Optimal vs. Actual Acreage Decisions: A Regression Analysis of Rational Expectations in US Potato Farming

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Abstract-This paper investigates how closely actual acreage decisions in U.S. potato farming align with predictions from the Rational Expectations Equilibrium (REE) model. While REE assumes that farmers make fully rational, profit-maximizing decisions, empirical evidence rarely confirms its accuracy for specialty crops like potatoes, which are liable to volatile prices and repeated uncertain production choices. This study uses a regression-based approach to compare REE-predicted optimal acreage with actual planted acreage, using recent U.S. agricultural data, building on econometric methods previously applied to grains and cereals. Farmer decisions are modelled as a function of price per hundredweight, cost per acre, and harvested production, with key coefficients estimated via ordinary least squares regression. Results show significant gaps between predicted and actual acreage, indicating that non-price factors, such as risk aversion, information asymmetries, and market sentiment, meaningfully influence decisions. These findings highlight the limitations of purely rational models in volatile agricultural markets and underscore the need for policies that account for observed behavioural deviations to improve crop supply forecasts and market stability. This study is novel in empirically testing REE predictions against real potato acreage, offering applicable insights for agricultural economists and policymakers aiming to optimize resource allocation under uncertainty.

Keywords: **Rational Expectation Equilibrium, potato farming, acreage decisions, regression analysis, agricultural policy**

I. Introduction

1.1 Agricultural Markets

Acreage is defined as “area in acres”, a term used to denote an area of land (measured in acres) that is used or planned to be used for growing a particular crop (“Acreage,” 2025b). 1 acre is approximately 4,047 square meters or 0.405 hectares (Taylor & Francis, n.d.-c). It is a standard unit of land measurement in U.S. agriculture and commonly used in farm planning, policy, and research. The United States is one of the largest potato producers globally, with main production locations such as Idaho, Washington, North Dakota and Wisconsin driving market dynamics (*Potatoes*, n.d.), with Idaho alone producing about 135 million cwt in 2024, which is over 30 % of the U.S. total output (*USDA/NASS 2024 State Agriculture Overview for Idaho*, n.d.). Global food production is seeing increasing uncertainty due to climate change, resulting in concerns regarding national food security (Wang et al., 2023). Accurate predictions are vital to ensure the efficiency and stability of agricultural markets, maintaining global food security. Their production is dependent on factors such as seed quality, input costs, labour, and harvesting methods, which determine efficiency and profitability (Devi et al., 2025). Farmers face a decision problem regarding the optimal number of acres to plant and harvest potatoes on, requiring them to make rational decisions based on all information available. Market equilibrium can be defined as the point where quantity of a good demanded is equal to the quantity of a good supplied (*Supply and Demand | Definition, Example, & Graph | Britannica Money*, n.d.-b). To solve this problem, we turn towards equilibrium models that extend beyond these classical supply and demand frameworks. One such model is the Rational Expectations Equilibrium.

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1.2 Rational Expectations

The concept of Rational Expectations (RE) is an informed prediction about a future event (Muth, 1961). The Rational Expectations Hypothesis suggests that economic agents utilize all available information when forming expectations, leading to predictions that align with actual outcomes. When applied to agricultural markets, this suggests that farmers adjust their planting and production decisions based on expected future prices. However, the extent to which the Rational Expectations Equilibrium- which refers to a market condition where traders make expectations about the equilibrium prices based on information that they initially possess (Radner, 1979)- accurately predicts market prices remains uncertain, given external factors like weather, government policies, and shocks. This introduces a degree of randomness in the outcomes of the effective yield, Y_{eff}, which can be understood as a random variable capturing the uncertainty of how many potatoes will actually reach the market.

1.3 Profit Maximisation and The Role of Linear Regression

Linear Regression is a tool, allowing one to predict the relationship between a dependant variable and multiple independent variables (Weisberg, 2014). In the context of agricultural markets, it allows us to quantify the impact of various factors on ultimate crop yield outcomes. The paper uses linear regression to find a value for the optimal acres to be planted by a farmer with the aim of maximising profit. This is done through solving the profit maximisation problem, which is an economic concept which helps firms maximise their profits. The problem can be viewed as having 2 subparts: minimising costs and maximising profits, both within the constraints of a cost function.

II. Literature Review

2.1 Rational Expectations

Rational expectations theory has increasingly been applied as a lens for understanding agricultural decision-making, particularly in the intersection between policies, uncertainty, and sustainable practices, where farmers maximise land productivity while minimising environmental harm. Farmers are the central decision makers in such practices, but their decisions are influenced by economic, social, and cultural constraints (Githinji, 2023). When farmers respond to these pressures, human agency theory suggests that land use is not solely dependent on objective factors such as prices and technological inputs, but in reality, depends on subjective factors and adaptive decisions made by agents. This means that famer's acreage decisions are influenced by both rational expectations as well as local perceptions. Regression aid in uncovering the proportion of variation in decisions that are because of rational expectations as opposed to other factors (S et al., 2025). Muth's (1961) foundational work on Rational Expectations Equilibrium asserts that the expectations hypothesis relies on 3 things. Firstly, that information is limited, and the economic system typically utilizes it efficiently. The way expectations are formed is closely tied to the specific structure of the economic system. Additionally, public predictions, as described by Grunberg and Modigliani (Grunberg & Modigliani, 1954), do not have a significantly influential effect on the workings of the economic system unless based on insider information. Radner's (1979) paper on the Rational Expectations Equilibrium further explores the Rational Expectations Equilibrium, emphasizing the finding that market prices can reveal the private information of all agents. These agents attribute the difference between expected and realised prices to information held by better informed agents. These agents then update their expectations based on observed price deviations, leading to continuous adjustments in their plans and outcomes. This phenomena aids the dissemination of information, theoretically resolving the problem of asymmetric information. The mechanism demonstrates how farmers, if behaving rationally, can rely on price signals in agricultural markets to make expectations about future prices, providing them with "private information" that can be utilised to maximise their profits. However, Radner further explains how this mechanism leads to a paradox: if all traders assume others will also acquire information, they may not choose to seek out information themselves under the assumption that the market prices will reveal the information eventually.

2.2 Rational Expectations in Agricultural Markets

The paper "A Rational Expectations Model of Agricultural Supply" by Zvi Eckstein in 1984 further explores rational expectations in agricultural markets. Eckstein develops a linear rational expectations model, using it to analyse land allocation decisions, and obtaining closed-form linear regression equations by employing a quadratic production technology. The equations are then validated using Egyptian agricultural data. The paper serves as a key example of the Rational Expectations Equilibrium (REE) in agriculture, assuming that farmers behave rationally by making land allocation decisions based on past land use, expected future prices, and other exogenous variables. The study is relevant to present research as it applies the REE model in the context of agricultural markets. However, while Eckstein derived decision rules, this paper aims to explicitly solve the profit maximisation problem in the context of US potato farming. Although Eckstein utilised linear regression as a robust estimation method, Miranda & Glauber (1993) employed a different approach in their paper "Intraseasonal Demand for Fall Potatoes under Rational Expectations", which applied stochastic-dynamic programming to develop a nonlinear rational expectations model for the U.S. fall potato market. The paper discusses the Fair-Taylor method and its application in studying the effects of stockholding on market dynamics. Miranda and Glaubner acknowledge the nonlinear nature of the U.S. fall potato market. The paper argues that the fixed price elasticity assumtion in linear models fails to account for demand accumulation over time, instead assuming that demand will always change by a fixed amount in response to a price change.

2.3 Forecasting Models in Agricultural Markets

In addition to this, there exist multiple papers discussing linear regression, including the tool's critique and alternatives. Apart from using linear regression to analyse the agricultural market, Sun et al. (2023) expands upon multiple other methodologies, emphasising that the key to successful forecasting of agricultural trends lies in the use of multiple forecasting methods. Traditional forecasting models, such as linear regression, time series models (ARIMA, SARIMA), and gray models, are widely applied but fall short in accuracy due to the failure to account for the nonlinear nature of agricultural price fluctuations. To address these shortcomings, intelligent prediction methods are discussed, such as the Baynesian prediction method, Support Vector Machine-Based method, and Neural Network-Based Prediction Method. However the paper expands on the shortcomings of these methods as well, describing the intelligent prediction methods as requiring large amounts of data, being challenging to adjust, prone to overfitting, and lacking interpretability. The paper goes on to recommend a combined model, asserting that hybrid forecasting approaches present the highest accuracy as compared to the use of individual techniques. Other studies have attempted to employ linear regression in the potato markets (Piekutowska et al., 2021) through the use of Poland's data on potatoes. The paper used the R^2 coefficient to determine the fit of the regression model in predicting potato yields, and found that while linear regression was a useful tool in yield estimations, it was limited in accuracy by external factors, and that neural models outperform traditional regression models in yield estimation. However, these neural models require large datasets to effectively train, leading linear regression to be a simpler tool in yield estimations. Below lies a table discussing the key aspects of key papers discussed above:

Table I: Table Summarising the Key Findings, Research Methodology, Future Scope, And Limitations of Key Papers Discussed

Paper	**KEY FINDINGS**	**RESEARCH METHODOLOGY**	**LIMITATIONS**
Eckstein (1984): A Rational Expectations Model of Agricultural Supply	A dynamic rational expectations model explains Egypt's shifting land use between cotton and wheat as rational responses to price and productivity shocks, with prices driving 15–50% of land allocation variance. Estimated parameters fit a cost-of-adjustment model, with short-run elasticity (-0.11) below long-run (-0.13).	A dynamic linear rational expectations model, based on maximizing expected profit and assuming quadratic production, was estimated via full-information maximum likelihood using Egyptian agricultural data (1913–1969) on cotton and wheat areas and prices, after an initial VAR analysis.	The model was rejected because the zero restrictions on the price equation didn't hold, suggesting that prices in Egypt's small open economy might not actually be exogenous. The estimation also ran into issues with a non–positive definite Hessian, so standard errors couldn't be reported. A simple linear–quadratic approximation was used.
Muth (1961): Rational Expectations and the Theory	The Rational Expectations Hypothesis suggests that people's expectations align with what economic theory predicts, meaning the economy generally makes full	A theoretical outline of the rational expectations hypothesis assumes linear equations, normally distributed shocks, and certainty	Relies on assumptions like linearity, normality, and certainty equivalents. The basic unpredictable-shock model has limited empirical value, and

of Price Movements	use of available information. In practice, average expectations tend to be more accurate than simple models, though they often underestimate the size of actual changes.	equivalents. The analysis focused on price fluctuations in a single market with fixed production lags and examined how inventory speculation influences market adjustments.	inventory speculation analysis uses a first-order utility approximation, assuming expected price changes are small relative to variance.
Sun et al. (2023): Agricultural Product Price Forecasting Methods: A Review	Future developments will focus on combining models, with the key being how they are integrated for accurate forecasting. Incorporating both structured and unstructured data, like text mining and sentiment analysis, will be crucial, ensuring accuracy in both predicted values and trends.	A comprehensive review of agricultural price forecasting methods, covering traditional approaches (regression, gray models, time series), intelligent methods (SVM, Bayesian networks, neural networks), and combination models.	Traditional methods struggle with complex, high-dimensional data and need a lot of prior knowledge. Deep learning requires large datasets and computing power, often sacrificing interpretability. Multi-time-scale approaches face challenges with complexity, alignment, and clarity.

2.4 Gaps in Literature

The above literature expands on the Rational Expectations Equilibrium model in agricultural decision-making, as well as its criticisms and alternatives. Existing literature highlights several well developed arguments and models, including econometric models focusing on crop choice, price forecasting, and acreage response functions, mainly applied to grains and cereals (Lin et al., 2023). Furthermore, while existing research touches upon improving farming efficiency through methods such as optimisation techniques (Gupta et al., 2023), few existing papers validate the deviation between optimal acreage predicted by rational expectations and actual farmer planting behavior within a regression setting emperically. Moreover, existing literature lacks studies done on the alignment of optimal acreage with actual acreage using recent data. Research on potato farming, which faces volatile markets and repeated uncertain decisions, is limited, especially in modeling how farmers decide on acreage. Therefore, the originality of this paper lies in combining rational expectations modelling with emperical agri-price data. By using regression analysis to compare optimal vs. actual acreage, this exploration investigates whether farmers' decisions align with REE predictions or whether they deviate due to other factors, offering evidence-based evaluation of rational expectations in a potato crop context.

Research Objectives

This study aims to empirically investigate the alignment between optimal acreage predicted by the Rational Expectations Equilibrium (REE) model and the actual acreage planted by U.S. potato farmers, using recent data and regression analysis. Specifically, it seeks to determine whether deviations are systematic and attributable to non-REE factors, thereby contributing novel evidence to agricultural economic modelling.

Research Questions

1. To what extent do actual acreage decisions of U.S. potato farmers align with REE model predictions?
2. What are the primary drivers of deviation between optimal and actual acreage in potato farming?
3. How can insights from this deviation inform agricultural policy and supply forecasting models?

Hypotheses

H_1: Actual acreage decisions in U.S. potato farming significantly deviate from REE model predictions.
H_2: Deviations between optimal and actual acreage are influenced by price volatility and non-price behavioural factors.
H_3: Incorporating empirical deviations into policy frameworks will improve forecasting accuracy and reduce supply inefficiencies.

III. Research Methodology

3.1 Model for the Optimal Acres Harvested

This section introduces the approach employed to examine whether the REE model is a good predictor of acreage decisions in the U.S. potato farming industry. The paper utilises data from the 2019 to 2023 on prices, acres harvested, utilised quantity, total quantity, and costs from the USDA to estimate this optimal acre a^*. Full details of the dataset used for this analysis can be found in the below table:

Table II. Data on Acres, Yield, Production and Prices of Potatoes From 2008-2023

Year	Area Planted (1000 acres)	Area Harvested (1000 acres)	Yield (cwt) per acre	Total Production (1000 cwt)	Utilised production (1000 cwt)	Price ($) per 1000 cwt	Value of Sales ($1000)	Total-utilized production
2008	931.1	922	411	378,588	353,635	8.49	1,880,920	24953
2009	936.7	917.2	429	393,544	365,559	7.62	2,751,550	27985
2010	894.3	881.8	416	366,505	343,116	8.79	2,981,528	23389
2011	957.7	939.5	416	391,180	364,489	8.87	3,197,096	26691
2012	1,001.70	988.8	423	417,963	390,353	8.05	3,111,362	27610
2013	947.2	936.1	429	401,500	372,258	9.09	3,342,230	29242
2014	942.6	935.3	434	406,080	379,997	8.34	3,130,731	26083
2015	950.5	943.8	434	409,281	383,582	8.28	3,132,640	25699
2016	935.8	921.6	448	412,688	386,688	8.46	3,231,305	26000
2017	919.7	914.7	445	406,800	382,136	8.28	3,135,521	24664
2018	914.7	906.6	457	414,499	389,807	8.48	3,269,884	24692
2019	960.3	934.3	453	423,189	398,232	9.93	3,921,625	24957
2020	919.5	911.6	460	419,781	396,369	9.3	3,649,788	23412
2021	939	929.6	444	412,639	389,097	10.2	3,939,588	23542
2022	923	918.2	438	402,054	379,922	12.9	4,837,261	22132
2023	966	961.1	458	440,132	412,112	12.3	5,003,241	28020
2024	930	925.4	454	420,242				

First, a farmer's decision problem is modelled as a profit maximisation problem, following an estimation of critical coefficients using past data through linear regression. The following section presents this methodology in detail. A farmer faces a decision problem of determining the optimal number of acres to plant and harvest for potato production. To solve this problem, they consider the following variables:

(i) Price per cwt

(ii) Cost per acre harvested, *C(a)=C·* a (Assume that costs are linear in acres)

(iii) Utilised production (i.e. the quantity of potatoes produced that reaches the market)

However, there is inherent randomness in the process of planting and harvesting potatoes: the yield per acre harvested depends on multiple factors (i.e. weather). Furthermore, not every potato that is yielded reaches the market. Hence, the utilised production can be modelled as:

$$q_{utilised} = a \cdot y_{effective}$$

where a is acres harvested and $y_{\text{effective}}$ is a random variable (normally distributed with a mean and variance) capturing this uncertainty surrounding the quantity of potatoes that will ultimately reach the market following the planting and harvesting process. A visual representation of a can be seen in below:

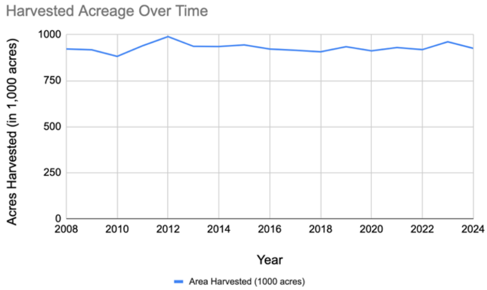

Figure 1: Acres Harvested in 1000 Acres (2008-2024)

Assume that the market clearing price for potatoes, p, is linearly related to the utilised production, q_{utilised}:

$$p = \alpha - \beta \cdot q_{\text{utilised}}$$

Given these assumptions, the farmer's decision problem can be modelled as the following expected profit maximisation problem, where

$$\pi(a) = p \cdot q_{\text{utilised}} - C(a)$$

Describes the profit for a given choice of acres harvested:

$$\max_{a} E[\pi(a)]$$

Using the assumptions of the model, this can be rewritten as

$$\max_{a} \ E[(\alpha - \beta a \cdot y_{\text{effective}})(a \cdot y_{\text{effective}})] - C(a)$$

Using the first-order condition for profit maximization, we differentiate the expected profit function with respect to acreage a and set it equal to zero:

$$\frac{d}{da} E[\pi(a)] = \alpha E[y_{\text{effective}}] - 2\beta a E[y^2{}_{\text{effective}}] - C = 0$$

Solving for a, we isolate it to obtain the expression for the optimal number of acres harvested, a^*:

$$a^* = \frac{\alpha \cdot E[y_{\text{effective}}] - C}{2\beta E[y^2{}_{\text{effective}}]}$$

From here, we use data on p and q_{utilised} to estimate α and β through linear regression. Next, we use data on q_{utilised} and acres harvested, a, to estimate $E[y_{\text{effective}}]$ and $E[y^2{}_{\text{effective}}]$.

Lastly, we employ data on total production (denoted by q_{total}), q_{utilised}, and p to compute a measure of costs, described as $p(q_{\text{total}} - q_{\text{utilised}})$. This in turn is used to compute average costs over the time period. This serves as a proxy for costs, since there exists limited data on costs per acre planted or harvested for potato crop in the US. Using these computations from the data, I now have an implied value for the optimal acres harvested for a farmer in this scenario.

3.2 Further Computations to Estimate Optimal Acreage

This section presents the key findings from the regression analysis and further computations. We examine the relationship between price and utilized production, estimate the expected effective yield, analyse total costs, and determine the optimal acreage for planting.

3.3 Regression Analysis: Estimating α and β

To comprehend the relationship between price and q_{utilised}, we conducted a straightforward linear regression with data from 5 years (2019 to 2023) with the model:

$$p = \alpha - \beta \cdot q_{\text{utilised}} + \epsilon$$

Where ϵ accounts for any randomness. However, for analytical convenience we assume a simplified form:

$$p = \alpha - \beta \cdot q_{\text{utilised}}$$

Through running the linear regression model, the following results are:

$$\alpha = \ 16.08913$$

$$\beta = -0.0000131$$
$$R^2 = 0.0097$$

The output of this regression can be seen in Figure 2 below:

```
      Source |       SS           df       MS      Number of obs   =        17
-------------+----------------------------------   F(1, 15)        =     45.41
       Model |  .000084796         1  .000084796   Prob > F        =    0.0000
    Residual |  .000028011        15  1.8674e-06   R-squared       =    0.7517
-------------+----------------------------------   Adj R-squared   =    0.7351
       Total |  .000112807        16  7.0505e-06   Root MSE        =    .00137

------------------------------------------------------------------------------
       price | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  q_utilized |   2.45e-11   3.64e-12     6.74   0.000     1.68e-11    3.23e-11
       _cons |  -.0001189   .0013456    -0.09   0.931    -.002987     .0027493
------------------------------------------------------------------------------

. scalar alpha = _b[_cons]

. scalar beta = _b[q_utilized]
```

Figure 2: Output From Linear Regression Using Data From 2008-2023

The negative slope suggests an inverse relationship between prices and utilised production, meaning that an increase in utilised production (supply) results in a slight decrease in prices. While the correlation is weak and statistically insignificant due to the low value of β, the results correspond to the law of supply. The low R^2 value means the variations in utilised production are only explained by 0.97% of changes in price, suggesting that other factors play a larger hand in the changes of utilised production.

3.4 Estimating $E[y_{effective}]$ and $E[y^2 effective]$

The effective yield represents the effective output per acre utilized, calculated as:

$$y_{\text{effective}} = \frac{q_{\text{utilised}}}{a}$$

From our dataset found in Appendix A, we computed the following mean values:

$$E[y_{\text{effective}}] = 424.4331$$
$$E[y^2{}_{\text{effective}}] = 180{,}199.1$$

3.5 Estimating a Costs Proxy

To measure total costs associated with productive inefficiencies, we used the formula:

$\text{Total Costs} = p \cdot (q_{\text{total}} - q_{\text{utilised}})$

This represents the portion of total production that goes unutilised. From the dataset, we compute the following mean value:

$$\text{Total Costs} = 267{,}166.4$$

3.6 Determining Optimal Acres a^* for Harvesting

We utilise the previously derived formula to determine the optimal acres to be harvested in order to maximise profit. Solving for a^*, we obtain:

Optimal acres$(a^*) = 55{,}283.97$

However, the data exists in the units "per 1000 acres". Hence, the actual value of a^* is 55,283,970 acres. This value of a^* is significantly higher than the area harvested values of all the years in the dataset, suggesting that the Rational Expectations Equilibrium is not a highly robust model in predicting the optimal acreage decision under real-world conditions. We rerun this regression for more years and scale the variables, but the coefficients become positive, raising concerns that including additional years may actually be worsening the model. The output of this second regression can be seen in Figure 3 below:

```
      Source |       SS           df       MS      Number of obs   =        17
-------------+----------------------------------   F(1, 15)        =     45.41
       Model |  .000084796         1  .000084796   Prob > F        =    0.0000
    Residual |  .000028011        15  1.8674e-06   R-squared       =    0.7517
-------------+----------------------------------   Adj R-squared   =    0.7351
       Total |  .000112807        16  7.0505e-06   Root MSE        =    .00137

------------------------------------------------------------------------------
       price | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  q_utilized |   2.45e-11   3.64e-12     6.74   0.000     1.68e-11    3.23e-11
       _cons |  -.0001189   .0013456    -0.09   0.931     -.002987    .0027493
------------------------------------------------------------------------------

. scalar alpha = _b[_cons]

. scalar beta = _b[q_utilized]
```

Figure 3: Output From Linear Regression Using Data From 2008-2023

We suspect the model requires more variables and more complexities to model what farmers' optimal behaviour should be in the market. This discrepancy between the value of a^* and the area harvested values of all the years in the dataset may arise due to several factors, which are examined in the following sections.

IV. Results and Discussion

This paper's regression-based analysis addresses the previously discussed gap in existing literature by modelling farmer acreage decisions as a profit maximisation problem and comparing REE-predicted optimal acreage to actual planted acreage using recent U.S. data. Results from the regression highlight a clear and significant differences from what REE predicts. Farmers frequently plant more or less land than the model recommends, even when market conditions are stable. This suggests systematic biases, caused by factors such as risk hedging, incomplete market information, price expectation errors, or local agronomic constraints, alongside the influence of prices. Comparing previous studies with our framework shows that, although REE is a strong theoretical concept, its ability to predict outcomes is limited in volatile agricultural settings such as potato farming. Our findings indicate that policy designs such as price supports, acreage subsidies, or forecasting tools should account for observed behavioural deviations. Recognizing that farmers' decisions may not always follow fully rational patterns can aid policymakers in creating more realistic supply models, potentially minimizing the risks of surpluses or shortages. This study contains limitations, such as relying on a simplified cost measure which may not fully capture actual expenses. It also assumes linear cost structures, ignoring factors like diminishing returns and seasonal variations. Furthermore, price volatility, extreme weather, and missing local data could affect acreage decisions in ways the model cannot account for.

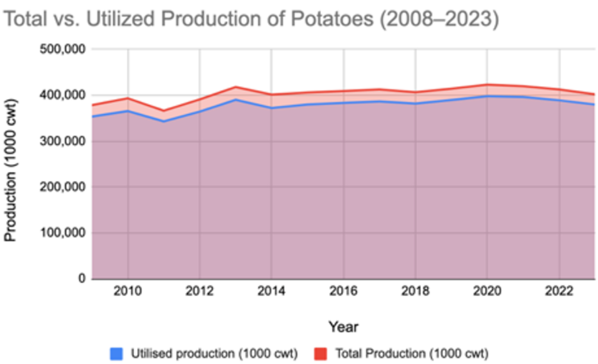

Figure 4: Total Versus Utilised Production Of Potatoes From 2008-2022

The cost proxy is illustrated in the figure above, where the red area highlights the difference between total and utilized potato production over multiple years. Future research could utilise more detailed datasets including inputs like fertilizer and labour, apply machine learning for more accurate multi-step forecasts, and compare different crops to test REE's validity across agricultural contexts. Maintaining a balance between model complexity and interpretability will be key to making predictions useful in practice.

V. Conclusion

This paper set out to examine whether the Rational Expectations Equilibrium (REE) model could accurately predict optimal acres harvested using historical data on price, production, and yield. The model yielded an optimal acreage of 55,283,970 acres, significantly higher than the area harvested values observed across all the years in the dataset. This suggests that the REE framework, while theoretically a structured approach, does not fully reflect the complexity of real-world farmer decision making. This study contributes to understanding the Rational Expectations Equilibrium (REE) framework in U.S. potato farming by examining how actual acreage decisions compare with model-predicted optima. Using regression analysis of recent data, we find that while price signals and costs strongly influence farmers' choices, consistent deviations from REE predictions point to behavioural and informational constraints. This suggests that farmer decision-making often reflects bounded rationality, risk aversion, and adaptive expectations rather than purely rational optimization. The findings indicate that agricultural policy and forecasting models should move beyond the strict assumptions of perfect rationality and include observed behavioural patterns and market feedback. By including improved parameters and behavioural considerations, the REE framework can help policymakers and researchers produce more accurate forecasts, improve resource allocation, and strengthen supply chain resilience.

References

1. Merriam-Webster. (2025). *Acreage*. In *Merriam-Webster Dictionary*. https://www.merriam-webster.com/dictionary/acreage
2. Taylor & Francis. (n.d.-b). *Acre – Knowledge and references*. Taylor & Francis. https://taylorandfrancis.com/knowledge/Engineering_and_technology/Engineering_support_and_special_topics/Acre/
3. *Agricultural Marketing Resource Center. (n.d.). Potatoes. https://www.agmrc.org/commodities-products/vegetables/potatoes*
4. *United States Department of Agriculture, National Agricultural Statistics Service. (n.d.). 2024 state agriculture overview for Idaho. https://www.nass.usda.gov/Quick_Stats/Ag_Overview/stateOverview.php?state=IDAHO&utm*
5. Wang, X., Ma, L., Yan, S., Chen, X., & Growe, A. (2023). Trade for Food Security: The stability of global agricultural trade networks. *Foods*, *12*(2), 271. https://doi.org/10.3390/foods12020271
6. Devi, R. A., Adarsh, A., Kumar, A., & Singh, A. P. (2025). Basics of economics and marketing practices in potato production. In *Advances in olericulture* (pp. 407–424). https://doi.org/10.1007/978-3-031-82710-5_18
7. *Supply and demand | Definition, Example, & Graph | Britannica Money*. (n.d.). Encyclopedia Britannica. https://www.britannica.com/money/supply-and-demand
8. Eckstein, Z. (1984). *A rational expectations model of agricultural supply*. Journal of Political Economy, 92(1), 1–19. https://www.jstor.org/stable/1830543
9. Sun, F., Meng, X., Zhang, Y., Wang, Y., Jiang, H., & Liu, P. (2023). Agricultural Product Price Forecasting Methods: A review. *Agriculture*, *13*(9), 1671. https://doi.org/10.3390/agriculture13091671
10. Miranda, M. J., & Glauber, J. W. (1993). Intraseasonal Demand for Fall Potatoes under Rational Expectations. *American Journal of Agricultural Economics*, *75*(1), 104–112. https://doi.org/10.2307/1242958
11. *Economics 101A section notes* (By D. Albouy). (n.d.). https://eml.berkeley.edu/~webfac/card/e101a_s05/neoclassicalfirm.pdf
12. Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica*, *29*(3), 315. https://doi.org/10.2307/1909635
13. Radner, R. (1979). Rational expectations equilibrium: generic existence and the information revealed by prices. *Econometrica*, *47*(3), 655. https://doi.org/10.2307/1910413
14. Weisberg, S. (2014). *Applied linear regression* (4th ed.). Hoboken, NJ: John Wiley & Sons. https://www.stat.purdue.edu/~qfsong/teaching/525/book/Weisberg-Applied-Linear-Regression-Wiley.pdf
15. Githinji, M. (2023). Farmer land-use decision-making from an instrumental and bounded rationality perspective. *Land Use Policy*, *134*, 106050. https://doi.org/10.1016/j.landusepol.2023.106050
16. S, A., Debnath, M. K., Gupta, D. S., Sarkar, D., Bandyopadhyay, S., Patra, P. S., & S, R. (2025). Investigating fine-tuning strategies in statistical and machine learning models for developing Region-Specific potato yield prediction models. *Potato Research*. https://doi.org/10.1007/s11540-025-09924-3
17. Grunberg, E., & Modigliani, F. (1954). The predictability of social events. *Journal of Political Economy, 62*(6), 465–478. http://www.jstor.org/stable/1827103

18. Piekutowska, M., Niedbała, G., Piskier, T., Lenartowicz, T., Pilarski, K., Wojciechowski, T., Pilarska, A. A., & Czechowska-Kosacka, A. (2021). The Application of Multiple Linear Regression and Artificial Neural Network Models for Yield Prediction of Very Early Potato Cultivars before Harvest. *Agronomy*, *11*(5), 885. https://doi.org/10.3390/agronomy11050885
19. Lin, Y., Li, S., Duan, S., Ye, Y., Li, B., Li, G., Lyv, D., Jin, L., Bian, C., & Liu, J. (2023). Methodological evolution of potato yield prediction: a comprehensive review. *Frontiers in Plant Science*, *14*. https://doi.org/10.3389/fpls.2023.1214006
20. Team, C. (2024, July 3). *Risk Averse Definition*. Corporate Finance Institute. https://corporatefinanceinstitute.com/resources/wealth-management/risk-averse-definition/