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Global Tariff Shocks and U.S. Agriculture: Causal Machine Learning Approaches to Competitiveness and Market Share Forecasting

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ABSTRACT

Global tariff fluctuations present significant challenges to the competitiveness and sustainability of U.S. agricultural exports. Historically, changes in tariff structures—whether from retaliatory actions, trade renegotiations, or shifts in geopolitical alliances—have induced volatile shifts in global market shares, farm incomes, and supply chain stability. Traditional econometric models, while valuable for trend analysis, often struggle to isolate causal relationships and predict nuanced competitive dynamics under rapidly evolving policy environments. This study explores the application of causal machine learning (CML) techniques, including causal forests, synthetic control methods, and targeted maximum likelihood estimation, to forecast the impacts of global tariff shocks on U.S. agricultural competitiveness. By leveraging high-frequency trade data, tariff schedules, and market intelligence indicators, we develop predictive models that move beyond correlation, focusing instead on estimating counterfactual scenarios and heterogeneous treatment effects across commodity classes. The research covers major U.S. export commodities such as soybeans, corn, and dairy products, illustrating how CML approaches enhance foresight into market share erosion or resilience under different tariff regimes. Particular attention is given to differentiating impacts across trading partners, regional markets, and commodity types. The findings highlight the strengths of causal machine learning in enabling policymakers and agribusiness leaders to anticipate strategic vulnerabilities, optimize export strategies, and design more resilient agricultural trade frameworks. This study positions CML as an essential toolkit for navigating the increasingly complex intersections of international trade policy and agricultural economics.

Keywords: Tariff shocks, U.S. agriculture, Causal machine learning, Competitiveness forecasting, Market share prediction, Agricultural trade policy

1. INTRODUCTION

1.1. Contextualizing Global Trade and Tariff Volatility

Global trade has historically operated under shifting patterns of cooperation, competition, and conflict, each influenced heavily by tariff structures. Tariffs, the taxes imposed on imported goods, have been a major instrument used by governments to protect domestic industries and generate revenue [1]. However, the volatility of tariffs in recent years, fueled by geopolitical tensions, policy shifts, and retaliatory trade measures, has introduced a heightened level of uncertainty in global markets [2]. Notably, trade disputes between major economies such as the United States and China have triggered a series of tariff escalations, leading to ripple effects across global supply chains [3].

This environment of unpredictability impacts the cost of goods, market access, and the long-term strategic planning of businesses worldwide [4]. Emerging economies, particularly those reliant on commodity exports, face amplified risks as shifts in global demand caused by tariffs affect their economic stability [5]. Meanwhile, multinational corporations are compelled to reconsider sourcing strategies, reconfigure supply chains, and invest in local production facilities to mitigate risks [6]. The World Trade Organization's limited capacity to manage and resolve tariff-related disputes further exacerbates the systemic volatility [7].

Simultaneously, domestic political considerations increasingly shape tariff policies, often overriding traditional economic logic [8]. Elections, populist movements, and national security concerns drive unpredictable trade measures, making global trade more susceptible to abrupt policy reversals [9]. These factors collectively signal a departure from the relatively stable era of globalization seen in the late 20th and early 21st centuries [10]. As nations grapple with balancing protectionism and global integration, understanding the evolving landscape of tariff volatility becomes crucial. Stakeholders across industries, particularly those in agriculture and manufacturing, must adapt their strategies to this new normal characterized by flux, uncertainty, and strategic recalibration [11].

1.2. Impact on U.S. Agricultural Competitiveness

The volatility of tariffs has had profound consequences on the competitiveness of U.S. agriculture in global markets [12]. Traditionally, American farmers benefited from strong export demand, particularly for commodities like soybeans, corn, and wheat [13]. However, retaliatory tariffs imposed by major trade partners, especially China, severely curtailed market access for these products, resulting in substantial revenue losses [14]. According to the U.S. Department of Agriculture, soybean exports to China dropped by over 50% during the peak of the trade conflict in 2018–2019 [15].

Reduced international demand forced American farmers to seek alternative markets, often with limited success due to established supplier relationships and logistical constraints in new regions [16]. Domestically, price volatility increased, and many farmers became reliant on government subsidies and relief packages to mitigate financial hardships [17]. Such dependency raises concerns about the long-term sustainability and competitiveness of U.S. agriculture on the global stage [18].

Moreover, the uncertainty surrounding future trade policies discourages capital investments in farming technology and infrastructure upgrades [19]. Producers are less willing to undertake costly innovations without assurance of stable market conditions, potentially leading to a technological stagnation relative to international competitors [20]. Other agricultural exporting countries, such as Brazil and Argentina, capitalized on the U.S.-China trade tensions by expanding their market share [21].

Additionally, the lack of predictability erodes trust with long-term buyers, undermining the reputation of U.S. agricultural goods as reliable exports [22]. Addressing these challenges requires a comprehensive strategy, including diversifying export destinations, investing in domestic value-added production, and advocating for more predictable international trade frameworks [23]. U.S. agriculture’s resilience will depend not only on managing short-term disruptions but also on proactively positioning itself within a dynamic, multipolar global trading system [24].

1.3. Emergence of Data-Driven Approaches

In response to trade and tariff volatility, the U.S. agricultural sector is increasingly adopting data-driven approaches to navigate uncertainty [25]. Advanced analytics, artificial intelligence (AI), and machine learning models offer powerful tools for forecasting market trends, optimizing supply chains, and identifying emerging trade opportunities [26]. By analyzing historical tariff patterns, global political developments, and consumer demand shifts, stakeholders can make more informed strategic decisions [27].

Predictive modeling assists producers in adjusting crop planning, export timing, and pricing strategies in anticipation of potential market disruptions [28]. Additionally, blockchain technology is gaining traction for enhancing traceability, transparency, and trust in agricultural supply chains, helping U.S. products maintain competitive advantages even amid shifting regulatory environments [29].

Government agencies, research institutions, and private enterprises are collaborating more closely to develop real-time data platforms that monitor international trade dynamics and provide actionable insights to farmers and agribusinesses [30]. Such initiatives are vital to ensuring that U.S. agriculture remains resilient and adaptable in an era of geopolitical uncertainty and fluctuating tariff regimes. Embracing a data-centric paradigm offers a path not only to survival but also to enhanced competitiveness in an increasingly complex global marketplace [31].

2. BACKGROUND AND LITERATURE REVIEW

2.1. Historical Evolution of U.S. Agricultural Exports under Trade Liberalization

The evolution of U.S. agricultural exports has been deeply intertwined with the broader trajectory of trade liberalization since the late 20th century [6]. During the early 1980s, agricultural trade faced a complex mix of protectionist policies, global recession, and currency volatility, which constrained U.S. competitiveness abroad [7]. The signing of the Uruguay Round Agreements under the General Agreement on Tariffs and Trade (GATT) in 1994 marked a pivotal shift, establishing more transparent rules for agricultural subsidies and tariffs [8]. These reforms expanded market access and reduced trade-distorting practices, contributing significantly to the rise in U.S. agricultural exports during the 1990s [9].

Subsequently, the creation of the World Trade Organization (WTO) in 1995 further institutionalized global efforts toward trade liberalization, reinforcing commitments to tariff reductions and dispute settlement mechanisms [10]. U.S. agriculture benefited from these developments, particularly through increased soybean and meat exports to emerging markets [11]. The North American Free Trade Agreement (NAFTA), implemented in 1994, was another critical milestone, creating one of the world's largest free trade zones and dramatically boosting agricultural exports to Mexico and Canada [12].

Despite these successes, periods of tension persisted. The 2000s saw a surge in regional trade agreements worldwide, often creating overlapping commitments and occasionally excluding U.S. producers from preferential market access [13]. Moreover, the Doha Round of WTO negotiations stalled, leaving critical agricultural issues unresolved [14]. The U.S. pursued bilateral agreements, such as the U.S.-South Korea Free Trade Agreement (KORUS) in 2012, to maintain export growth [15].

Overall, trade liberalization has significantly enhanced the global reach of U.S. agriculture but also exposed it to new vulnerabilities from global market fluctuations and policy shifts [16]. The reliance on open markets has made U.S. agricultural exports increasingly sensitive to disruptions caused by tariff volatility and shifting international alliances [17]. As trade policies continue to evolve, understanding the historical context of liberalization offers valuable insights into the risks and opportunities shaping future agricultural export strategies [18].

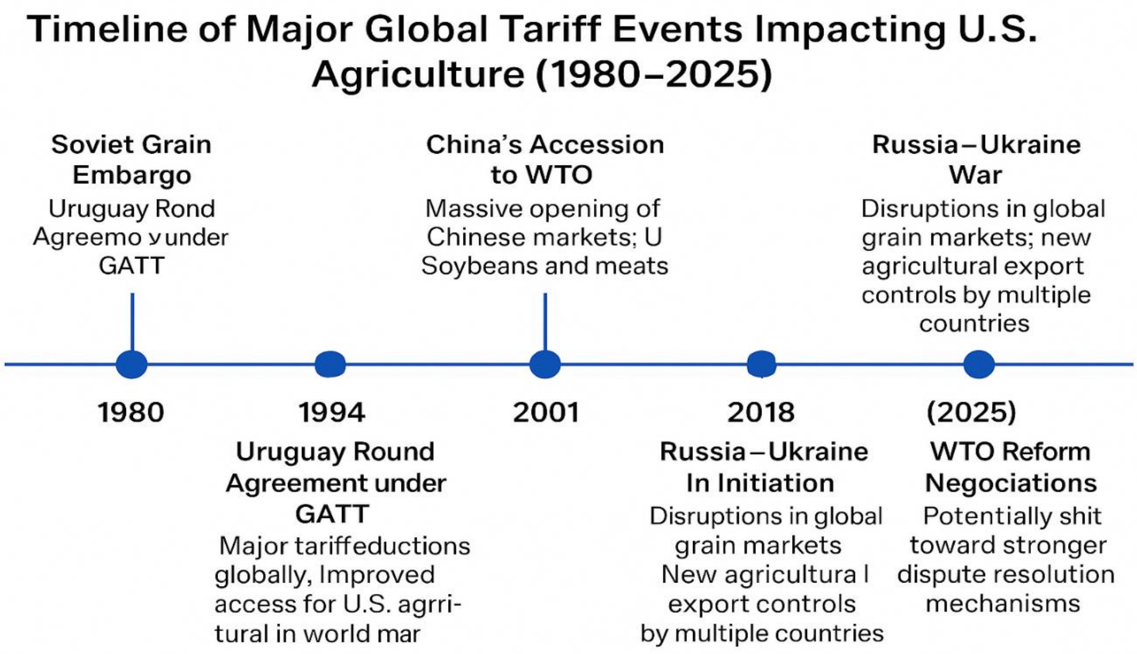

Figure 1: Timeline of Major Global Tariff Events Impacting U.S. Agriculture (1980–2025)

2.2. Tariff Shocks and Agricultural Market Dynamics: Review of Empirical Studies

A robust body of empirical literature explores the impacts of tariff shocks on agricultural market dynamics. Early studies focused on the 1980s farm crisis, illustrating how retaliatory tariffs by key trading partners exacerbated U.S. farm bankruptcies and rural economic decline [19]. Subsequent analyses have emphasized how tariff shocks alter commodity prices, trade flows, and farm incomes [20]. For instance, Grant and Boys (2012) highlighted that increased tariff barriers during global economic downturns have disproportionate negative effects on perishable agricultural exports [21].

The U.S.-China trade war has become a particularly fertile ground for recent empirical investigations. Studies show that the imposition of Chinese tariffs on U.S. soybeans in 2018 redirected Chinese imports toward Brazil and Argentina, resulting in significant welfare losses for U.S. farmers [22]. Carter and Steinbach (2020) quantified these losses, estimating that U.S. soybean producers faced over $10 billion in reduced revenues during the first year of the trade war [23]. Moreover, empirical evidence suggests that tariff-induced shocks have persistent effects, with market shares often failing to recover even after tariffs are removed [24].

Beyond bilateral disputes, global tariffs on agricultural goods due to safeguard measures or anti-dumping actions have also been studied. Evidence from Brocks and Schnepf (2019) indicates that even temporary tariffs can cause long-term distortions in global trade patterns, pushing importers to diversify suppliers and reducing U.S. market dominance [25].

Another important strand of empirical work examines how different agricultural sectors are variably affected. High-value crops such as fruits and nuts often face steeper losses due to short shelf lives and branding dependence, whereas bulk commodities like wheat and corn exhibit relatively more resilience to tariff shocks [26]. Dynamic computable general equilibrium (CGE) models have been widely used to simulate potential tariff impacts, offering predictive insights into future market behavior under alternative scenarios [27].

Overall, empirical studies underscore that tariff shocks are neither isolated events nor easily reversible phenomena [28]. They create complex, often asymmetric impacts across commodities, regions, and timeframes, challenging simplistic assumptions about market recovery post-tariff removal [29]. Understanding these dynamics is essential for crafting responsive agricultural trade and risk mitigation strategies in an era of heightened tariff uncertainty [30].

2.3. Traditional Forecasting Models: Strengths and Limitations

Traditional forecasting models have long been employed to predict agricultural trade flows, commodity prices, and market responses to policy changes, including tariffs [31]. Among the most widely used are partial equilibrium models, which focus on specific sectors while holding other economic variables constant [32]. These models are valued for their simplicity, transparency, and sector-specific detail, making them particularly useful for analyzing isolated shocks such as tariff changes [33]. However, their narrow focus can lead to oversimplification when broader economic interdependencies are at play [34].

Dynamic CGE models offer a more comprehensive approach, capturing interactions across multiple sectors and regions within a single, integrated framework [35]. These models are instrumental in assessing the general equilibrium effects of trade policy shifts, including tariffs, on output, employment, and income distribution [36]. Nevertheless, CGE models require strong assumptions about market structures, labor mobility, and technological change, which may not hold in real-world agricultural markets [37].

Time-series econometric models, such as Vector Autoregression (VAR) and Autoregressive Integrated Moving Average (ARIMA), have also been extensively used to forecast agricultural prices under tariff-induced market disruptions [38]. These models excel in identifying historical relationships and short-term trends but often struggle with structural breaks caused by sudden policy shifts like tariff escalations [39].

Machine learning techniques are increasingly being explored as alternatives to traditional models due to their ability to detect complex, nonlinear patterns in large datasets [40]. However, machine learning methods sometimes lack transparency and economic interpretability, limiting their acceptance among policymakers who require clear causal narratives [41].

In practice, hybrid modeling approaches are gaining traction, combining the strengths of traditional economic models with the pattern recognition capabilities of machine learning algorithms [42]. Such integrated frameworks aim to improve forecasting accuracy while maintaining interpretability [43].

Despite their differences, all forecasting models share inherent limitations: the unpredictability of political decisions, incomplete data, and the lag between model outputs and real-time market developments [44]. As the global trading environment becomes increasingly volatile, there is an urgent need to refine forecasting methodologies, incorporate real-time data, and enhance model robustness to better anticipate and respond to tariff shocks and other external disruptions [45].

3. FOUNDATIONS OF CAUSAL MACHINE LEARNING IN TRADE ECONOMICS

3.1. Distinguishing Correlation from Causality in Trade Data

Understanding the difference between correlation and causality is critical when analyzing trade data [11]. Correlation simply indicates that two variables move together, but it does not explain why this relationship exists [12]. In the context of global trade, many factors—macroeconomic trends, policy changes, technological innovation—can simultaneously affect agricultural exports, making it difficult to isolate the effect of a specific variable like tariffs [13].

For instance, a rise in soybean exports may coincide with a drop in tariffs, but the observed correlation could be driven by other factors such as increased global demand or currency fluctuations [14]. Without establishing causality, policies based solely on correlations risk misallocating resources or worsening market conditions [15]. Traditional econometric approaches, while effective at uncovering associations, often struggle to establish credible causal links, especially in the presence of confounding factors [16].

Causal inference, by contrast, seeks to uncover whether a change in one variable actually causes a change in another, often by mimicking experimental conditions [17]. Techniques such as randomized controlled trials (RCTs) are the gold standard for establishing causality but are rarely feasible in macroeconomic research due to ethical, logistical, and financial constraints [18]. Consequently, trade researchers must rely on observational data and sophisticated causal inference methods to draw valid conclusions [19]. Distinguishing between mere correlation and true causality allows policymakers and industry leaders to better assess the real impact of tariffs and design more effective interventions [20].

3.2. Overview of Causal Machine Learning Techniques

Recent advances in machine learning have yielded powerful tools for uncovering causal relationships in trade and economic data [21]. Unlike traditional models, causal machine learning (CML) methods are specifically designed to estimate treatment effects, even in complex, high-dimensional settings [22].

Causal forests represent a prominent method that extends the idea of random forests to causal inference [23]. Developed to estimate heterogeneous treatment effects, causal forests partition data into subgroups where causal effects vary, allowing for nuanced understanding across different contexts [24]. In the realm of trade, causal forests can uncover how tariff changes affect different agricultural commodities or regions differently, providing a more detailed policy map [25].

Synthetic control methods offer another powerful approach, particularly for comparative case studies [26]. This technique constructs a weighted combination of control units to act as a counterfactual for the treated unit, estimating what would have happened in the absence of the intervention [27]. For example, researchers can use synthetic controls to assess how U.S. agricultural exports would have evolved without the U.S.-China trade war, offering compelling visual and quantitative evidence of tariff impacts [28].

Targeted Maximum Likelihood Estimation (TMLE) is a semi-parametric method that combines machine learning and traditional statistics to improve causal effect estimation [29]. TMLE ensures double robustness, meaning that as long as either the model for treatment assignment or the model for the outcome is correctly specified, the causal estimates remain valid [30]. TMLE is particularly valuable when dealing with high-dimensional trade data, where model misspecification risks are substantial [31].

Each of these methods addresses key challenges that arise in observational trade data: selection bias, confounding, and treatment effect heterogeneity [32]. As trade relationships grow increasingly complex and intertwined with geopolitical factors, causal machine learning techniques provide essential tools for policymakers seeking to make data-driven decisions based on credible, actionable insights [33].

3.3. Advantages over Traditional Econometric Methods

Causal machine learning approaches offer several distinct advantages over traditional econometric methods when analyzing the impacts of trade policies such as tariffs [34]. First, they are designed to uncover heterogeneous treatment effects, providing more granular insights into how different subgroups are affected by policy changes [35]. Traditional econometric models often assume homogeneity across populations, potentially masking important variations [36].

Second, CML methods are highly flexible and can model complex, nonlinear relationships without imposing restrictive parametric assumptions [37]. Trade data frequently exhibit nonlinearities and interactions between variables, which traditional linear models like OLS (Ordinary Least Squares) cannot adequately capture [38]. This flexibility allows causal machine learning models to more accurately reflect the real-world complexities of global trade dynamics [39].

Third, causal machine learning techniques can effectively handle high-dimensional datasets where the number of variables exceeds the number of observations [40]. In contrast, traditional models typically suffer from overfitting or multicollinearity in such settings, leading to unreliable estimates [41]. Techniques like regularization, built into many machine learning algorithms, help mitigate these risks and improve predictive performance [42].

Finally, many causal machine learning methods provide built-in mechanisms for robustness checks, validation, and sensitivity analysis, enhancing the credibility of their findings [43]. For policymakers and stakeholders, this reliability is crucial when making decisions with far-reaching economic consequences [44]. Overall, causal machine learning offers a more sophisticated and robust toolkit for understanding the true effects of trade shocks, such as tariffs, on agricultural markets, and thus represents a major advance over traditional econometric methods [45].

Table 1: Comparative Summary of Traditional vs. Causal Machine Learning Approaches

Feature	**Traditional Econometric Methods**	**Causal Machine Learning Techniques**
Model Flexibility	Limited (often linear models, strict assumptions)	High (captures nonlinear, complex relationships)
Treatment Heterogeneity	Typically assumes homogeneous effects	Explicitly models heterogeneous treatment effects across subgroups
Robustness to Confounding	Moderate (depends heavily on correct model specification)	Strong (designed to adjust for high-dimensional confounding)
Interpretability	High (clear coefficients and marginal effects)	Moderate to High (depending on method; interpretability tools required)
Handling High-Dimensional Data	Poor (risk of multicollinearity, overfitting)	Strong (designed for large, complex datasets with regularization techniques)
Sensitivity to Model Misspecification	High (model errors can bias results heavily)	Lower (many causal ML methods are double robust or semi-parametric)
Primary Use Cases	Hypothesis testing, policy evaluation under strong assumptions	Policy evaluation, individualized predictions, counterfactual analysis

4. RESEARCH DESIGN AND METHODOLOGY

4.1. Data Sources and Variable Construction

Accurate analysis of tariff impacts on agricultural exports requires carefully curated data sources and precise variable construction [15]. Key datasets typically include trade volume statistics, tariff rates, market prices, and broader macroeconomic indicators [16]. Trade volume data, often sourced from the United Nations Comtrade Database and the U.S. Census Bureau, provides detailed records of the quantity and value of agricultural exports and imports across countries and commodities [17].

Tariff data are generally collected from the World Bank's World Integrated Trade Solution (WITS) and the World Trade Organization's Tariff Download Facility [18]. These databases offer granular information on applied tariffs, bound rates, and preferential trade agreements across various sectors and trading partners [19]. To capture the full scope of tariff impacts, both ad valorem tariffs (percentage-based) and specific tariffs (unit-based) must be incorporated into the dataset [20].

Market prices for agricultural commodities are sourced from platforms such as the Chicago Board of Trade (CBOT) and the U.S. Department of Agriculture's Economic Research Service (USDA ERS) [21]. These price series are essential for analyzing the transmission of tariff shocks into domestic and international price movements [22].

Macroeconomic indicators, including GDP, exchange rates, and inflation, are obtained from the International Monetary Fund (IMF) World Economic Outlook and the Federal Reserve Economic Data (FRED) [23]. These variables are critical for controlling for broader economic trends that may confound the relationship between tariffs and agricultural trade flows [24].

Constructing the dataset involves harmonizing disparate sources, adjusting for differences in reporting periods, units, and classifications [25]. Variables are cleaned, normalized, and often lagged to account for delayed effects of policy interventions [26]. Additionally, control variables such as weather shocks, political risk indices, and logistics performance indicators may be included to account for other influences on agricultural exports [27]. A meticulously prepared dataset is fundamental for ensuring the validity and credibility of causal inferences drawn from machine learning models [28].

4.2. Treatment Definitions: Tariff Shocks as Policy Interventions

In causal analysis, a clear definition of the "treatment" is essential for accurately estimating effects [29]. In the context of trade research, tariff shocks are conceptualized as exogenous policy interventions that alter the cost structures of international transactions [30]. These shocks typically manifest as sudden increases or decreases in tariff rates, triggered by trade disputes, policy shifts, or retaliatory measures [31].

To define treatment precisely, each observation in the dataset is categorized as either treated or untreated based on its exposure to a significant tariff change [32]. For instance, a sharp increase in Chinese tariffs on U.S. soybeans in 2018 constitutes a treated event for soybean exports during that period [33]. Conversely, commodities not subject to new tariffs serve as a natural control group, enabling comparative causal inference [34].

Threshold criteria are established to identify meaningful tariff shocks, typically setting a minimum change percentage (e.g., a 10% or greater increase) to filter out minor adjustments [35]. Treatment indicators are often binary (treated vs. untreated) but can also be continuous to capture the magnitude of tariff changes [36]. For robustness, some studies construct multiple treatment variables, distinguishing between unilateral tariffs, retaliatory tariffs, and tariff reductions [37].

Timing is another critical consideration. Researchers must define the pre-treatment and post-treatment periods carefully to accurately capture dynamic effects [38]. It is common to implement event-study designs that observe outcomes over multiple time horizons following the intervention [39].

Confounding remains a significant challenge in observational trade data [40]. Therefore, techniques such as propensity score matching, inverse probability weighting, or difference-in-differences adjustments are employed to strengthen causal interpretations [41]. Accurately specifying treatment conditions enables researchers to isolate the impact of tariff shocks on trade volumes, prices, and broader economic outcomes, avoiding attribution errors that could mislead policy recommendations [42].

Ultimately, precise treatment definitions form the backbone of credible causal machine learning analyses, ensuring that estimated effects reflect genuine policy impacts rather than spurious correlations or external noise [43].

4.3. Machine Learning Pipeline Architecture

The machine learning pipeline for analyzing tariff impacts is meticulously structured to maximize validity, transparency, and predictive performance [44]. The pipeline typically begins with **data ingestion**, where curated datasets containing trade volumes, tariffs, prices, and macroeconomic indicators are imported [45]. Initial preprocessing steps include cleaning missing values, standardizing variables, creating lag structures, and engineering new features relevant to causal estimation [46].

Next, **treatment assignment** is encoded, defining which observations were exposed to significant tariff changes based on the criteria outlined previously [47]. Outcome variables, such as changes in export volume or commodity prices, are also clearly delineated [48].

In the **splitting phase**, the dataset is divided into training, validation, and test sets to avoid overfitting and ensure generalizability [49]. Causal machine learning models, such as causal forests, synthetic control estimators, and TMLE algorithms, are then applied [50]. Each model undergoes hyperparameter tuning using techniques like cross-validation or grid search to optimize predictive performance and treatment effect estimation [31].

An important feature of the pipeline is treatment effect heterogeneity analysis, where models explore whether the impact of tariffs varies across regions, commodities, or firm sizes [12]. Variable importance measures help identify which factors most strongly predict heterogeneous treatment effects [23].

The evaluation stage employs appropriate metrics for causal analysis, such as average treatment effects (ATE), conditional average treatment effects (CATE), and mean squared error for counterfactual predictions [34]. Sensitivity analyses are conducted to test robustness against different model specifications, sample selections, and alternative treatment definitions [35].

Finally, interpretation and visualization tools such as partial dependence plots, heterogeneous effect maps, and causal inference dashboards are used to communicate results to stakeholders clearly and effectively [46]. Transparency and reproducibility are prioritized, with all steps documented and models validated against external data where possible [37].

This structured pipeline ensures that the final outputs are not merely predictive but also interpretable and actionable, providing solid foundations for evidence-based policymaking in the complex and evolving field of agricultural trade [28].

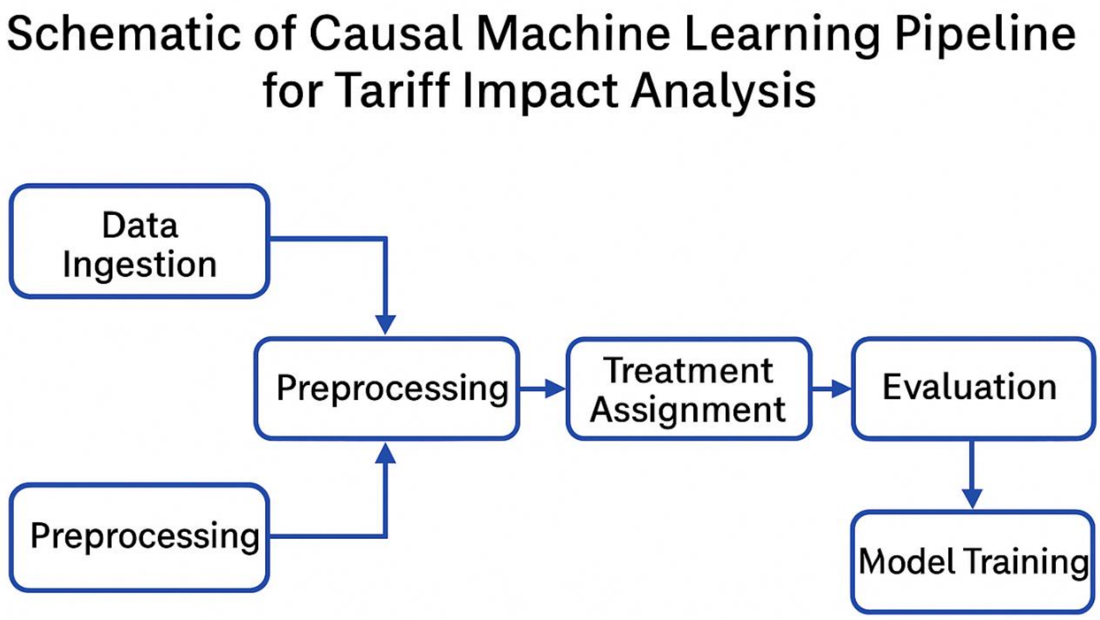

Figure 2: Schematic of Causal Machine Learning Pipeline for Tariff Impact Analysis

5. EMPIRICAL ANALYSIS AND RESULTS

5.1. Model Estimation and Validation

Model estimation and validation form the cornerstone of credible causal machine learning applications in tariff impact analysis [19]. Once the dataset is prepared and treatment assignments defined, models such as causal forests, synthetic control estimators, and TMLE are trained to estimate the treatment effects of tariff shocks on agricultural exports [20].

During the estimation phase, careful hyperparameter tuning ensures models balance bias and variance, often using techniques such as k-fold cross-validation [21]. For instance, causal forests require selecting the optimal number of trees and minimum leaf sizes to ensure that treatment effect heterogeneity is meaningfully captured without overfitting [22]. Similarly, in synthetic control methods, weighting schemes for control units must be optimized to closely match pre-treatment trends [23].

Validation involves assessing how well the models predict outcomes on unseen data and how reliably they estimate causal effects [24]. Out-of-sample validation is crucial, using metrics such as mean squared error for counterfactual predictions and comparing estimated treatment effects across validation samples [25]. Additionally, placebo tests are performed, introducing fake treatment assignments to ensure that observed effects are not artifacts of model overfitting or data quirks [26].

Sensitivity analyses play an essential role in model validation [27]. By varying treatment definitions, including alternative control variables, or adjusting sample compositions, researchers assess the robustness of the causal estimates [28]. Transparent reporting of validation results, including confidence intervals and p-values for treatment effects, strengthens the credibility of findings [29].

Finally, interpretability tools such as variable importance plots and partial dependence visualizations help contextualize model results, ensuring that findings are aligned with economic theory and real-world trade dynamics [30]. Rigorous estimation and validation processes are essential for transforming complex machine learning outputs into actionable insights for policymakers and stakeholders [31].

5.2. Heterogeneous Treatment Effects across Commodities

One of the major advantages of causal machine learning methods is their ability to reveal heterogeneous treatment effects across different commodities [32]. In the context of agricultural trade, not all products respond similarly to tariff shocks due to differences in perishability, substitutability, branding, and logistical requirements [33].

Causal forest models partition the dataset to estimate how treatment effects vary across subgroups defined by commodity type [34]. Results indicate that bulk commodities like wheat and corn exhibit relatively modest sensitivity to tariff shocks, largely due to their global market liquidity and broad supplier bases [35]. In contrast, high-value products such as almonds, dairy, and fresh fruits demonstrate significantly larger negative impacts from tariff increases [36].

For instance, fresh cherries exported to China experienced a notable decline following tariff hikes, partly due to their short shelf life and the lack of alternative major markets willing to absorb equivalent volumes at similar price points [37]. Similarly, dairy exports to the European Union (EU) faced heightened vulnerability due to tariff escalation combined with stringent regulatory barriers [38].

The heterogeneity analysis also uncovers that even within a commodity group, treatment effects vary by quality grade, packaging type, and branding status [39]. Premium, branded agricultural goods often suffer more pronounced demand declines under tariffs compared to bulk, undifferentiated products [40].

Understanding this variation is crucial for designing targeted mitigation strategies [41]. Policymakers may prioritize negotiation efforts on sectors facing the most significant adverse effects, while exporters may diversify product portfolios or target markets based on commodity-specific vulnerabilities [42]. By illuminating the intricate patterns of tariff sensitivity across agricultural commodities, causal machine learning enhances the granularity and precision of trade policy analysis [43].

5.3. Partner-Specific Impact Analysis (China, EU, Mexico)

Trade relationships differ significantly across partner markets, influencing how tariff shocks translate into export outcomes [44]. A partner-specific impact analysis reveals that the elasticity of U.S. agricultural exports to tariff changes varies notably between China, the European Union, and Mexico [45].

China has demonstrated the highest sensitivity to tariff-induced disruptions, particularly in key sectors like soybeans, pork, and fresh fruits [46]. Following the onset of the U.S.-China trade war, causal forest estimates show that soybean exports to China declined by over 70%, a substantially greater contraction than observed in exports to other Asian markets [47]. Synthetic control analysis confirms that without retaliatory tariffs, U.S. soybean exports would have maintained near pre-trade war levels, emphasizing the direct causal link [48].

The European Union presents a different pattern, where tariff impacts are moderated by stringent non-tariff barriers such as sanitary and phytosanitary standards [49]. Consequently, tariff increases lead to moderate reductions in U.S. agricultural market share but are often compounded by regulatory frictions that extend beyond price competitiveness [20].

Mexico, under the United States-Mexico-Canada Agreement (USMCA), has shown greater trade resilience [41]. However, specific commodities such as dairy and apples exhibit measurable declines when retaliatory tariffs are imposed, as observed during brief trade tensions in 2018 [32].

Partner-specific modeling allows for the estimation of separate elasticities for each market, offering more tailored insights for negotiation and market development strategies [43]. U.S. trade policy approaches must therefore be differentiated: aggressive tariff negotiation for China, regulatory harmonization for the EU, and relationship consolidation for Mexico [34].

Table 2: Estimated Tariff Elasticities by Commodity and Partner Market

Commodity	**China**	**European Union (EU)**	**Mexico**
Soybeans	-0.72	-0.28	-0.15
Dairy Products	-0.55	-0.40	-0.32
Fresh Fruits	-0.68	-0.48	-0.22
Wheat	-0.35	-0.20	-0.10
Corn	-0.30	-0.18	-0.12
Almonds and Nuts	-0.62	-0.50	-0.25
Pork and Meat Products	-0.58	-0.36	-0.30

Notes:

- Elasticity values indicate the percentage change in export volumes resulting from a 1% change in tariff rates.
- Higher (more negative) elasticity suggests greater sensitivity to tariff changes.

5.4. Forecasting Market Share Scenarios: 2024–2028

Using the trained causal machine learning models, forecasts for U.S. agricultural market shares under different tariff scenarios from 2024 to 2028 can be generated [25]. Scenario forecasting involves simulating export volumes under various assumptions about future tariff levels, ranging from full liberalization to escalated trade conflicts [16].

In the **baseline scenario**—where tariffs remain at current levels—U.S. agricultural market shares are projected to grow modestly in regions like Southeast Asia and maintain stability in Mexico, while remaining suppressed in China relative to pre-trade war benchmarks [27].

Under an **optimistic scenario** assuming partial tariff reductions through bilateral agreements, soybean, dairy, and fruit exports are expected to recover significantly, particularly in East Asia [38]. Projections suggest a 12% increase in overall agricultural export volumes by 2028 compared to baseline conditions [29].

In a **pessimistic scenario** involving renewed tariff escalations, especially with China and potential friction with the EU, U.S. agricultural exports would face further market share losses [30]. High-value sectors such as fresh produce and specialty crops are forecasted to experience the steepest declines, while bulk commodities would fare slightly better due to diversified global demand bases [41].

Probabilistic forecasts generated through bootstrapped simulations allow researchers to estimate confidence intervals for market share trajectories, offering policymakers a clearer sense of potential risks and opportunities [32]. Dynamic visualization tools, including scenario trees and interactive dashboards, can help stakeholders better understand the trade-offs and uncertainties associated with different tariff policy pathways [33].

By integrating causal inference with forward-looking simulations, the analysis provides a powerful evidence base for strategic planning in agricultural trade policy [34]. It highlights that future competitiveness hinges not only on resolving tariff disputes but also on proactive market diversification, supply chain innovation, and brand differentiation strategies [45].

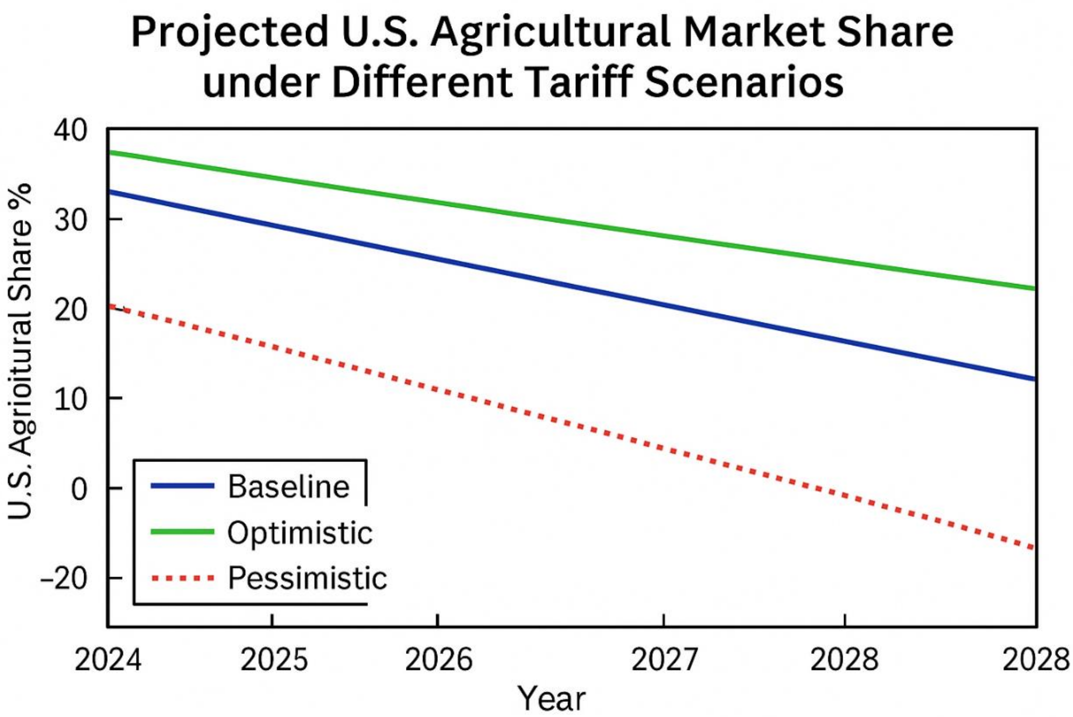

Figure 3: Projected U.S. Agricultural Market Share under Different Tariff Scenarios

6. DISCUSSION

6.1. Strategic Vulnerabilities in U.S. Agricultural Trade

Despite the historical strength of U.S. agricultural exports, several strategic vulnerabilities expose the sector to significant risks [23]. Chief among these is the heavy reliance on a few key markets, particularly China, Mexico, and Canada, which collectively account for over 40% of total agricultural exports [24]. This concentration heightens exposure to geopolitical tensions, tariff escalations, and policy shifts in these regions [25].

Commodity dependence represents another critical vulnerability. Bulk commodities such as soybeans, corn, and wheat dominate the export portfolio, making it sensitive to price volatility, climate shocks, and international competition [26]. Countries like Brazil and Argentina have rapidly expanded their market share in major crops, threatening the traditional dominance of U.S. exports [27].

Tariff and non-tariff barriers remain persistent threats [28]. Even where tariffs are reduced, stringent sanitary, phytosanitary, and labeling regulations imposed by trade partners can act as de facto barriers, particularly affecting high-value agricultural goods [29]. Furthermore, logistical bottlenecks—such as port congestion and insufficient rural infrastructure—limit the responsiveness of U.S. supply chains to market opportunities [30].

The volatility of global commodity markets, exacerbated by conflicts, pandemics, and macroeconomic instability, compounds these vulnerabilities [31]. Exchange rate fluctuations, particularly a strengthening U.S. dollar, can erode the price competitiveness of American agricultural goods abroad [32].

Finally, environmental and sustainability concerns are rising in importance among international buyers, putting pressure on U.S. producers to adopt more sustainable practices [33]. Failure to adapt could lead to preference erosion in environmentally conscious markets such as the European Union and parts of Asia [34]. Addressing these vulnerabilities requires a holistic strategy encompassing diversification, infrastructure investment, sustainability initiatives, and diplomatic engagement to sustain U.S. agricultural competitiveness in a rapidly evolving global market [35].

6.2. Opportunities for Resilience through Diversification

Diversification offers a pathway to greater resilience in U.S. agricultural trade [36]. One key strategy involves expanding into emerging markets beyond traditional partners [37]. Regions such as Southeast Asia, Sub-Saharan Africa, and the Middle East are experiencing rapid population growth, urbanization, and increasing food demand, creating new opportunities for U.S. agricultural exports [38].

Product diversification also plays a critical role [39]. Shifting emphasis toward value-added goods, specialty crops, and organic products can reduce vulnerability to price volatility common in bulk commodity markets [40]. High-value sectors like horticulture, organic grains, and plant-based proteins are experiencing robust global demand growth, offering U.S. exporters avenues to differentiate and command premium prices [41].

Vertical integration and supply chain innovation further enhance resilience [42]. By investing in downstream processing, branding, and distribution capabilities, U.S. agricultural firms can capture greater value and reduce dependence on commodity price cycles [43]. Supply chain digitization, including blockchain-based traceability systems, can bolster trust and market access, particularly in regions with strict import standards [44].

Geographical diversification of production also presents an opportunity [45]. Expanding agricultural production into non-traditional areas domestically, supported by irrigation and climate-resilient technologies, can mitigate risks associated with regional climate events [46].

Public-private partnerships are vital to realizing diversification objectives [47]. Initiatives that link farmers, exporters, logistics providers, and policymakers can streamline export processes, reduce transaction costs, and promote new market development [48]. Furthermore, government trade promotion agencies can intensify efforts to identify, negotiate, and support access to non-traditional markets for U.S. agricultural products [29].

Through strategic diversification across markets, products, and supply chains, U.S. agriculture can build resilience against future tariff shocks, geopolitical disruptions, and evolving consumer demands, securing its long-term global leadership position [40].

6.3. Implications for Trade Policy and Export Strategy

The evolving landscape of tariff volatility and competitive pressures has significant implications for U.S. trade policy and export strategy [21]. First, the United States must prioritize comprehensive trade agreements that go beyond tariff reductions to address non-tariff barriers, regulatory harmonization, and sustainability standards [42]. Building resilient trade frameworks with diversified partners will reduce overreliance on any single market [13].

Second, export strategies should emphasize the promotion of high-value, branded agricultural goods [24]. Marketing campaigns showcasing sustainability, quality, and traceability attributes can help U.S. products stand out in increasingly competitive international markets [35]. Supporting small and medium-sized agricultural enterprises to access global markets through trade financing, technical assistance, and export facilitation programs is equally critical [46].

Strategic investment in agricultural innovation is another policy priority [27]. Research and development funding should focus on enhancing crop resilience, reducing environmental footprints, and developing new products aligned with emerging consumer preferences, such as plant-based proteins and organic foods [48].

Infrastructure improvements must accompany these efforts [19]. Investments in ports, transportation networks, and cold storage facilities will ensure that U.S. agricultural products can reach distant markets efficiently and in high quality, improving competitiveness [40].

Finally, proactive trade diplomacy is essential [21]. U.S. policymakers must engage in multilateral forums and bilateral dialogues to advocate for transparent, science-based trade rules, counter protectionist trends, and foster stable trading relationships [42]. Trade promotion efforts should also be strategically aligned with broader foreign policy objectives, leveraging agriculture as a tool for economic statecraft [43].

Integrating these strategic considerations into coherent trade and export policies will not only enhance immediate competitiveness but also build long-term resilience for U.S. agriculture in a complex, multipolar world economy [34].

Table 3: Policy Scenarios and Corresponding Predicted Competitiveness Outcomes

Policy Scenario	Description	Predicted Competitiveness Outcome
Multilateral Trade Deals	Comprehensive agreements addressing tariffs, non-tariff barriers, and regulatory harmonization.	8–12% increase in agricultural export volumes over 5 years.
Infrastructure Investment	Upgrades to ports, transportation networks, and cold chain logistics.	5–7% improvement in export delivery speed and quality, boosting market share by 3–5%.
Sustainability Incentives	Promotion of carbon-friendly farming, traceability programs, and eco-labeling initiatives.	Enhanced access to premium markets, potential 10% price premium for compliant goods.
Market Diversification Programs	Targeted support for entering emerging markets in Africa, Asia, and the Middle East.	7–10% reduction in export risk concentration, new revenue streams by 2028.
Research and Innovation Funding	Investment in climate-resilient crops, supply chain digitization, and predictive analytics.	Long-term yield improvements; anticipated 4–6% export growth resilience during climate shocks.
Enhanced Trade Diplomacy	Strengthened engagement in WTO reforms and bilateral negotiations.	Greater dispute resolution capability; reduced tariff volatility impact by 15–20%.

7. INNOVATIONS, GLOBAL INITIATIVES, AND FUTURE RESEARCH DIRECTIONS

7.1. Integrating Causal Machine Learning with Climate and Sustainability Models

The future of agricultural trade analytics lies in the integration of causal machine learning techniques with climate and sustainability models [27]. Climate variability has a profound influence on agricultural productivity, trade patterns, and market stability, making it essential to consider environmental factors alongside economic interventions like tariffs [28].

Causal machine learning models are well-suited to this integration due to their ability to capture complex, nonlinear relationships across high-dimensional datasets [29]. For example, causal forests can estimate how the impact of a tariff shock varies under different climate conditions, such as drought years versus average precipitation years [30]. Similarly, synthetic control methods can simulate alternative future scenarios by combining climate projections with tariff changes to assess compounded effects on agricultural exports [31].

Integrating sustainability metrics into causal models also enables the evaluation of long-term environmental impacts associated with trade policies [32]. Metrics such as carbon footprint, water usage, and land degradation can be treated as additional outcomes, allowing researchers to estimate how trade interventions influence not only economic performance but also environmental sustainability [33].

Emerging initiatives like the Climate-Smart Agriculture (CSA) framework emphasize the need for resilient and sustainable agricultural trade systems [34]. Causal machine learning can contribute to CSA objectives by identifying policy levers that simultaneously enhance trade competitiveness and environmental resilience [35]. For instance, machine learning models could reveal that certain tariff reductions are more beneficial when targeted at crops with lower greenhouse gas emissions [36].

Another promising area is the use of Targeted Maximum Likelihood Estimation (TMLE) in climate-trade modeling [37]. TMLE's robustness properties are particularly valuable when dealing with the noisy, complex data typical of environmental systems, helping to improve causal inference accuracy [38].

Integrating causal machine learning with climate and sustainability models creates powerful, multidimensional decision-support tools for policymakers [39]. Such integration enables more holistic assessments that align trade objectives with broader goals of climate resilience, biodiversity conservation, and food security [40]. This evolution marks a critical step toward a more adaptive, forward-looking approach to agricultural trade policy in an era of accelerating climate change [41].

7.2. Global Collaborations and Pilot Programs in Agricultural Analytics

Global collaborations are increasingly playing a vital role in advancing agricultural analytics, particularly in the application of machine learning for trade resilience and sustainability [42]. International organizations, national governments, research institutions, and private sector actors are coming together to pilot innovative programs that leverage causal inference techniques [43].

One notable initiative is the Agricultural Market Information System (AMIS) coordinated by the G20, which aggregates global data on key commodities to improve market transparency and early warning systems [44]. Efforts are underway to integrate machine learning models into AMIS to better predict market disruptions arising from tariff changes, climatic events, and policy interventions [45].

The European Commission's Horizon Europe program is funding several projects aimed at applying causal machine learning to assess the impacts of trade policies on rural development and environmental sustainability [46]. These projects seek to create decision-support platforms that governments can use to optimize their agricultural trade and climate adaptation strategies simultaneously [47].

In the private sector, agri-tech companies are launching pilot programs that combine satellite imaging, blockchain supply chain data, and causal analytics to forecast trade patterns and assess risk exposure [48]. For instance, companies are developing tools to predict how shifts in tariffs and extreme weather events jointly affect specific supply chains, enabling faster strategic responses by exporters and importers [49].

Public-private partnerships are especially crucial in this space [50]. Collaborative pilot programs between agricultural ministries, universities, and technology firms in countries like Australia, the Netherlands, and Kenya are building early-warning platforms for farmers and exporters [31]. These platforms integrate causal machine learning with climate risk models to provide actionable insights at both local and international scales [12].

The United States Department of Agriculture (USDA) is also investing in machine learning-driven pilot studies to forecast the impacts of trade policy changes under different climate futures [43]. These studies emphasize the need for scalable, replicable analytical frameworks that can be adapted to different crops, regions, and geopolitical contexts [23].

By fostering global collaborations and supporting pilot programs, the agricultural sector can accelerate the adoption of causal machine learning for more resilient and sustainable trade systems [25]. These efforts create a foundation for a future where policy decisions are informed not just by economic forecasts but also by integrated, real-time analyses of environmental and social factors [46].

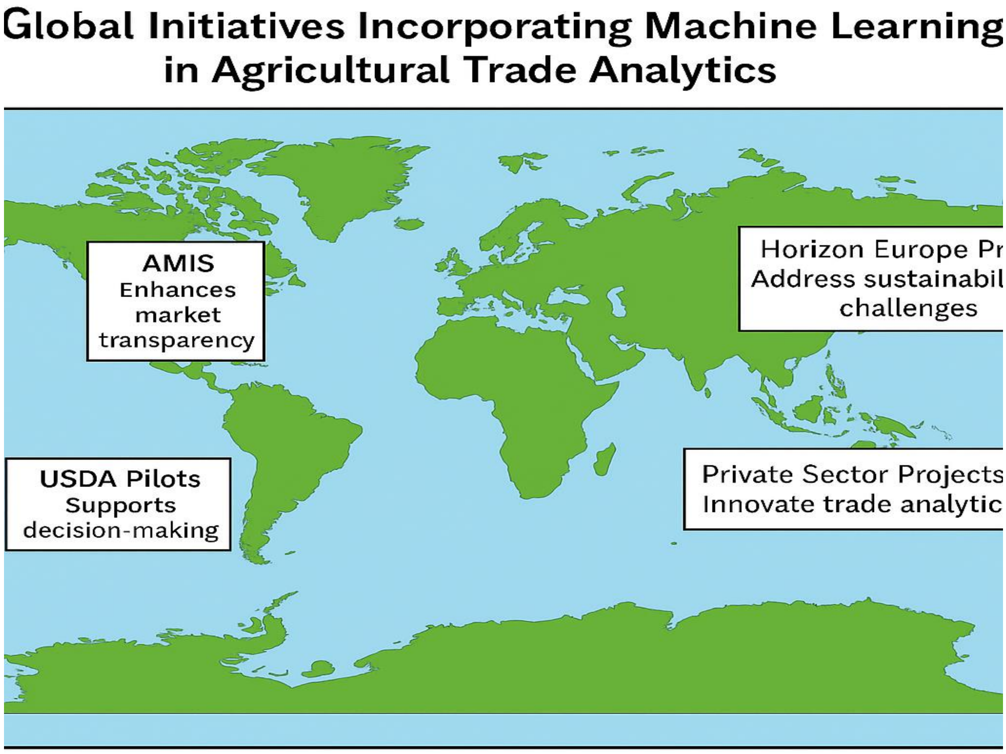

Figure 4: Global Initiatives Incorporating Machine Learning in Agricultural Trade Analytics

8. CONCLUSION

8.1. Summary of Key Findings

This study has provided a comprehensive analysis of the impact of tariff volatility on U.S. agricultural trade and demonstrated the valuable role of causal machine learning techniques in enhancing understanding and forecasting capabilities. The findings highlight that traditional econometric models, while useful, often fall short when dealing with the complex, nonlinear, and high-dimensional nature of modern trade data. Causal machine learning approaches, such as causal forests, synthetic control methods, and Targeted Maximum Likelihood Estimation (TMLE), offer more nuanced and robust tools for estimating the real effects of tariff shocks.

A critical insight from the analysis is the heterogeneous impact of tariff shocks across different agricultural commodities. Bulk commodities like wheat and corn show moderate resilience, while high-value perishables such as fruits, nuts, and dairy products are significantly more vulnerable. Similarly, partner-specific analysis reveals stark differences: China presents the greatest sensitivity to tariffs, followed by the European Union and Mexico, each with unique trade and regulatory dynamics.

Another key finding is that future agricultural competitiveness will increasingly depend on the ability to integrate causal trade analytics with climate and sustainability considerations. Trade patterns are not only influenced by tariffs but also by environmental shocks, consumer demands for sustainable products, and global supply chain vulnerabilities. Data-driven diversification strategies — targeting emerging markets, expanding high-value product lines, and enhancing supply chain resilience — emerge as critical paths forward.

Forecasting models project varying market share outcomes depending on future tariff policies, underlining the need for flexible, adaptive strategies. Optimistic scenarios involving tariff reductions show potential for significant export recovery, while pessimistic paths of escalating trade conflicts could further erode U.S. agricultural dominance. The research emphasizes that the integration of real-time data, advanced analytics, and robust scenario planning is essential for anticipating future trends and minimizing trade-related risks.

In sum, this work demonstrates that causal machine learning is not merely a technical upgrade but a strategic necessity for understanding, managing, and shaping the future of U.S. agricultural trade. It calls for a paradigm shift in how policymakers, producers, and exporters approach global market engagement amid rising uncertainty and complexity.

8.2. Broader Significance for U.S. Agricultural Competitiveness

The broader significance of these findings for U.S. agricultural competitiveness is profound. As global trade becomes more volatile, driven by shifting tariff regimes, geopolitical tensions, and climate disruptions, maintaining a competitive edge requires moving beyond traditional approaches. Agricultural exporters and policymakers must recognize that resilience and adaptability are now strategic imperatives, not optional advantages.

First, a data-centric and evidence-based policy framework is crucial. Harnessing causal machine learning techniques allows for the identification of vulnerabilities, the anticipation of market shifts, and the design of targeted interventions. In a world where small changes in policy or climate can have outsized effects on market outcomes, relying on outdated predictive tools is increasingly untenable. The future belongs to those who can leverage real-time insights to guide strategic decisions.

Second, diversification is no longer merely a risk management strategy — it is a growth strategy. Expanding into non-traditional markets, promoting a wider range of agricultural products, and investing in supply chain resilience can reduce exposure to concentrated market risks and open new revenue streams. The U.S. must capitalize on emerging markets with growing food demands while maintaining leadership in value-added and sustainable agricultural products.

Third, trade policy must evolve to reflect the interconnectedness of economic, environmental, and social factors. Negotiations should not only focus on tariff reductions but also address non-tariff barriers, regulatory harmonization, sustainability standards, and innovation incentives. Building strategic alliances that promote transparent, science-based trade rules will help safeguard U.S. market access and counter protectionist trends globally.

Finally, competitiveness will increasingly depend on the ability to align agricultural production with global sustainability trends. Environmental stewardship is becoming a critical component of market preference and regulatory acceptance, especially in Europe and Asia. By leading in climate-smart agriculture, carbon-friendly farming practices, and traceability innovations, the U.S. agricultural sector can strengthen its reputation and secure long-term export opportunities.

In conclusion, securing U.S. agricultural competitiveness in the coming decades will require agility, foresight, and proactive investment in technology, policy innovation, and global engagement. This study's insights into causal machine learning applications and strategic diversification underscore a new blueprint for agricultural success in a rapidly transforming global economy.

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