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An evaluation of gravity models and artificial neuronal networks on bilateral trade flows in wood markets

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ABSTRACT

Trade fuels economic development in interwoven international wood markets, while economic shocks and structural changes jolt market response behavior. In this context, both accurate predictions and forecasts of trade flows and a deep understanding of their influencing factors are essential for policymakers and stakeholders to enhance economic planning and decision-making affecting trade policies. A popular method for analyzing bilateral trade flows is the deterministic Gravity model of trade due to its intuitive design and effectiveness. However, data-driven machine learning methods such as artificial neural networks (ANN) could enhance the accuracy of deterministic modeling approaches through their complex and potentially nonlinear nature. To the best of our knowledge, no study exists that uses an ANN approach to assess bilateral trade for different wood-based products was. Therefore, it remains unclear whether ANN is an appropriate method to predict and forecast trade flows in forest product markets or if Gravity models of trade might yield better results. This study compares the ability of Gravity models and feedforward neuronal networks (FFNN) to predict existing and forecast future bilateral trade flows of four main product categories in international wood product markets. Our findings highlight that it is essential to consider the purpose of the analysis alongside the specific product group under investigation. The FFNN approach outperforms Gravity models for predicting past and present trade flows, delivering more accurate predictions across all product categories. Looking at the accuracy of forecast, we see that the superiority of FFNNs is present but decreases as the forecast horizon increases.

1. Introduction

Trade fuels economies. International trade flows resemble a complex network woven together by exchanging goods and the regional imbalances in supply and demand (Mathieu and Roda, 2023). Also, trade in forest-based products has been increasing for decades.[1] Due to being key in sourcing, providing, and exchanging goods satisfying economic and consumer needs, predicting trade directions and volumes is essential for stakeholders to enhance informed business decisions, strategic planning, and practical policy making (Minakawa et al., 2022). Thus, understanding trading mechanisms has been the goal of various analytical approaches with varying degrees of success.

Different types of models are used to simulate trade flows, including, but not limited to, Computed General Equilibrium (CGE) and Partial Equilibrium (PE) Models, Gravity models of trade, predictive models like artificial neuronal networks, and (Social) Network Analysis (SNA) approaches. Despite the variety of models, forest-based trade studies have three main goals: analyzing trade mechanisms, forecasting of trade, and/or policy impact analyses (Mathieu and Roda, 2023).

Effectively studying international trade of forest-based products is confounded by several factors. First, it is hard to grasp the complexity of dynamic trade networks in simplified mathematical models and equations. While helpful, models always remain an abstraction of the real world. Second, analyzing trade flows in forest product markets applies the same narrow set of recurring factors, targets, and model conceptions while persistently new and potentially influencing components are not considered (Mathieu and Roda, 2023). Economic shocks that disrupt market response behavior further complicate analysis. Third, reports on international economic data and forest sector statistics, as well as (bilateral) trade flows, often remain inconsistent and fragmented (Gaulier and Zignago, 2010; Buongiorno and Johnston, 2018; Kallio and Solberg, 2018; Chen et al., 2022). Model analyses heavily depend on the

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[1] Between 1961 and 2022, the export of Roundwood increased by around 192 %, exports of Sawnwood by around 279 %, exports of Wood-based panels increased by around 3309 %, and paper and paperboards increased by around 777 % (FAOSTAT, 2023)

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data quality and assumptions they rely on. Primarily for machine learning, data quality is imperative for successful model outcomes (Nummelin and Hänninen, 2016).

The majority of studies on trade flows in forest markets adopt policy-oriented analytical approaches, focusing on simulating the impacts of various policy interventions (Mathieu and Roda, 2023) with PE models like the GFPM by Buongiorno (2015a), FOROM by Nepal et al. (2021), EFI-GTM by Solberg et al. (2021), or FORMEQ by Kallio (2021). Given demand and supply functions and costs of trade, economic market models compute equilibrium prices as well as manufacture and trade quantities in interconnected markets (Polyakov and Teeter, 2007) by optimizing linear or nonlinear objective functions. Most studies based on PE only project aggregated future trade flows (i.e., each country imports to and exports from the global market), while only a few studies analyze bilateral trade relations (Olofsson et al., 2018).

In contemporary international trade analysis, Gravity models have become one of the most widely used deterministic tools for studying bilateral trade flows (Anderson and van Wincoop, 2003; Polyakov and Teeter, 2007; Head and Mayer, 2014; Olofsson et al., 2018; Wohl and Kennedy, 2018). In contrast to linear and nonlinear economic market models, Gravity models investigate the determinants of trade to explain how trade occurs. (Olofsson et al., 2018). Gravity models use trade data reports to test the significance of different variables in trading relations between countries (Polyakov and Teeter, 2007; Wohl and Kennedy, 2018).

The traditional Gravity model of trade was introduced as an analogy to the theory of Gravity in physics in the 1960s by Tinbergen (1962). It explains bilateral trade flows between countries dependent upon the income of both trade partners and the distance between them. The theoretical foundation of these models has improved over time, and several variations of Gravity models consider a broader set of factors influencing trade (Anderson and Yotov, 2012). Studies that have demonstrated the effectiveness of Gravity models as a tool for forecasting trade include, but are not limited to, the work of Polyakov and Teeter (2007) and Wong et al. (2024).

Unlike the many policy-oriented studies that rely on PE models to examine aggregated trade flows, analyses of bilateral trade flows within the forest sector are relatively uncommon (Olofsson et al., 2018). However, a few studies on Wood-based products' predictions or forecasts have been undertaken in recent years. Among these are Buongiorno (2015b), Buongiorno (2016) and Olofsson et al. (2018) who applied Gravity models based on (log-) linear panel regressions, Larson et al. (2018) who used a nonlinear Poisson pseudo-maximum likelihood (PPML) estimator to project long term bilateral trade, and Morland et al. (2020) who employed a structural Gravity approach to improving the explanation of bilateral trade flows for different forest-based commodities. In addition, there have been several case studies for Asian countries, such as the work of Nasrullah et al. (2020), who analyzed China's bilateral trade flows for different groups of forest products, Tang et al. (2015) who used an augmented Gravity model to understand trade of pulp and paper products between China and its trading partners, and (Vu et al., 2019) who applied the Gravity approach to analyze wood products traded between Vietnam and its major trading partners.

More recently, data-driven machine learning methods, including artificial neural networks (ANN), have emerged that may improve the accuracy of predictions for complex nonlinear relationships (Hill et al., 1994). Unlike deterministic Gravity models, predictive methods such as ANN focus on the question "what" occurs instead of explaining "how and why" something will happen. They estimated or predicted the dependent variable's value based on specific conditions set by the independent variables (Wohl and Kennedy, 2018). So, ANN assesses the response of dependent variables by considering a set of independent variables of potential predictors, utilizing both supervised and unsupervised approaches (Argatov, 2019; Gopinath et al., 2020). While minimizing the difference between the ANN output and the empirical input value, ANN learns, remembers, and establishes relationships among data (Vafaeipour et al., 2014; Wohl and Kennedy, 2018). There are various forms of ANN, e.g., feedforward neuronal network (FFNN), single or multi-layer perceptron (MLP) (Abiodun Oludare et al., 2018), or a radial basis function (Sharif Ahmadian, 2016).

ANN are particularly effective at combining independent variables in complex, nonlinear ways, enabling them to produce highly accurate predictions (Wohl and Kennedy, 2018). Additionally, ANNs can enhance, for example, database records by identifying missing or erroneous entries or filling data gaps. This could improve the accuracy of subsequent analyses and decision-making based on this data.

The predictive performance of different regression-based models against neuronal network approaches has already been explored for several sectors in the literature, including but not limited to the work of (Verstyuk and Douglas, 2022; Wohl and Kennedy, 2018; Kaytez et al., 2015; Bennedsen et al., 2023). Kaytez et al. (2015) and Wu et al. (2022) found that neuronal networks can outperform linear Gravity models for the prediction of electricity consumption and development of forest resources (forest coverage and stocking volume), respectively, by comparing a neural network and a linear regression approach. Circlaeys et al. (2017) and Verstyuk and Douglas (2022) found that the prediction accuracy of a FFNN exceeds those of a Gravity model for global bilateral trade flows. The analysis of Wohl and Kennedy (2018) and Ruzicska et al. (2024) evaluates the performance of Gravity models and ANN to model U.S. trade flows showing that ANN can (marginally) outperform Gravity models. A first examples for the application of machine learning techniques to predict bilateral of a wood product is the work of Nummelin and Hänninen (2016) who employed machine learning techniques, including Support Vector Machines, ANN, and Random Forest models for the projections of bilateral Sawnwood trade. However, contradictory to the previous results on entire economies, total trade flows, or the prediction of resource endowment, Nummelin and Hänninen (2016) found the performance of ANN to be lower than that of other approaches. Thus, while in many applications, ANN seemingly outperforms regression-based models, the results of Nummelin and Hänninen (2016) for the trade of Sawnwood contradict this general trend and raise questions about the validity in the timber market as well as for individual wood products.

However, to the best of our knowledge, prior to this analysis, no study of bilateral trade using an ANN approach and considering different wood-based products was undertaken. As these market-specific features have yet to be investigated, it remains unclear whether ANN is an appropriate method to predict and forecast trade flows in forest product markets or if Gravity models of trade might yield better results here. However, accurate predictions of bilateral trade flows are essential for policymakers, researchers, and firms to enhance trade-related policies and support economic planning, benefiting all stakeholders involved in international trade (Wohl and Kennedy, 2018).

To enhance forest product market analysis by identifying the most appropriate tool for specific purposes, this paper evaluates the suitability of these two approaches (Gravity models and FFNN) for improving the prediction and forecasting of bilateral trade flows in the forest-based sector.

In particular, the goals of the present study are to:

- determine whether one model achieves greater accuracy in predicting existing (past and present) trade flows, making it better suited for tasks like database validation (e.g., gap filling and outlier detection)
- analyze the forecasting performance of the models to identify which more effectively predicts future trade flows, potentially serving as a validation tool for other economic modeling approaches, such as equilibrium-based projections, by benchmarking their outcomes

To achieve these objectives, we employ Gravity models of trade and a FFNN. We both analyze (i.e., predict) and forecast bilateral trade flows in international wood product markets on a global scale based on CEPII data on bilateral trade flows for 200 countries (CEPII, 2023a). Following the recommendations for future research of Wohl and Kennedy (2018), this study concentrates on analyzing bilateral trade for specific commodities, namely four main categories of wood products: Roundwood, Sawnwood, Wood-based Panels, and Paper and Paperboard. The modeling results are compared by evaluating the accuracy of their predictions and forecasts. To ensure comparability, we propose employing an FFNN incorporating the same trade determinants used in constructing the Gravity model. Additionally, both modeling approaches use the same dataset for prediction and forecasting exercises. Specifically, the root mean square errors (RMSE) are calculated to assess each approach's predictive and forecasting quality, examining the suitability of the Gravity model and the FFNN for this application.

2. Material and methods

2.1. Gravity models

In a first step, we employ a Gravity model to predict the bilateral trade flows in four main categories of traditional forest product markets. Eq. (1) describes a structural definition of Gravity following Head and Mayer (2014) p. 138:

$$X_{i,j} = \frac{Y_j}{\Omega_j}\frac{X_i}{\Phi_i}\varphi_{i,j} \tag{1}$$

Where trade between two countries (i refers to the importing and j to the exporting country) can be expressed by: the expenditures in i for products from j ($X_{i,j}$), which are dependent on the production in j (Y_j), the total expenditures in i (X_i), the bilateral accessibility ($\phi_{i,j}$) expressed as an index of market potential in j (Ω_j), and the set of purchasing alternatives for consumers in i (Φ_i). On one hand, the bilateral trade flow between two countries increases with (i) a rising production in the exporting country, (ii) an increasing overall consumption in the importing country, (iii) and a growing bilateral market accessibility. On the other hand, bilateral trade between the two countries decreases as the exporting country purchases more wood products from domestic suppliers while the importing country extends its demand for wood products from other countries.

Eq. (2) depicts the linearized form of eq. (1) for the Gravity model regression, where β_0 is the intercept, β_1 to β_5 are the coefficients, and ε is the error term.

$$lnX_{i,j} = \beta_0 + \beta_1 lnY_j + \beta_2\, ln\Omega_j + \beta_3\, lnX_i + \beta_4\, ln\Phi_i + \beta_5\, ln\varphi_{i,j} + \varepsilon \tag{2}$$

Following Morland et al. (2020), this study splits the production of the exporting country (Y_j) into five variables: (i) the overall production of a wood product group, which covers the size of the specific industry (production), (ii) the overall exports of a wood product group, which cover the weight of exports of such wood product group in the exporting country (trade export value), (iii) forest sector rents, which cover the size of the overall forest sector in comparison to the overall economy of the exporting country (forest rents), (iv) the GDP per capita, which is implemented as a parameter to cover the effects of per capita income (GDP pc), and (v) the overall population of the exporting country (population). In the same way, the consumption of the importing country (X_i) is split into five parameters: (i) the overall production of a wood product group to cover the size of the specific industry in the importing country (production), (ii) total imports of a wood product group, which cover information about the overall demand for imports (total import value), (iii) forest sector rents, which cover the overall size of the forest sector in comparison to the overall economy of the importing country (forest rents), (iv) GDP per capita, which cover the per capita income (GDP pc), and (iv) overall population, which cover the overall size of the importing country (population). As a proxy for bilateral accessibility (ϕi,j), the distance in km between capital cities is chosen (distcap). Total imports in the exporting country are used as proxies for market potential (Ω_j), and total exports in the importing country i serve as a proxy for the degree of competition. Fig. 1 shows the independent and target variables used for the econometric regression approach in analogy to the notation of ANN using nodes and layers (see Chapter 2.2):

Due to the presence of heteroscedasticity in the data, as identified by the Breusch-Pagan test (Breusch and Pagan, 1979), regressions were performed using a Poisson pseudo-maximum likelihood (PPML) estimation. This approach is robust to frequently occurring heteroscedasticity and ensures more reliable results (Silva and Tenreyro, 2006).

To benchmark the quality of our approach, we also include a more traditional form of the Gravity model, comparable to those used by Buongiorno (2016) and Larson et al. (2018). This version incorporates only GDP per capita, the total population of both trading partners, and the distance between them as independent variables. At the same time, it is also estimated using a PPML approach. Comparing both approaches will indicate whether the structural form of the Gravity model provides additional benefits for analyzing the bilateral trade in wood markets compared to the more traditional model.

2.2. Artificial neuronal networks

In a second step, we integrate an ANN, which offers an approach for capturing complex and nonlinear relationships that may enhance predictive accuracy for bilateral trade flows (Hill et al., 1994; Wohl and Kennedy, 2018). To compare the performance of Gravity models with an ANN approach, we constructed an ANN that mirrors the Gravity model structure (described above) to ensure comparability between their predictions of bilateral trade flows in wood markets.

For this study, various configurations of the ANN were evaluated using a combination of manual tuning and a grid search approach to identify the optimal setup. Precisely, the layer architecture and optimizer were adjusted manually. At the same time, grid search was employed to optimize parameters such as the number of hidden layers, nodes per layer, activation function, learning rate, and batch size (see Table A1 3 for more details in the Appendix). Eventually, a FFNN with 10 hidden layers and 52 nodes per each layer yielded the lowest mean squared error (MSE) while maintaining reasonable computational efficiency across all product groups. This structure was adopted for our analysis.

The FFNN consists of three primary types of interconnected layers (input layer, intermediate hidden layers, and output layer) that are linked to each other to varying degrees as determined by associated weights (Abiodun et al. 2018). FFNN can be linear and nonlinear depending on the choice of the activation functions used in their layers (Emmert-Streib et al., 2020). In the present study, we adopt the nonlinear approach with Rectified Linear Unit (ReLU) as the activation function[2] (Emmert-Streib et al., 2020; Lee and Song, 2019). ReLU was chosen based on the grid search approach. We also tested alternative activation functions (sigmoid, linear, and tanh); however, these either produced less desirable results or imposed significantly higher computational demands. We built the FFNN in Python using Keras (Chollet et al., 2015) and the nonlinear Adam optimizer (Kingma and Ba, 2014). An overview of the underlying structure of the FFNN is shown in Table 1. Input data used to construct FFNNs are the same data used for the Gravity model of trade, and the input and output layers are designed the same way as for the Gravity model of trade (see Fig. 2), with 13 variables in the input layer and one (trade value) in the output layer.

2.3. Data

This study uses CEPII data on bilateral trade flows for 200 countries comprising approximately 410,000 data points before data cleansing

[2] ReLU function describes a linear activation function f(x) = max (0, x).

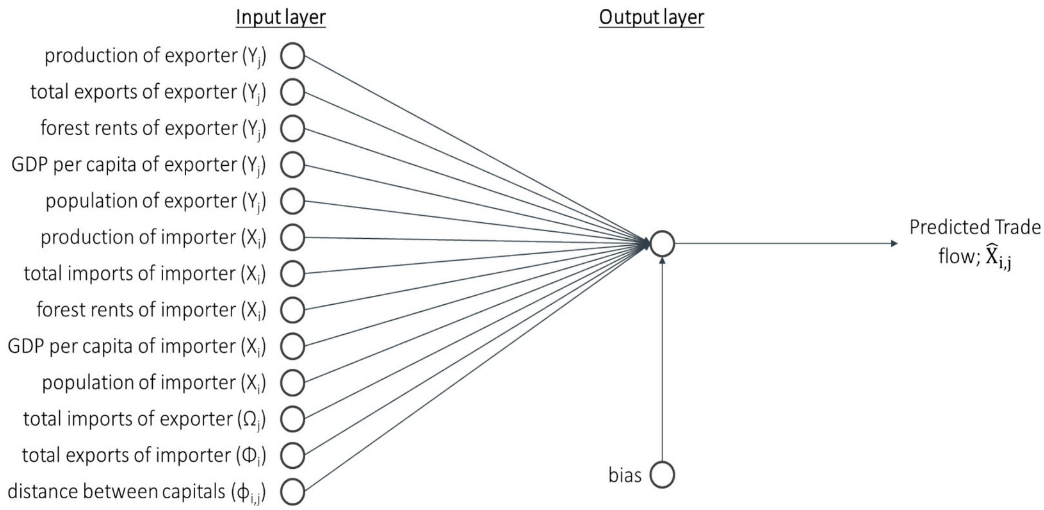

Fig. 1. Depiction of the econometric regression approach for the Gravity model of trade in wood markets.

Table 1
Detailed information about the implementation of the FFNN (table design based on Abrishami and Aliakbary (2019).

FFNN implementation details	
Neuronal network API	Keras
Input dimensions	13
Output layer	Dense layer
Activation function	ReLU
Epochs	200
Optimization algorithm	Adam
Learning rate	1.0E-04
Loss function	MSE

(CEPII, 2023a; Gaulier and Zignago, 2010). The dependent target variable is the bilateral trade flow of selected wood products between two countries. Table A1 2 in the Appendix summarizes the data and main characteristics of the independent variables used in modeling. The independent variables used for the Gravity model and FFNN are production, total imports, total exports, forest rents, GDP pc, population, and distance between capitals (see sections 2.1 and 2.2 for their description). Data on the volume of bilateral trade are taken from CEPII (Centre d'Etudes Prospectives et d'Informations Internationales) (CEPII, 2023a). The dataset, derived from UN-Comtrade, comprehensively covers all relevant 6-digit HS Codes (Harmonized System) for the four product categories analyzed in this study, resolves discrepancies in data, and provides a single report for each trade flow. (Gaulier and Zignago, 2010).

Data for production aggregated total imports and aggregated total exports of forest products are retrieved from FAO (FAOSTAT, 2023). Forest rents, GDP per capita, and population are taken from the World Development Indicators (WDI) (World Bank, 2023), and the distance in km between capital cities is taken from the Gravity database prepared by CEPII (CEPII, 2023b).

For the present analysis, we pre-process the data to refine and transform them: Bilateral trade data from CEPII for wood products are reported on the 6-digit HS Code level. We group them into four superordinate categories: Roundwood, Sawnwood, Wood-based panels, and Paper and Paperboard. The product-specific HS Codes and category alignment are presented in Table A1 1 in the Appendix. Data for production, total imports, total exports, forest rents, GDP per capita, and population are unilateral country reports and thus, need to be assigned to the bilateral trade data for exporting as well as importing countries; hence, all data given in current US$ (like bilateral trade values from CEPII, aggregated trade from FAO or GDP from the WDI) are converted to constant 2015 US$ using the GDP deflator of the WDI (World Bank, 2023). We excluded data points with missing values in the independent

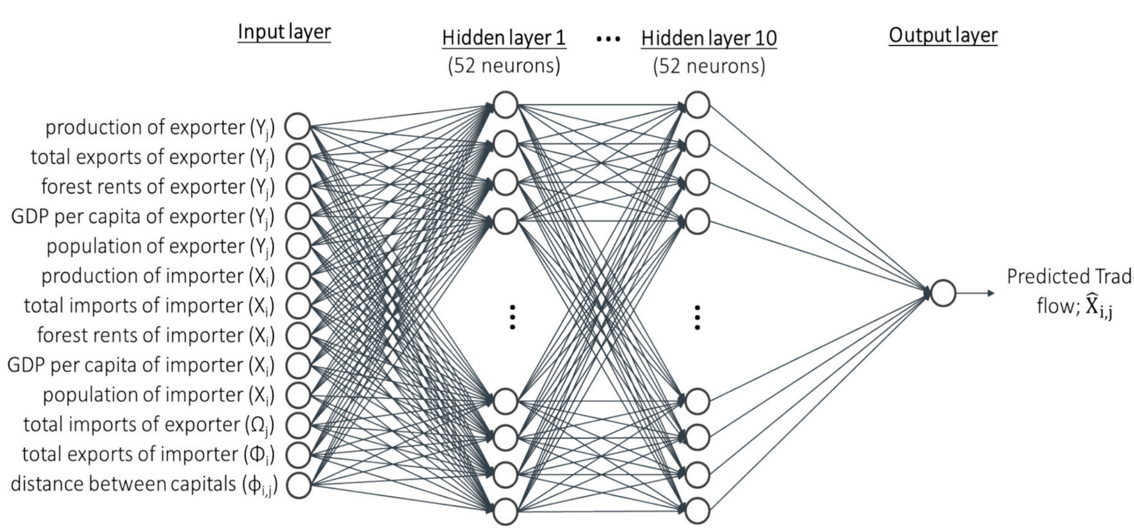

Fig. 2. Depiction of the FFNN approach to analyze bilateral trade in wood markets.

variables to ensure the completeness of data sets and maintain data integrity. This resulted in a reduction in the total number of data points from approximately 410,000 to 245,000.[3]

2.4. Modeling

To achieve the objectives of the present study, we processed the input data in two ways to develop predictive models for (i) existing trade flows and (ii) forecast of future trade flows. Both approaches build on training and test data, enabling us to evaluate the model's performance effectively.

We split the original data set into two sets to predict existing trade flows. One set is used for model training, and the other for model testing. Data are randomly allocated to each of the two groups, with the training data containing 80 % and the testing data 20 % of the entire data set (see Fig. 3). We split the dataset to reduce data dependency and enhance the generalizability of our model prediction and forecasts. The model is fitted and improved during the training phase using the training data as input. In a subsequent step, model performance is assessed using the test data.

The target variable is predicted based on the training data to estimate the coefficients of the structural and traditional Gravity model of trade. The resulting coefficients state the influence of each of the independent variables shown in Fig. 1 Figure 1on bilateral trade in wood markets.

Training data are also used as input for the FFNN's training. Internally, within the hidden layers of the FFNN, the input data are iteratively adjusted, and the model's parameters are fine-tuned until the conditions (e.g., threshold and weights of the parameters) for a well-performing FFNN are stabilized.

In the next step, the capability of the structural and traditional Gravity model and the FFNN to predict bilateral trade in wood markets is examined by running the models with test data as input. The accuracy of each model is determined by comparing the predicted bilateral trade value (generated using test data and FFNN or Gravity model) with the observed bilateral trade value (reported data from CEPII). The root mean square error (RMSE) between the observed and predicted values is used to measure accuracy (the higher the value, the lower the accuracy).

To address the second objective of this study, analyzing the forecasting performance of the models to determine which more effectively predicts future trade flows, we split the original data (covering the time horizon from 2003 to 2020) into temporal windows (w). This first window entails data from the first year of the time series (w1 = 2003). Each subsequent window adds one year (w2 = 2003–2004, w3 = 2003–2005) until the final window covers 17 years (w17 = 2003–2019).

This procedure resulted in 17 sets of data with "past" and "future" data of varying lengths (see Fig. 4).

Within each defined temporal window w_i, we split data again into training (80 %) and test (20 %) data. Training data are again used to set up and train the model within each window w_i. Afterward, test data will be applied to forecast trade flows until 2020. Depending on the window, the length of the forecast differs: since w1 only entails training and test data for one year, the forecast period until 2020 is 17 years, while in w17, training and test data comprises 17 years, so the forecast period is only 1 year.

2.5. Testing prediction and forecast accuracy

To evaluate the prediction and forecast accuracy of the Gravity models and FFNN, the correlation coefficient R^2 and root mean square error (RMSE) were calculated after estimating trade values using both test and training data. Each model was run ten times to ensure that the random selection of training and test data did not influence the results. This analysis was conducted for the FFNN and the two Gravity model approaches (structural and traditional) applied in the study.

The correlation coefficient R^2 measures the alignment between observed and predicted values. It is derived from a linear regression where predicted trade values serve as the independent variable and observed trade values as the dependent variable. RMSE quantifies the difference between predicted trade flows, forecasted future trade flows, and observed values (reported trade data from the database). This provides an indicator of prediction error.

3. Results

In the following, we present the modeling results obtained for four categories: (i) Roundwood, (ii) Sawnwood, (iii) Wood-based panels, and (iv) Paper and Paperboard. First, we analyze the precision metrics by using the Gravity model and the FFNN to analyze bilateral trade in forest product markets by predicting existing trade data, and second, by forecasting future trade flows with temporal windows.

3.1. Analysis of trade: Prediction of existing trade data

As mentioned in section 2.5, after estimating trade flows, R^2 and RMSE were used to examine the suitability of the different models to predict existing trade flows. Table 2 and Table 3 summarize the measured relationship between observed trade values as officially reported by CEPII (see section 2.3) and predicted trade values from the FFNN, structural, and traditional Gravity models over the period 2003–2020. After evaluating the ability of the models to predict existing data using the 2003–2020 panel, we assess their accuracy in forecasting future trade flows.

When analyzing the quality of the FFNN predictions for the test dataset across all four wood product groups, we see that the lowest R^2 value of the FFNN predictions is obtained for the prediction of trade in the Roundwood group, with a mean of 0.578. The R^2 values of the FFNN estimations tend to increase for further processed wood product groups, such as Sawnwood (mean $R^2 = 0.666$), Wood-based Panels (mean $R^2 = 0.612$), and Paper and Paperboard (mean $R^2 = 0.743$). When comparing the results for the test data to those for the training data, the R^2 values for FFNN predictions for the training data are significantly higher, which indicates overfitting. However, the degree of overfitting varies across the product groups. In the Paper and Paperboard group, the percentage deviation in mean R^2 values between the training and test datasets is approximately 4.7 %. This deviation increases to 8.5 % for Sawnwood, 8.9 % for Wood-based Panels, and reaches as high as 11.5 % for Roundwood.

Table 2 also summarizes the R^2 values representing the relationship between observed and predicted trade values for both Gravity models. The results indicate that the structural Gravity model, specifically developed for wood markets as outlined in Section 2.1, outperforms the traditional Gravity model across all product groups. The structural Gravity model achieves a mean R^2 value of 0.397 for Roundwood, compared to only 0.160 for the traditional approach. Similarly, Sawnwood's structural model achieves a mean R^2 of 0.473, while the traditional model reaches 0.206. This trend persists for Wood-based Panels (structural model mean $R^2 = 0.443$; traditional model mean $R^2 = 0.278$) and Paper and Paperboard (structural model mean $R^2 = 0.563$; traditional model mean $R^2 = 0.331$).

Based on Table 2, we can summarize that the traditional Gravity model consistently exhibits the lowest R^2 values, followed by the structural Gravity model. The FFNN estimations exhibit the highest R^2 values, thus showing the highest predictive performance with the lowest deviation between observed and predicted data. However, unlike the FFNN predictions, neither the structural nor the traditional Gravity models exhibit significant signs of overfitting.

Table 3 summarizes the RMSE (Root Mean Squared Error) of the predicted trade values in relation to the observed (reported) value,

[3] The data and the code used in this research has been made freely available by Morland et al., 2025 at https://zenodo.org/records/14727300.

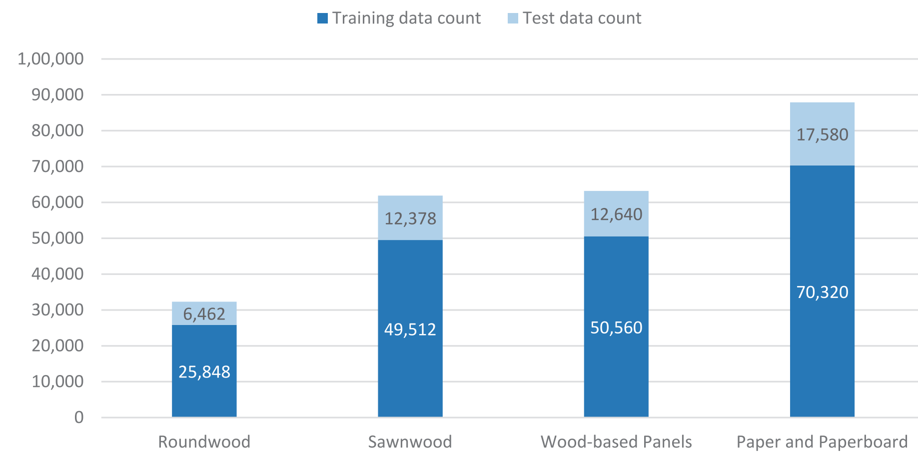

Fig. 3. Amount of data points used for model training and testing data set for different wood product groups.

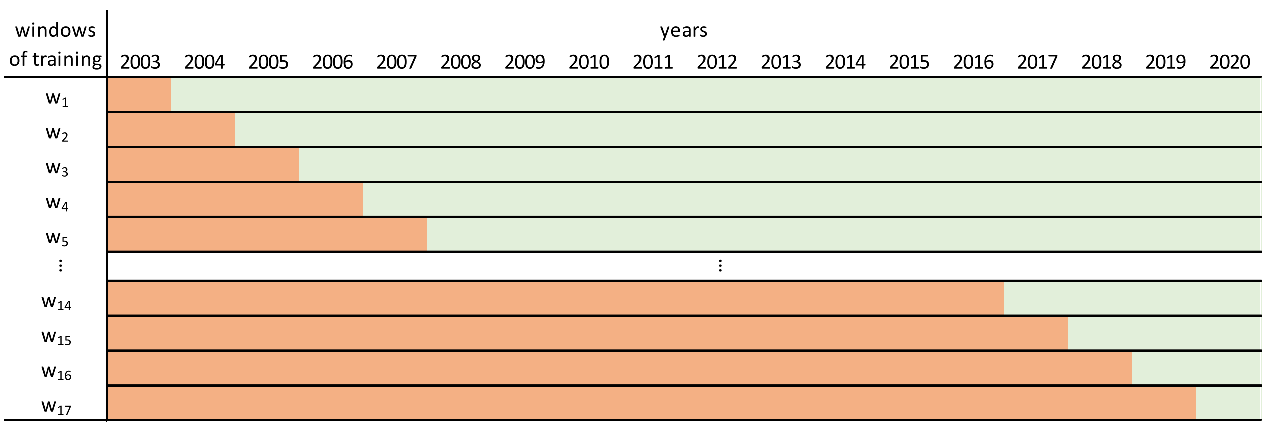

Fig. 4. Depiction of temporal windows used to train the models (orange) and to validate the prediction made by the trained models (green). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
R^2 values for the relationship between observed and predicted trade values.

		Training			Test		
Commodity	Model	Min	Mean	Max	Min	Mean	Max
Roundwood	FFNN	0.629	0.654	0.672	0.563	0.578	0.592
Roundwood	struct. Gravity	0.397	0.401	0.404	0.387	0.397	0.410
Roundwood	trad. Gravity	0.160	0.163	0.166	0.149	0.160	0.169
Sawnwood	FFNN	0.716	0.728	0.753	0.650	0.666	0.687
Sawnwood	struct. Gravity	0.469	0.472	0.474	0.462	0.473	0.482
Sawnwood	trad. Gravity	0.206	0.208	0.210	0.200	0.206	0.215
Wood-based P.	FFNN	0.649	0.671	0.693	0.599	0.612	0.623
Wood-based P.	struct. Gravity	0.441	0.444	0.447	0.433	0.443	0.456
Wood-based P.	trad. Gravity	0.278	0.280	0.284	0.264	0.278	0.288
Paper and Pb.	FFNN	0.774	0.780	0.787	0.735	0.743	0.752
Paper and Pb.	Struct. Gravity	0.563	0.564	0.566	0.555	0.563	0.570
Paper and Pb.	trad. Gravity	0.330	0.331	0.333	0.326	0.331	0.334

Table 3
RMSE values for the relationship between observed and predicted trade values.

		Training			Test		
Commodity	Model	Min	Mean	Max	Min	Mean	Max
Roundwood	FFNN	0.105	0.107	0.109	0.116	0.117	0.118
Roundwood	struct. Gravity	0.142	0.142	0.144	0.141	0.142	0.144
Roundwood	trad. Gravity	0.168	0.168	0.170	0.166	0.168	0.169
Sawnwood	FFNN	0.086	0.090	0.093	0.097	0.100	0.102
Sawnwood	struct. Gravity	0.126	0.126	0.127	0.125	0.126	0.128
Sawnwood	trad. Gravity	0.154	0.155	0.155	0.154	0.155	0.156
Wood-based P.	FFNN	0.097	0.100	0.102	0.107	0.108	0.110
Wood-based P.	struct. Gravity	0.130	0.130	0.131	0.129	0.130	0.132
Wood-based P.	trad. Gravity	0.148	0.148	0.149	0.147	0.148	0.150
Paper and Pb.	FFNN	0.087	0.088	0.090	0.094	0.096	0.098
Paper and Pb.	struct. Gravity	0.125	0.125	0.125	0.124	0.125	0.127
Paper and Pb.	trad. Gravity	0.155	0.155	0.155	0.154	0.155	0.156

where lower RMSE indicates higher prediction accuracy. Consistent with the results obtained from the analysis of the R^2, the Gravity models exhibit lower accuracy, resulting in larger RMSE values compared to the FFNN predictions. Product-specific RMSE values are highest for Roundwood, with a mean of 0.117 for the FFNN, a mean of 0.142 for the structural Gravity model, and a mean of 0.168 for the traditional Gravity model. The lowest RMSE values are observed for Paper and Paperboard, with a mean of 0.096 for the FFNN, a mean of 0.125 for the structural Gravity model, and a mean of 0.155 for the traditional Gravity model.

3.2. Forecast of trade flows based on temporal windows

In the following, we assess the accuracy of different models in forecasting future trade flows. The forecasts are generated using the methodology outlined in Section 2.4.

The temporal training windows (w1 to w17) are designed to capture the influence of past data on forecasting future trade values (Fig. 4). However, the forecast results from different windows are not directly comparable, as each window is trained on a different volume of data, introducing bias due to varying data sizes. To address this, we split the analysis of future trade forecasts into two steps. First, we assess the impact of varying training data sizes by comparing model performance in predicting a specific number of years ahead across all temporal windows. Specifically, for Fig. 5, we analyze all windows (w1 to w17) for a one-year forecast.

Second, analyzing each temporal window individually is crucial to evaluating model performance across different forecasting periods. Accordingly, we compare the performance of specific windows over varying forecasting horizons (1 to 17 years; see Fig. 6).

For the one-year forecast, it can be expected that the RMSE decreases as the amount of training data increases. This effect is illustrated in Fig. 5, which shows how adding more data to successive training windows impacts the accuracy of each model for one year ahead. For the product groups Roundwood and Sawnwood, all three models (structural and traditional Gravity model and FFNN) exhibit decreasing RMSE values as the input data increases, with the FFNN showing a steeper decline than the Gravity models. However, only the FFNN predictions show decreasing RMSE values with increasing input data for the product groups Wood-based Panels and Paper and Paperboard. In contrast, the RMSE for the Gravity models increases as the input data grows.

To evaluate the forecast accuracy of each model across different forecasting horizons, it is essential to analyze each temporal window individually and examine how the models perform for forecasts into the future. Based on, e.g., only one year of model training using data for the temporal window in 2003 (w1), the RMSE of the FFNN is the highest for the category Roundwood (ranging from 0.137 for the year 2004 to 0.162 in 2020; see Table A1 4 in Appendix). A similar pattern is also observed for the Gravity model, where the highest RMSE values for w1 are similar for the Roundwood product group, ranging from 0.149 in 2003 to 0.159 in 2020 (see Table A1 4).

Notably, there is a gap in RMSE between the FFNN forecasts and those of the structural Gravity model, with FFNN generally yielding lower RMSE values. However, for Roundwood and Sawnwood, this trend reverses as the forecast horizon increases, where the Gravity

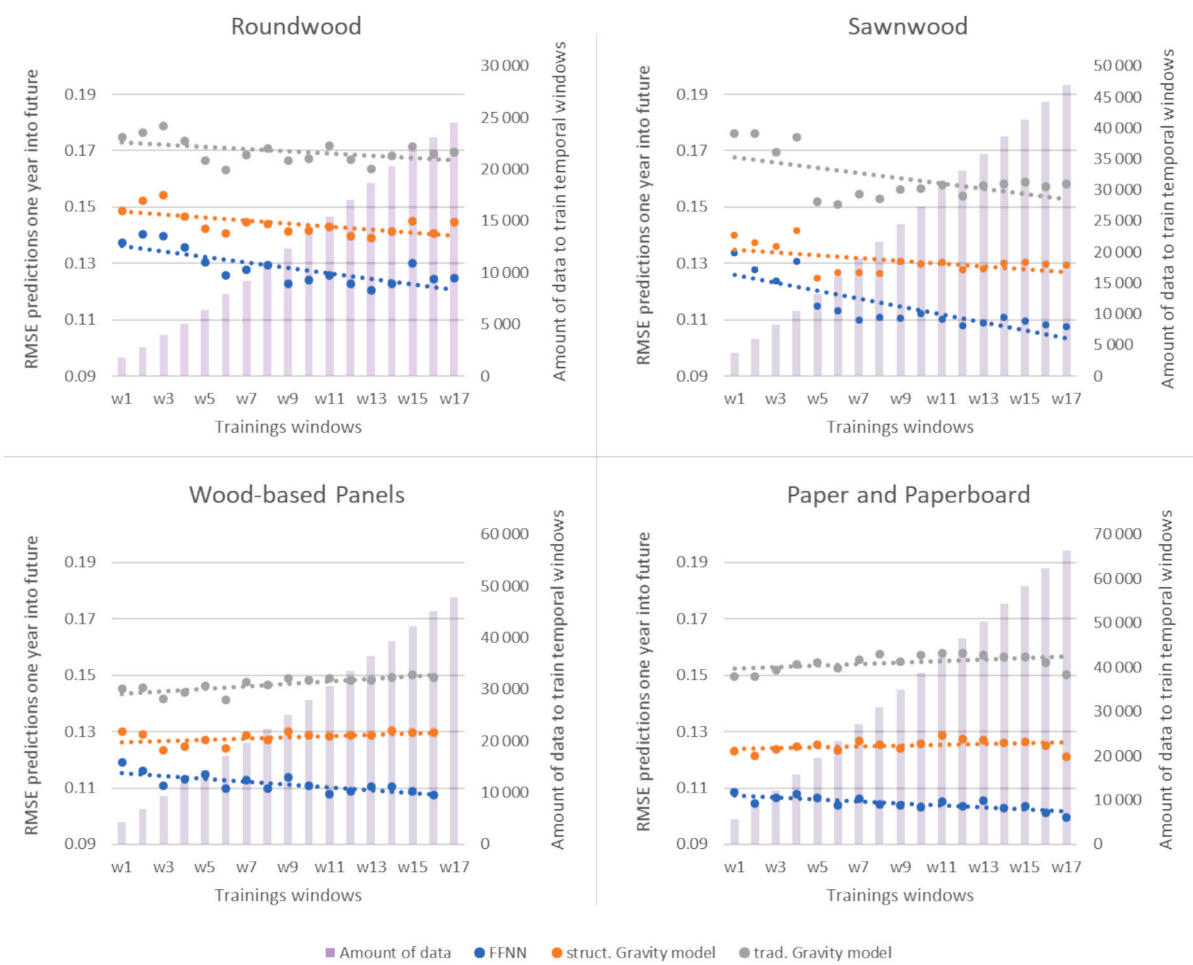

Fig. 5. Development of RMSE values across all training windows for one-year-ahead forecasts. Note: Forecasts with all models made for 2020 in the product group Wood-based panels differ significantly from previous years. To ensure consistent representation, 2020 is excluded from this figure for this product group. The dotted lines are the linear trends across all training windows.

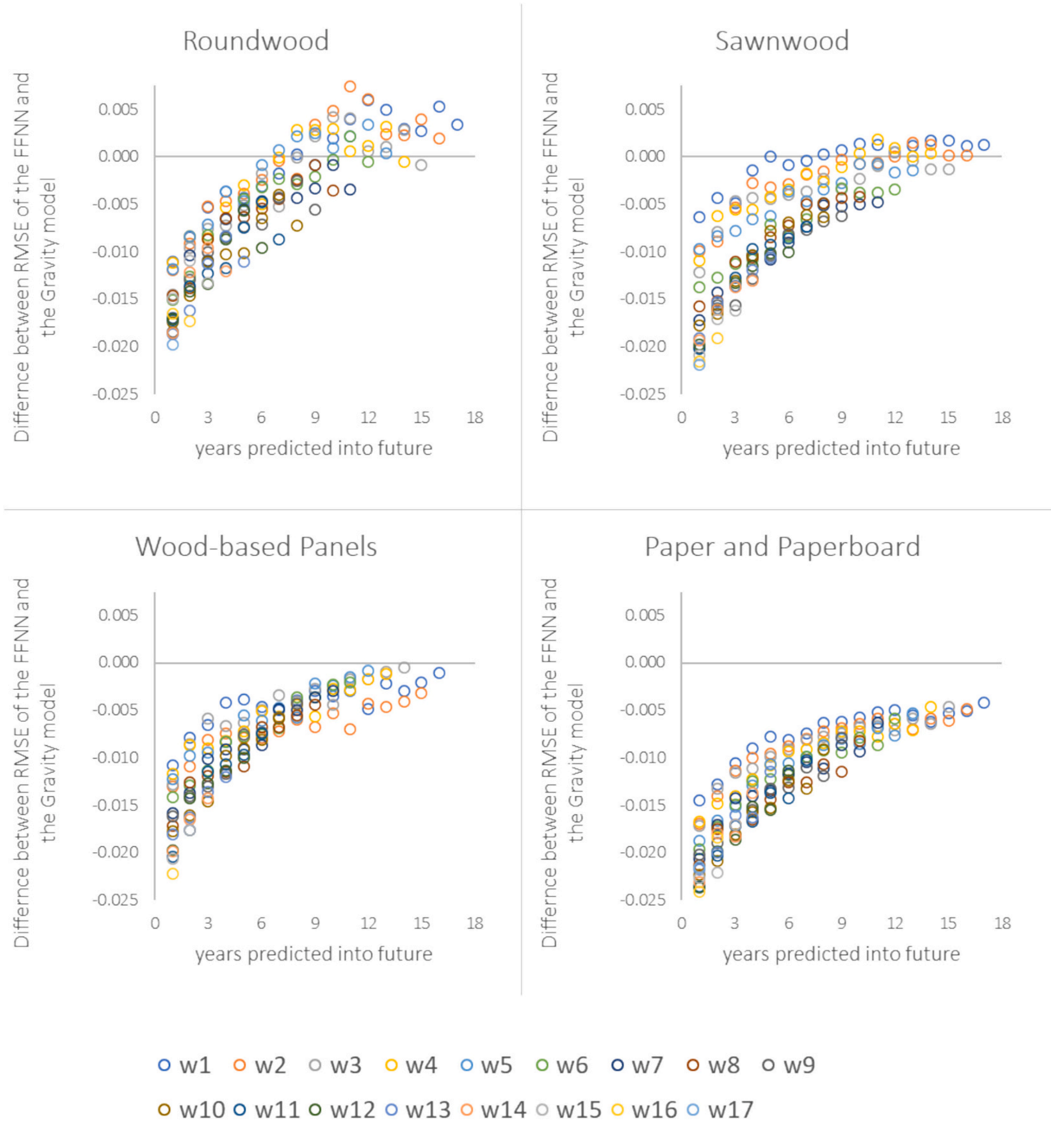

Fig. 6. Difference of the RMSE between FFNN and the structural Gravity model overall training windows for the respective number of years ahead. Note: Negative values depict a smaller RMSE value for the FFNN compared to the RMSE value of the Gravity model. Forecasts with all models made for 2020 in the product group Wood-based panels differ significantly from previous years. To ensure consistent representation, 2020 is excluded from this figure for this product group.

model achieves lower RMSE values than the FFNN (see Fig. 6). Although this does not apply to forecasts for the product groups Paper and Paperboard and Wood-based Panels, it is noteworthy that the gap between FFNN and Gravity model predictions narrows as the forecast horizon extends further into the future (see Fig. 6).

For a more detailed overview of the predictive accuracy across all wood product groups, see Table A1 4 for Roundwood, Table A1 5 for Sawnwood, Table A1 6 for Wood-based Panels, and Table A1 7 for Paper and Paperboard in the Appendix. These tables map the effect of the data quantity N along the main diagonal, while the predictive accuracy across different forecasting horizons is displayed in the horizontal rows.

4. Discussion

4.1. Discussion of results

The predictive performance of different regression-based models against ANN approaches has already been explored for several sectors in the literature, including but not limited to the work of Kaytez et al. (2015), Wohl and Kennedy (2018), Verstyuk and Douglas (2022), Bennedsen et al. (2023) and Ruzicska et al. (2024) with mixed outcomes. While in many applications, ANN can outperform regression-based models, the results of Nummelin and Hänninen (2016) for the trade of Sawnwood contradict this general trend and raise questions about the validity in the timber market as well as for individual wood products. The latter finding also confirms Wohl and Kennedy (2018), who conclude from their work that the analysis model's suitability to predict and forecast bilateral trade should be applied to trade flows of specific goods instead of total trade. Such an approach is important, especially in forest product markets, as this sector spans a wide range of products, from raw materials to finished goods. Thus, analyzing products like Roundwood, Sawnwood, Wood-based panels, and Paper products separately is vital due to their distinct market dynamics and trade limitations. Here, while our model results look similar for the different products at first glance, they reveal some key differences. For instance, models for further processed products consistently yield more accurate predictions, even with varying amounts of input data (see Table A1 4 to Table A1 7), again underscoring the importance of a detailed and differentiated approach.

Overall, the FFNN approach outperforms both Gravity models for predicting past and present trade flows, delivering more accurate predictions across all product categories. These results align with previous studies showing that the FFNN approach outperforms Gravity models, delivering more accurate predictions (Circlaeys et al., 2017; Verstyuk and Douglas, 2022). However, when looking at the accuracy of the forecast, we see in our study that the superiority of FFNNs is present but decreases as the forecast horizon increases. This reminds of the results of Wohl and Kennedy (2018), who found that the ANN estimations mainly provide reasonable results for forecasts close to observed trade values, and Ruzicska et al. (2024), who state that the marginal superiority of the model is mainly due to their strength in explaining cross-sectional variation instead of time-series changes. This would explain why the FFNN's superiority diminishes with increasing time horizon. For Roundwood and Sawnwood, the structural Gravity model outperforms the FFNN in predictive accuracy over time. The findings for Roundwood and Sawnwood align with those of Nummelin and Hänninen (2016), who found that ANNs perform worse than regression-based models in forecasting bilateral Sawnwood trade flows. Although our results indicate that FFNNs exhibited greater overfitting for these products, which may help explain why structural Gravity models outperformed them, we also observed that the RMSE gap between FFNNs and the Gravity model narrowed significantly across all products as the forecast horizon extended.

To align these results to the objectives of this study, we found that FFNN and Gravity models have strengths in different application areas: the FFNN approach may be better suited for tasks like database validation, while Gravity models could be more effective as a validation tool for other economic modeling approaches, such as equilibrium-based projections and policy impact analysis, by benchmarking their simulation results.

4.2. Discussion of methodology

The approach used in this study has several limitations. First, we employed a grid search to identify the optimal hyperparameter configuration. We recognize that the selected grid may not be exhaustive, and expanding it—such as incorporating alternative activation functions like leaky ReLU—could lead to alternative setups that might yield better results.

Second, we manually tested various layer architectures and ANN approaches, concluding that an FFNN with a uniform layer structure was most effective for this study's objectives. Nonetheless, alternative architectures, such as LSTMs, RNNs, or a narrowing layer structure, might also be able to provide accurate predictions for trade values in forest product markets.

Third, incorporating additional categorical variables into the Gravity model could improve prediction accuracy, such as whether two countries share a common border (Anderson and van Wincoop, 2003) or a common language (Melitz, 2008). Including two-way country fixed effects, in particular, might significantly enhance the model's performance. However, such variables would introduce product-specific influences, requiring different model configurations for each product group. While it is feasible to apply this approach down to individual 6-digit HS codes for forest product markets, this study focuses on validating bilateral trade data and the outcomes of complex models. We prioritized providing a broader market overview to achieve this objective, ensuring that results across different product groups remain comparable through a consistent input layer rather than pursuing highly detailed, product-specific analyses.

Fourth, the results presented in this study are heavily influenced by the data quality. Any inconsistency within the data could affect and alter the outcomes. Additionally, the dataset covers a limited time horizon from 2003 to 2020, restricting the comparison between FFNN and the Gravity model to forecasts extending only up to 17 years into the future. While using databases with a longer time horizon, such as UN Comtrade, could enable comparisons over a greater forecast period, such datasets may also lack harmonization and include more data errors, significantly impacting the models' prediction accuracy.

Finally, while FFNNs process input data and identify patterns, interpreting their exact weights remains challenging. As a result, this study's comparison of Gravity models and FFNNs is limited to the accuracy of the predictions and the predicted values themselves.

Future research may analyze how the predictive accuracy of the models is affected by the quality of the input data. The main advantage of CEPII data used for this study is that the dataset is already adjusted for inconsistencies and errors present in the UN Comtrade database, thus providing an analysis-ready version of international trade data for research and improving the data quality for economic analysis. However, using other datasets for this type of research would be interesting to see if and how results are affected. Alternative databases for the proposed experiment could be, for example, the GTAP database, ITC Trade Map, Eurostat, or OECD ITBOP for regional analysis. However, the suitability of these sources needs to be further examined. This project goes beyond the scope of the present work. Another extension of the present work would be a combination of both methods (Gravity approach and FFNN) to identify uncertainties in predictions of existing trade data with FFNN and projections for future trade with the Gravity model. Integrating both techniques in this way, e.g., FFNN to address existing data gaps and Gravity models to predict future data, could be a promising approach.

5. Conclusion

More accurate predictions and forecasts of trade flows and their influencing factors are crucial for policymakers and stakeholders to improve trade-related policies and support economic planning. In this study, we employ two distinct modeling approaches for predicting bilateral trade flows. First, we utilize a well-established and robust deterministic Gravity model of trade, and second, we employ a feed-forward neuronal network (FFNN), a more recent approach that is gaining prominence. The objective of this study was to assess which of the two approaches performs better in terms of the accuracy of the modeling results. Thereby, we distinguish between predictions of bilateral trade flows for replicating past trade data and the simulation of future trade data and compare them with observed values (reported trade data from the database). Both methods are applied using the same dataset. We predict bilateral trade flows for four categories of wood products (Roundwood, Sawnwood, Wood-based panels, and Paper and Paperboard).

Our findings highlight no "one-size-fits-all" approach to trade flow analysis. Instead, it is essential to consider the purpose of the analysis alongside the specific product group under investigation. For instance, our results suggest that FFNNs can effectively analyze present trade flows within the wood product market. These models might enhance existing datasets by filling data gaps and identifying inconsistencies, thereby enabling more accurate analyses and better-informed decision-making.

However, a notable limitation of ANNs is their lack of interpretability, particularly regarding their parameters and underlying weights. This contrasts with regression-based models, where coefficients can be interpreted as elasticities, reflecting the influence of parameters on the target variable (Hill et al., 1994; Wohl and Kennedy, 2018). Our findings further indicate that regression-based Gravity models can partially close the prediction accuracy gap with FFNNs as the forecast horizon increases. Therefore, we recommend using Gravity models, with their robust theoretical foundation and interpretability, especially for forecasting future trade flows where understanding the relationships between dependent and independent variables is critical. The theoretical foundation offers a transparent framework for analyzing causal relationships. It is an excellent validation tool for other economic modeling approaches, such as equilibrium-based projections and policy impact analyses. It enables benchmarking simulation results, facilitates the derivation of policy-relevant insights, and ensures clarity in complex policy environments.

Authors statement

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Christian Morland: Writing – review & editing, Writing – original draft, Software, Methodology, Data curation, Conceptualization. **Julia Tandetzki:** Writing – review & editing, Methodology, Conceptualization. **Franziska Schier:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
HS02 codes for the used product groups.

Commodity	HS02 Codes
Roundwood	440110,440320,440391,440392,440341,440349,40399,440320,440391,440392, 440341,440349, 440399,440341,440349,440399
Sawnwood	440710,440791,440792,440724,440725,440726,440729,440799
Wood-based panels	440810,440831,440839,440890,441219,441292,441293,441299,441031,441032, 441033,441039,441090,441021,41029,441111,441119,441121,441129,441131, 441139, 441191,441199
Paper and Paperboard	480100,480261,480262,480269,480261,480262,480269,480210,480220,480230, 480254,480255,480256,480257,480258,480910,480920,481013,481014,481019, 481022,480300,480411,480419,480511,480512,480519,480524,480525,480591, 480592,480442,480449,480451,480452,480459,480591,480592,480593,481032, 481039,481092,481151,481159,480421,480429,480431,480439,480530,480610, 480620,480640,480810,480820,480830,480890,481031,481099,480592,480593, 480240,480431,480439,480441,480540,480550,480593,480630,480990,481029, 481099,481110,481141,481149,481160,481190,481200,481310, 481320,481390

Table A2
Information about the underlying input data from 2003 to 2020. 1Distance between capitals.

Commodity	Variable	Maximum	Mean	Unit	Source
–	Distcap[1]	19.9	3.8	in 1000 km	CEPII
–	Forest Rents	34.2	0.7	in % of GDP	WDI
–	GDP	19,929.0	274.8	in b USD (2015)	WDI
–	GDP per Capita	112,417.9	11,757.4	in USD (2015)	WDI
–	Population	1411.1	23.0	in m people	WDI
Roundwood	Trade Value	2790.8	0.2	in m USD (2015)	CEPII
Roundwood	Production	467,347.4	11,573.5	in m m^3	FAO
Roundwood	total Import	12,423.1	31.8	in m USD (2015)	FAO
Roundwood	total Export	4681.1	33.3	in m USD (2015)	FAO
Sawnwood	Trade Value	5712.9	0.3	in m USD (2015)	CEPII
Sawnwood	Production	97,019.6	1235.6	in m m^3	FAO
Sawnwood	total Import	11,365.1	80.1	in m USD (2015)	FAO
Sawnwood	total Export	11,056.3	83.7	in m USD (2015)	FAO
Wood-based panels	Trade Value	4926.6	0.3	in m USD (2015)	CEPII
Wood-based panels	Production	172,779.0	864.4	in m m^3	FAO
Wood-based panels	total Import	7974.5	149.3	in m USD (2015)	FAO
Wood-based panels	total Export	7607.2	102.1	in m USD (2015)	FAO
Paper and P.board	Trade Value	10,203.1	0.8	in m USD (2015)	CEPII
Paper and P.board	Production	117,150.0	953.7	in m t	FAO
Paper and P.board	total Import	15,189.9	658.7	in m USD (2015)	FAO
Paper and P.board	total Export	17,215.6	271.6	in m USD (2015)	FAO

Table A3
Parameters used for grid search.

Parameters	Values				
Epochs	50	100	***200***	300	
Hidden layers	1	2	5	***10***	15
Nodes	13	26	39	***52***	65
Activation	sigmoid	***relu***	linear	tanh	
Learning rate	0.01	***0.0001***	0.00001		
Batch size	***32***	64			

Table A4
RMSE of prediction in varying training temporal windows for Roundwood. Accuracy is measured by RMSE (the higher the value, the lower the accuracy). N train is the amount of data used to train each temporal window. This analysis is executed ten times with randomly selected training datasets to ensure that the random selection of training and test data does not affect the results. The table reports the mean RMSE values across these executions.

Model	Training window	N train	2004	2005	2010	2015	2020
FFNN	w1	1789	0.137	0.146	0.156	0.160	0.162
FFNN	w2	2824		0.140	0.152	0.158	0.159
FFNN	w7	9245			0.128	0.136	0.143
FFNN	w12	17,094				0.123	0.136
FFNN	w17	24,574					0.125
Gravity model	w1	1789	0.149	0.154	0.157	0.154	0.159
Gravity model	w2	2824		0.152	0.154	0.151	0.157
Gravity model	w7	9245			0.145	0.141	0.147
Gravity model	w12	17,094				0.140	0.146
Gravity model	w17	24,574					0.145
trad. Gravity model	w1	1789	0.175	0.179	0.181	0.182	0.185
trad. Gravity model	w2	2824		0.176	0.179	0.180	0.183
trad. Gravity model	w7	9245			0.168	0.168	0.171
trad. Gravity model	w12	17,094				0.167	0.170
trad. Gravity model	w17	24,574					0.169

Table A5
RMSE of prediction in varying training temporal windows for Sawnwood. Accuracy is measured by RMSE (the higher the value, the lower the accuracy). N train is the amount of data used to train each temporal window. This analysis is executed ten times with randomly selected training datasets to ensure that the random selection of training and test data does not affect the results. The table reports the mean RMSE values across these executions.

Model	Training window	N train	2004	2005	2010	2015	2020
FFNN	w1	3718	0.134	0.135	0.143	0.148	0.150
FFNN	w2	5974		0.128	0.139	0.145	0.148
FFNN	w7	18,889			0.110	0.121	0.127
FFNN	w12	33,068				0.108	0.120
FFNN	w17	46,985					0.108
Gravity model	w1	3718	0.140	0.139	0.144	0.148	0.149
Gravity model	w2	5974		0.137	0.142	0.146	0.147
Gravity model	w7	18,889			0.127	0.130	0.132
Gravity model	w12	33,068				0.128	0.130
Gravity model	w17	46,985					0.129
trad. Gravity model	w1	3718	0.176	0.178	0.175	0.178	0.183
trad. Gravity model	w2	5974		0.176	0.173	0.176	0.181
trad. Gravity model	w7	18,889			0.155	0.157	0.162
trad. Gravity model	w12	33,068				0.154	0.159
trad. Gravity model	w17	46,985					0.158

Table A6
RMSE of prediction in varying training temporal windows for Wood-based Panels. Accuracy is measured by RMSE (the higher the value, the lower the accuracy). N train is the amount of data used to train each temporal window. This analysis is executed ten times with randomly selected training datasets to ensure that the random selection of training and test data does not affect the results. The table reports the mean RMSE values across these executions.

Model	Training window	N train	2004	2005	2010	2015	2020
FFNN	w1	4366	0.119	0.124	0.129	0.130	0.193
FFNN	w2	6785		0.116	0.124	0.126	0.190
FFNN	w7	19,732			0.113	0.120	0.191
FFNN	w12	33,568				0.109	0.189
FFNN	w17	47,925					0.187
Gravity model	w1	4366	0.130	0.131	0.134	0.135	0.183

(*continued on next page*)

Table A6 (*continued*)

Model	Training window	N train	2004	2005	2010	2015	2020
Gravity model	w2	6785		0.129	0.132	0.133	0.180
Gravity model	w7	19,732			0.129	0.129	0.176
Gravity model	w12	33,568				0.129	0.176
Gravity model	w17	47,925					0.175
trad. Gravity model	w1	4366	0.145	0.148	0.153	0.155	0.191
trad. Gravity model	w2	6785		0.146	0.151	0.152	0.188
trad. Gravity model	w7	19,732			0.148	0.149	0.185
trad. Gravity model	w12	33,568				0.148	0.185
trad. Gravity model	w17	47,925					0.185

Table A7
RMSE of prediction in varying training temporal windows for the category Paper and Paperboard. Accuracy is measured by RMSE (the higher the value, the lower the accuracy). N train is the amount of data used to train each temporal window. This analysis is executed ten times with randomly selected training datasets to ensure that the random selection of training and test data does not affect the results. The table reports the mean RMSE values across these executions.

Model	Training window	N train	2004	2005	2010	2015	2020
FFNN	w1	5636	0.109	0.109	0.121	0.123	0.118
FFNN	w2	8916		0.104	0.119	0.122	0.117
FFNN	w7	27,172			0.106	0.116	0.115
FFNN	w12	46,509				0.104	0.110
FFNN	w17	66,412					0.100
Gravity model	w1	5636	0.123	0.122	0.128	0.128	0.122
Gravity model	w2	8916		0.121	0.127	0.128	0.122
Gravity model	w7	27,172			0.127	0.128	0.121
Gravity model	w12	46,509				0.127	0.121
Gravity model	w17	66,412					0.121
trad. Gravity model	w1	5636	0.150	0.150	0.156	0.159	0.151
trad. Gravity model	w2	8916		0.150	0.156	0.159	0.151
trad. Gravity model	w7	27,172			0.156	0.158	0.150
trad. Gravity model	w12	46,509				0.158	0.150
trad. Gravity model	w17	66,412					0.150

Data availability

Data will be made available on request.

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