



POLITECNICO
MILANO 1863

Nonparametric Analysis of Agricultural Productivity In U.S.



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Nonparametric Statistics (5 CFU)
MSc. Mathematical Engineering





RESEARCH QUESTIONS

The project addresses **Policymakers** of US and their **Economic Advisers**

01

How Agricultural Growth has changed from the past

02

Which are the Primary Drivers of the agricultural sector's growth

03

Which States are leading in Agricultural Production and why





DATASET PRESENTATION

For each U.S. State

National Level Observations

YEAR
from 1960 to
2004

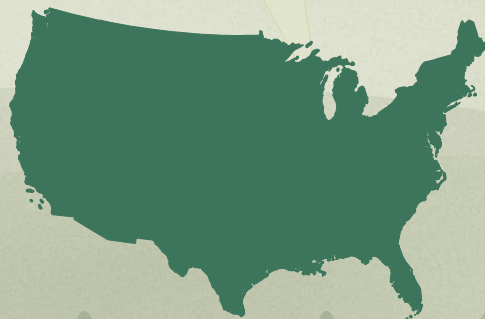
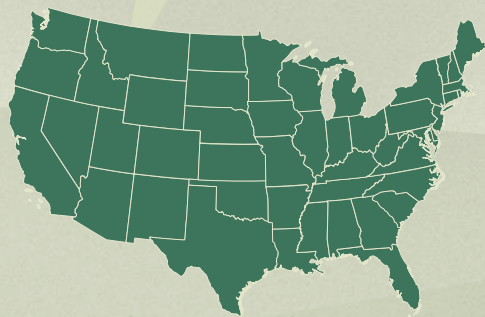
Total Agricultural Output

Intermediate Input

Labor Input

Capital Input

YEAR
from 1948 to
2019





DATASET PRESENTATION



The variables are indexes of growth with respect to year 2015

Total Agricultural Output
Gross production leaving the farm

Capital Input
Wide range of physical assets used in agricultural activities

- Durable Equipment
- Service Buildings
- Inventories
- Land

Labor Input
Total human effort in agricultural production

- Hired Labor
- Self Employed & Unpaid Family

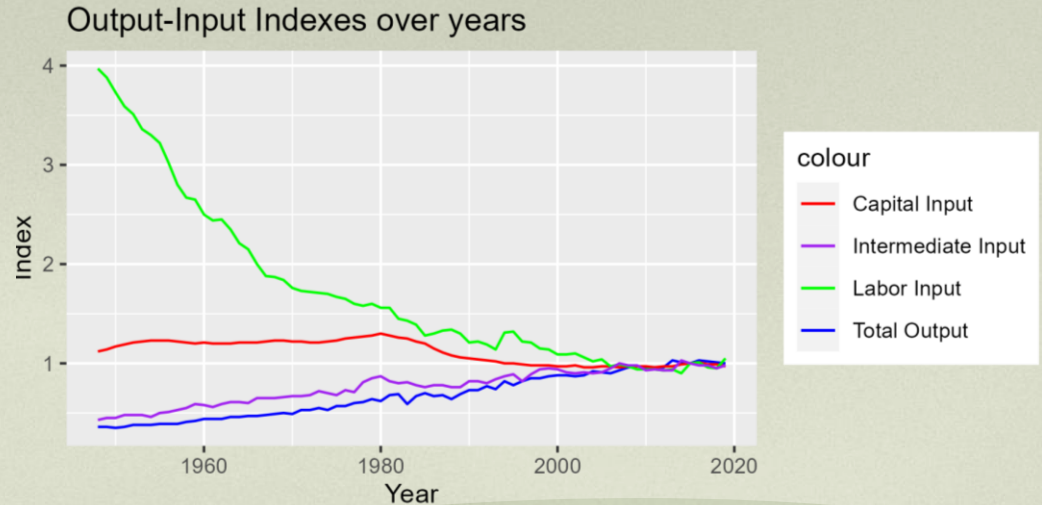
Intermediate Input
Resources used within the production process but not directly transformed into the final output

- Feed and Seed
- Fertilizer
- Energy
- Pesticides
- Purchased Services



GENERAL TRENDS IN DATA

Different composition of *Inputs* along Years



From

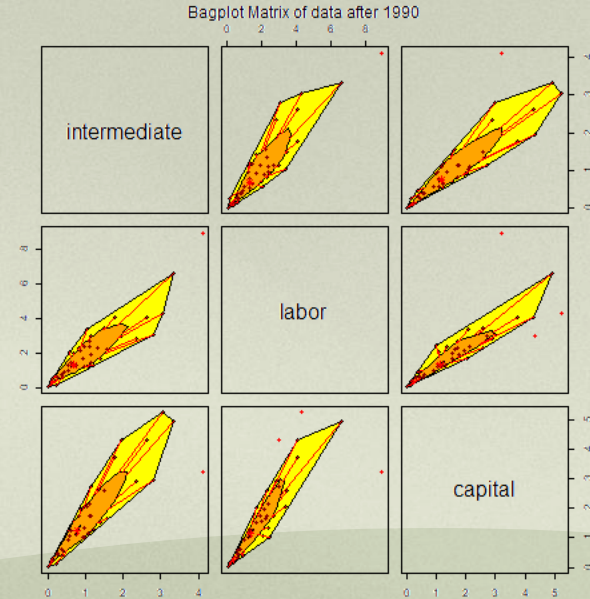
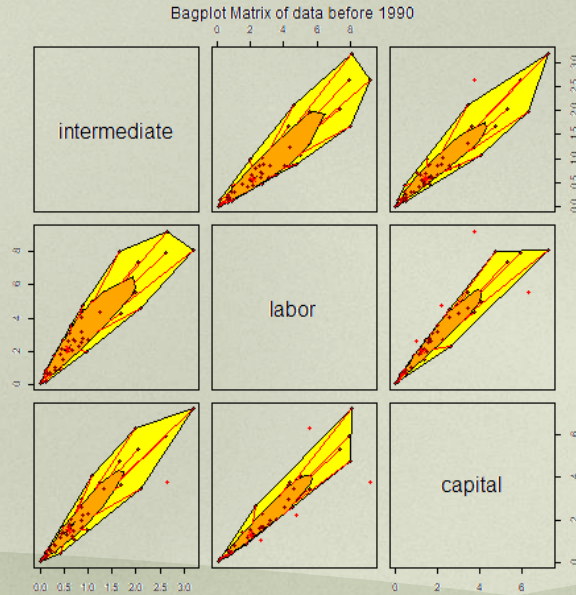
Human Labor
&
Land (Capital Input)

Towards

Farm Machinery
(Capital Input)
&
Intermediate Resources



GENERAL TRENDS IN DATA



Two Paired Samples Multivariate Permutational test

There is statistical evidence of difference between the means of first period and second period



SPEARMAN CORRELATION

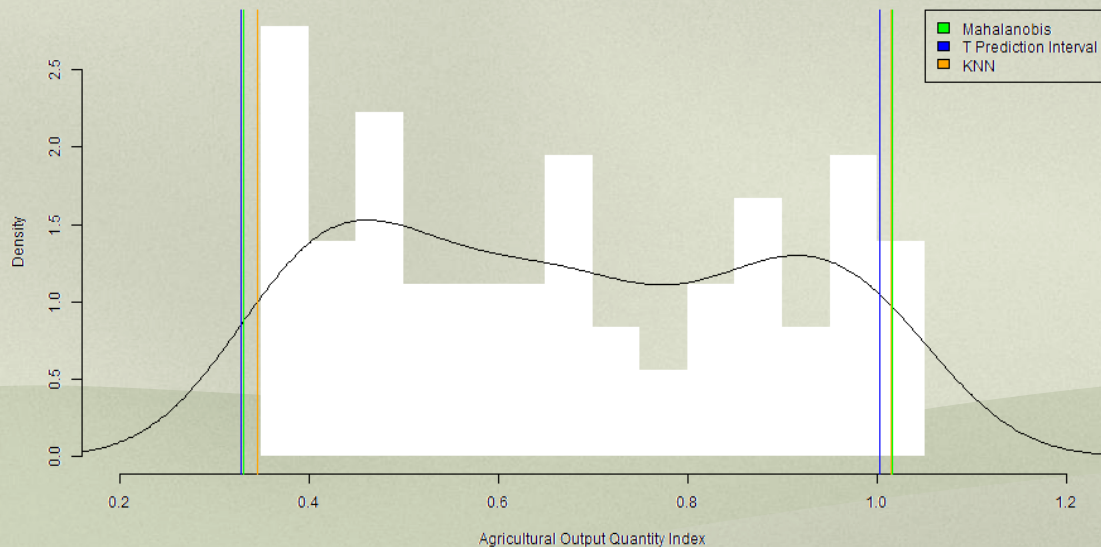
	Total Output 48-90	Total Output 90-2015
Capital Input	0.1656040	- 0.3183969
Labor Input	- 0.9876408	- 0.8513482
Intermediate Input	0.9568786	0.7858585

- **Intermediate Input:** strongly positive correlation
- **Labor Input:** excessive or inefficient allocation of labor → reduction in productive efficiency
- **Capital Input :** shift from weakly positive to negative → changes in agricultural technologies, resource allocation or market dynamics



CONFORMAL PREDICTION

Histogram of Agricultural Output Quantity Index



Conformal Intervals

➡ Mahalanobis distance

➡ T prediction interval

➡ KNN distance

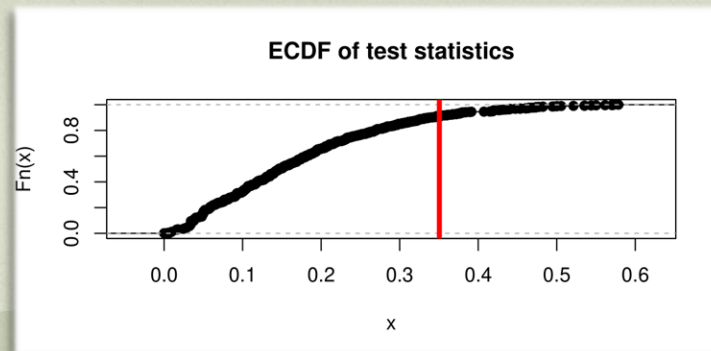
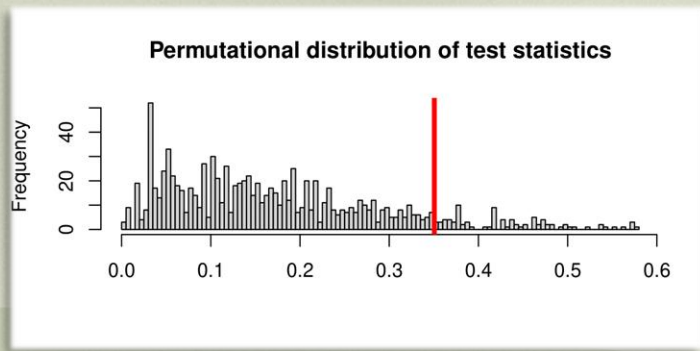


GAM

Multiple Permutation Tests

$$H_0: \beta_{Feed} = 0 \text{ vs } H_1: \beta_{Feed} \neq 0$$

to assess the significance of each covariate



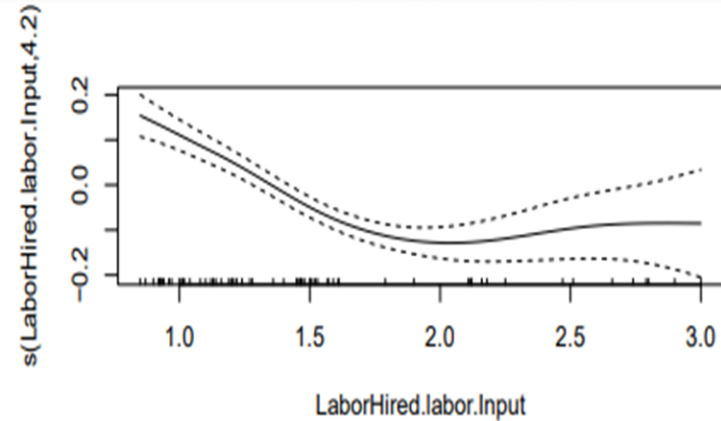
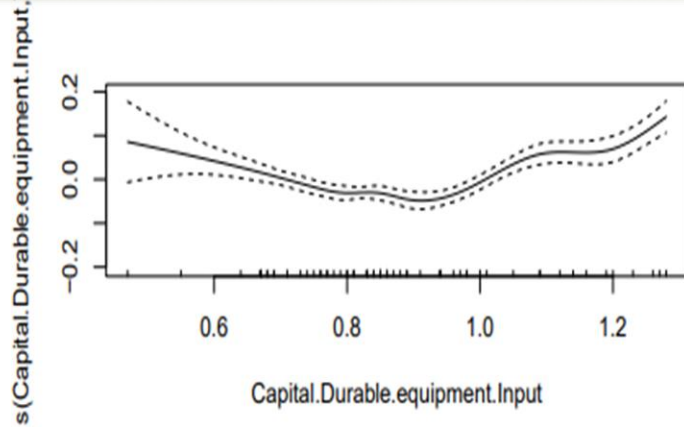
$$pval = 0.334$$



GAM

$$\begin{aligned} \text{Total.Agricultural.Output}_i = & \beta_0 + \beta_1 * \text{Intermediate.Energy.Input}_i \\ & + \beta_2 * \text{Intermediate.Pesticides.Input}_i \\ & + \beta_3 * \text{Capital.Service.Buildings.Input}_i : \text{Period}_i \\ & + \beta_4 * \text{Self.Employed.Unpaid.Family}_i : \text{Period}_i \\ & + f_1(\text{Capital.Durable.Equipment.Input}_i) \\ & + f_2(\text{Labor.Hired.Labor.Input}_i) + \varepsilon_i \end{aligned}$$

$$\begin{aligned} \beta_1, \beta_2, \beta_{3,2} &> 0 \\ \beta_{3,1}, \beta_{4,1}, \beta_{4,2} &< 0 \end{aligned}$$





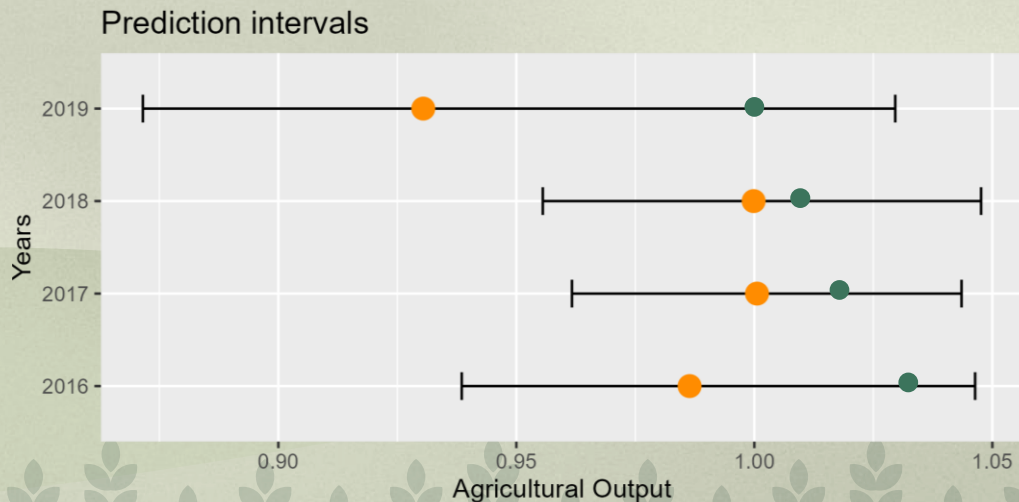
GAM

Prediction of years 2016-2019 using GAM covariates

+

Reverse Percentile (Bootstrap) intervals $\alpha=0.1$

Comparison with true data



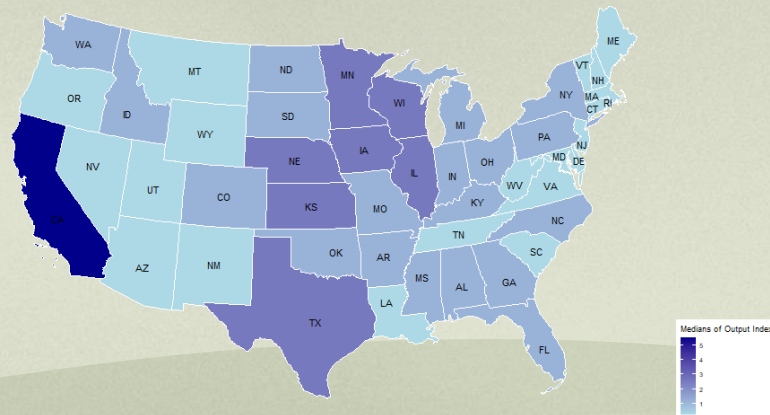
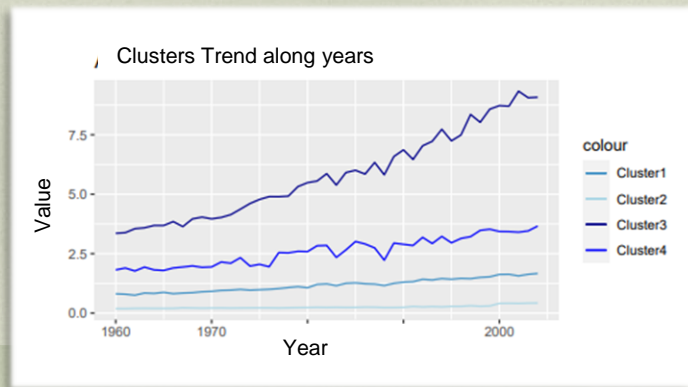
Prediction of 2019 underscores the challenge of accurately predicting outcomes when considering dynamic, external factors



SEQUENTIAL CLUSTERING

Sequential Clustering based on Agricultural Output Index

Identify **4 clusters** exhibiting similar patterns over years



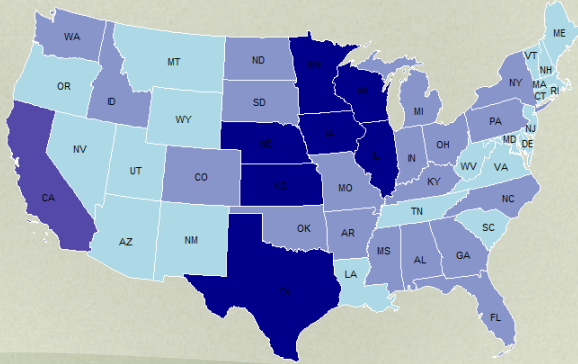
Singleton California has values significantly higher than those of other state



PERMUTATIONAL MANOVA

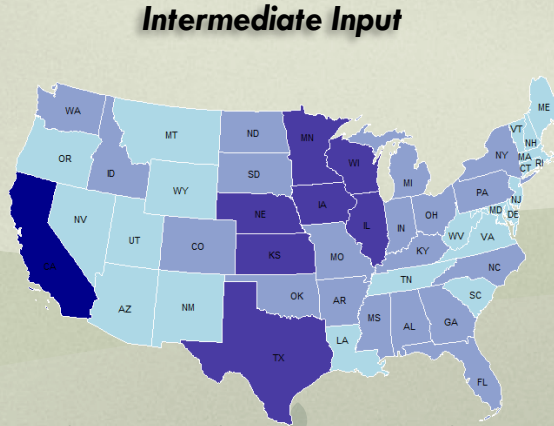
Permutational Manova Analysis on Capital Input, Labor Input and Intermediate Input

Clustering not only captures output distinctions but also reflects **statistically significant variations** in the use of inputs



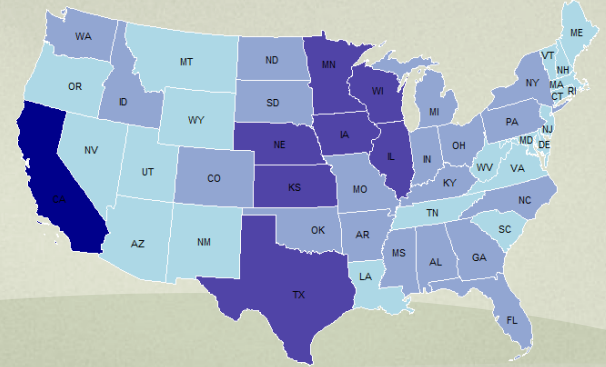
Medians of capital index
1 2 3 4

Capital Input



Medians of intermediate index
1 2

Intermediate Input



Medians of labor index
2 4 6 8

Labor Input



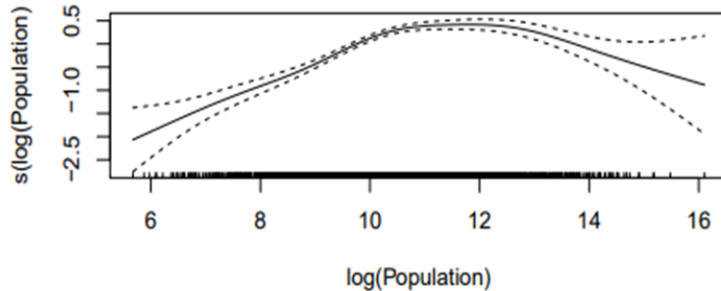
SPATIAL ANALYSIS

Spatial GAM to identify regions with the highest sales of agricultural commodities

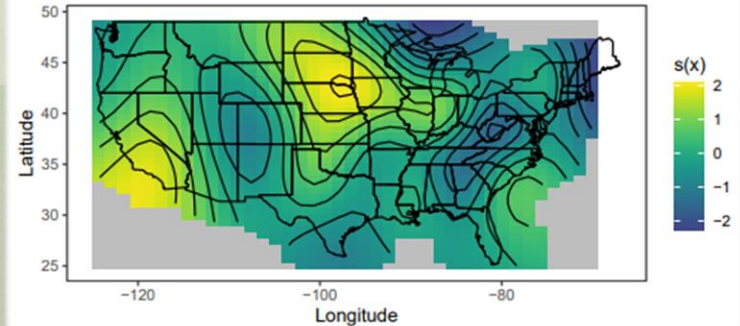
Areas with **high sales** could indicate regions with a **strong demand** for agricultural commodities and a **higher necessity** for agricultural productivity

$$\log(\text{Total_Commodities_Sales}) = f_1(\text{Latitude, Longitude}) + f_2(\log(\text{Population}))$$

Population effect



Smooth coefficients of interaction





CONCLUSIONS

Conclusions

01

Changes In Input Usage



Permutational Tests

02

**Primary drivers of the
agricultural sector**



GAM + Bootstraps Intervals

03

Spatial Agricultural Trends



Permutational Manova
+ Spatial GAM

Further Developments

- ➡ Include in the analysis external factors, such as weather conditions or characteristics of the soil
- ➡ Employ more sophisticated modeling techniques to understand complexity of the dynamics of agricultural systems



Thanks for your attention!





References

- Ball et al. *Is u.s. agricultural productivity growth slowing? Applied Economic Perspectives and Policy*, 2013.
- Wang et al. *Public r&d, private r&d, and us agricultural productivity growth: Dynamic and long-run relationships*. American journal of agricultural economics, 2013.
- Sun Ling Wang, Paul Heisey, David Schimmelpfennig, and V Eldon Ball. *Agricultural productivity growth in the united states: Measurement, trends, and drivers*. Economic Research Service, 2015.
- Sun Ling Wang, Richard Nehring, and Roberto Mosheim. *Agricultural productivity growth in the united states: 1948-2015. Amber Waves: The Economics of Food, Farming, Natural Resources, and Rural America*, 2018(2), 2018.