blob/main/%234_5_6_ml_producer_train_predict_evaluate.ipynb">https://github.com/jcburga/python_final_research/blob/main/%234_5_6_ml_producer_train_predict_evaluate.ipynb</a>
6	Model Evaluation:	

References

1 Data Collection:	Kelleher, J. D., Mac Namee, B., & D'Arcy, A. (2015). Fundamentals of Machine Learning for Predictive Data Analytics: Algorithms, Worked Examples, and Case Studies. MIT Press.
2 Data Preprocessing:	Garcia, S., Luengo, J., & Herrera, F. (2015). Data Preprocessing in Data Mining. Springer.
3 Feature Selection:	Guyon, I., & Elisseeff, A. (2003). An Introduction to Variable and Feature Selection. Journal of Machine Learning Research, 3, 1157-1182.
4 Model Training:	Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer.
5 Model Evaluation:	Sokolova, M., & Lapalme, G. (2009). A Systematic Analysis of Performance Measures for Classification Tasks. Information Processing & Management, 45(4), 427-437.
6 Prediction:	Hastie, T., Tibshirani, R., & Friedman, J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer.

Comparative Hierarchical Methodological Decision-Making Matrix

selected

Method	Supervised Learning	A type of machine learning where the model is trained on a labeled dataset to make predictions.	Supervised Learning	A type of machine learning where the model is trained on a labeled dataset to make predictions.	Supervised Learning	A type of machine learning where the model is trained on a labeled dataset to make predictions.	Supervised Learning	A type of machine learning where the model is trained on a labeled dataset to make predictions.
Technique	Random Forest	An ensemble learning method that operates by constructing multiple decision trees during training and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.	Support Vector Machines (SVM)	A set of supervised learning methods used for classification, regression and outliers detection.	Logistic Regression	A statistical model that uses a logistic function to model a binary dependent variable.	Neural Networks	A series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates.
Model	Trained Random Forest Model	A model that has been trained using the Random Forest technique on a specific dataset.	Trained SVM Model	A model that has been trained using the SVM technique on a specific dataset.	Trained Logistic Regression Model	A model that has been trained using the Logistic Regression technique on a specific dataset.	Trained Neural Network Model	A model that has been trained using the Neural Network technique on a specific dataset.
Tool	Scikit-learn	A Python library that provides simple and efficient tools for predictive data analysis, equipped to work with numerical tables or data frames.	Scikit-learn	A Python library that provides simple and efficient tools for predictive data analysis, equipped to work with numerical tables or data frames.	Scikit-learn	A Python library that provides simple and efficient tools for predictive data analysis, equipped to work with numerical tables or data frames.	TensorFlow	An open-source platform for machine learning that provides a comprehensive ecosystem of tools, libraries, and community resources for developing and deploying ML models.

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7. Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... & Kudlur, M. (2016). TensorFlow: A System for Large-Scale Machine Learning. In OSDI (Vol. 16, pp. 265-283).

# Data from CSV/XLSX

Step	Method	Description	Example Code
1	Databases	Data is extracted from a database using SQL queries or a database API.	<code>import sqlite3&lt;br&gt;import pandas as pd&lt;br&gt;conn = sqlite3.connect('database.db')&lt;br&gt;df = pd.read_sql_query("SELECT * FROM table_name", conn)</code>
2	Web Scraping	Data is extracted from a website using web scraping tools.	<code>import requests&lt;br&gt;from bs4 import BeautifulSoup&lt;br&gt;response = requests.get("https://www.website.com")&lt;br&gt;soup = BeautifulSoup(response.content, 'html.parser')&lt;br&gt;data = soup.find_all('div', class_='class-name')</code>
3	APIs	Data is accessed in a structured format using APIs provided by websites and platforms.	<code>import requests&lt;br&gt;response = requests.get("https://api.website.com/data")&lt;br&gt;data = response.json()</code>
4	Surveys and Questionnaires	Data is collected using surveys or questionnaires.	N/A
5	CSV/Excel Files	Data is loaded from CSV or Excel files into a DataFrame.	<code>import pandas as pd&lt;br&gt;df = pd.read_csv('data.csv')</code>
6	Preexisting Datasets	Data is collected from preexisting datasets available on the internet.	N/A

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