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REVIEW ARTICLE

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Two-stage multilateral trade-based prediction model for freight transport carbon emission of Belt and Road countries along Eurasian Landbridges

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ABSTRACT

Global freight distribution patterns have been affected by trading policies and the pandemic outbreak. The Belt and Road Initiative, trade conflicts, and the COVID-19 pandemic have changed the global logistics flow, shifting cargos from maritime and air transport to railway transport along the countries in the Eurasian Landbridge. Though railway freight emits less carbon than road truck transportation, the increased use of railway freight brings in a higher volume of carbon emissions to cities located along the landbridges. Achieving net zero carbon emission is becoming more important, but there is a lack of literature in assessing the environmental impact of cross-border railway logistics transportation among Belt and Road countries. A novel two-stage multilateral trade-based prediction model is developed, integrating a modified gravity model and nonlinear autoregressive neural network for trade and emission forecasting. The model evaluates railway freight along the landbridge over ten years and forecasts the impact of carbon emissions from trading and logistics along the corridor in the subsequent five years. It further analyses the emissions impact of the proposed Third Eurasian Landbridge and the extended Second Eurasian Landbridge. The findings provide insights for the development of railway freight transport, considering trade and logistics flow, carbon emission mitigation strategies, and sustainability impact between China and other Belt and Road countries. While countries such as India and Kazakhstan were forecast to have significant amounts of carbon emissions in the projected period, the rapid growths in locations with smaller emission amounts such as Kunming and Georgia should draw attention and require continuous monitoring.

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1. Introduction

Despite the effect of the COVID-19 pandemic on global trade, and the US–China trade conflicts that have led to a restructuring of the landscape of trading patterns, the volume of land-based cross-border trade of goods and services is increasing. China and nearby Belt and Road countries remain committed to pursuing greater economic integration (Shahriar, 2019), despite the impact of deglobalisation (in the form of the US–China trade conflicts) and initiatives by countries to reduce their dependence on China during the COVID-19 pandemic and beyond (Park, 2021). The rapid growth of cross-border trade, however, has been accompanied by an increased volume of cargo flow between China and Belt and Road countries that are connected by railways along the Eurasian Landbridge. This has intensified the burden of emissions on China and nearby Belt and Road countries. Emission reduction targets have been set to ensure that the CO_2 emissions per unit of gross domestic product (denoted 'carbon intensity') in China are decreased by more than 65% from 2005 levels by 2030 (Kerry, 2020). Consequently, it is necessary to quantify and forecast the impact of carbon emissions from railway vehicles moving between China and nearby Belt and Road countries, especially their impact on climate change.

1.1. Silk Road railway in Belt and Road Initiative (BRI)

BRI consists of the Silk Road Economic Belt and the Maritime Silk Road, and was initiated by the Chinese President in September 2013 to promote the connectivity of Asian, European and African continents, enhance land and sea transportation networks, and support increased trade and business activities between neighboring countries. It has attracted considerable attention worldwide (Wang et al., 2020), as it is China's largest economic and international development strategy, which aims to enhance China's economic status in Central Asia and China's connectivity with other Asian countries (Cai, 2017). The Silk Road Economic

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Figure 1. Silk Road Economic Belt and the twenty first century Maritime Silk Road.

Belt connects China, Central Asia, Russia and Europe, thereby strengthening links between China and the Persian Gulf and the Mediterranean Sea. The Maritime Silk Road focuses on realizing a direct connection from the Chinese coast to European coasts, *via* the South China Sea, Indian Ocean and South Pacific Ocean (Figure 1). The BRI action plan references the outlook and geographical network expansion outlined in 2015 (Framework, 2015), and aims to reinforce the connectivity between BRI countries provided by the Eurasian Landbridge. The amount of railway freight transported along the landbridges increased by 65% in 2020 compared to that in 2019, despite the global disruption caused by the COVID-19 pandemic (Pomfret, 2021).

Governments associated with the BRI are promoting commercial and infrastructural landbridge-related projects. China has invested considerably in BRI partner countries (e.g. India and Uzbekistan) to develop transport infrastructure, such as highways or railways, to establish a landbridge corridor connecting over 40 Asian and European countries (Baltensperger & Dadush, 2018; Hilmola et al., 2021). Since the establishment of the US$40 billion Silk Road Fund in 2015 (Habova, 2015), various initiatives pertaining to railway development have been commenced, e.g. the China Rail Express (CR Express) (Zhang et al., 2020), Chengdu International Railway Port (Zhang & Liu, 2020) and a Lianyungang railway logistics hub (Audonin et al., 2020). The traffic volume of China–EU–China trains increased dramatically from 46,000 TEU to 546,900 TEU from 2015 to 2020, with an average annual increase of 67% (Pomfret, 2021). Rail freight has less carbon emissions than air freight and maritime transport; for example, the amounts of CO_2 produced during the transport of 12,000 kg of cargo from Chengdu to inland Western Europe by rail, sea and air are 2.8, 3.3 and 54 tonnes, respectively (Daltona et al., 2015; EUCCC, 2020). Rodemann and Templar (2014) highlighted the strategic advantages of choosing rail transport: it has shorter lead times than those of sea transport, and lower costs and higher capacities than those of air transport. The paradigm shift from sea and air transport to rail transport can be attributed to the pandemic, trade promotion *via* the BRI and carbon emission-reduction targets. Traffic volume along the landbridges is expected to continually increase, leading to increases in the impacts of emissions on Belt and Road countries (Mardani et al., 2019).

1.2. Eurasian Landbridges

The Eurasian Landbridge is a rail transport route for moving freight and passengers between Russia, China and Europe. It consists of the Trans-Siberian Railway (also called the Northern East–West Corridor) and the New Eurasian Landbridge that runs through China and Kazakhstan. The Eurasian Landbridge connects economic spaces and links China, Russia, Kazakhstan and Europe; thus, it is considered a critical corridor for China and countries in Europe, Africa, Russia and the Middle East who are in the BRI. The first part of the Eurasian Landbridge, i.e. the Trans-Siberian Railway, is a 13,000 km route from eastern Russia to Rotterdam, and runs across Russia, Kazakhstan, Belarus, Poland, Germany and The Netherlands. Thus, this transcontinental railroad connects Asia and Europe, and has several advantages over sea transportation. First, the Trans-Siberian

Figure 2. Routes of Eurasian landbridges.

Railway reduces the shipping time of goods by more than twofold; for example, container trains take about three weeks to travel from China to Finland while it requires about six weeks transit time by sea transport (Kettunen & Alvstam, 2022). In addition, 90% of the railway route passes through a single country, Russia, which minimizes political risks. Moreover, the railway reduces the need for transhipments. Furthermore, the railway creates job opportunities for people in China and partner countries. Finally, given the increased investment in the transport infrastructure in neighboring countries, China can promote the introduction of domestic products to new markets by exploiting the faster delivery that is achievable *via* the railway compared to sea transport (Chen, 2021; Imomnazar, 2018). Jiang et al. (2018) analyzed the usage and freight-cost structure of the CR Express under BRI and reported that government subsidies to railway express operators decreased the freight cost by more than half. Shao et al. (2018) provided a selection scheme based on the current priorities for the construction of high-speed railway infrastructure.

The Second Eurasian Landbridge, also known as the New Eurasian Landbridge, is a 10,900 km route from Lianyungang in East Asia to Rotterdam in Europe, and thus connects the Pacific and Atlantic oceans. The Second Eurasian Landbridge extends west in China through seven provinces and cities: Jiangsu, Anhui, Henan, Shanxi, Gansu, Qinghai and Xinjiang. Compared with the Trans-Siberian Landbridge, the Second Eurasian Landbridge reduces the transit time to Middle and West Asia by decreasing the distance by 2000 to 3000 km and handling costs by nearly 20% (Neafie, 2022). In 2007, approximately 92% (by weight) of China–EU trade was conducted by maritime transport, and this proportion reached 94% in 2016 (Hillman, 2019). In particular, large amounts of automotive parts and electronic components move into and out of China *via* sea and land transportation. Given these requirements for increased trading, China is planning to build the Third Eurasian Landbridge. Herrero and Xu (2017) noted that the Eurasian Landbridge can serve as a trade corridor between China and Europe to increase trade volumes. Casarini (2015) stated that the cooperation between the People's Bank of China and European central banks under the BRI framework has reduced transaction costs, due to the success of currency-swap agreements and yuan clearing banks. These findings were validated by Vinokurov and Tsukarev (2018), who focused on trade flows, railway tariffs, existing restrictions and the efficiency of individual routes.

The development of the Third Eurasian Landbridge was proposed by the Yunnan government and is aimed at accelerating the overland connection of South China to Rotterdam *via* Turkey, as highlighted in the 'Building Third Eurasian Landbridge—Scholars Strategic Forum' held in Yunnan in 2007. The statement of intent for development was shared at the fifth Pan-Pearl River Delta Regional Cooperation Development Forum in Nanning in 2009. The Third Eurasian Landbridge will start at the coastal port of Shenzhen, run across Kunming to Myanmar, Bangladesh, India, Pakistan, Iran, and Turkey, and terminate at Rotterdam; thus, it will traverse 15,000 km through 20 countries (Maró & Török, 2022). Notably, it offers a shorter route when compared with the original sea route, which involves entering the Indian Ocean from the southeast coast *via* the Strait of Malacca (Engdahl, 2012), by 3,000 to 6,000 km. Although two Eurasian landbridges already link Asia with Europe, the Third Eurasian Landbridge is expected to be the most convenient corridor for conducting trading business in the Pearl River Delta Region.

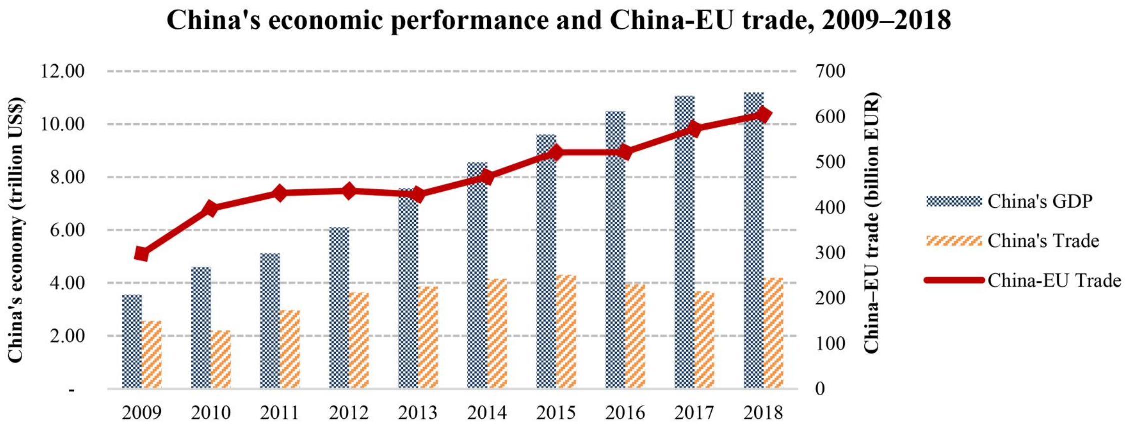

Figure 3. China's economic performance and China–EU trade (2009–2018).

Figure 2 shows the three landbridge routes from Asia to Europe. Smith (2016) highlighted that Chinese manufacturers aim to use these landbridges to increase the reliability and speed of exports (by up to 20 d) relative to those for sea transport and decrease costs by up to 65% relative to that for air transport. The development of a high-speed rail will also help to promote the integration of Eurasian economies and gain time for China's domestic economic restructuring.

1.4. Trade growth along Landbridge and its carbon emissions impact

The Gross domestic product (GDP) of China has doubled over the past decade, with an average growth of 7% in the total trade volume. The total trade in goods between China and Europe has grown continually, from €298 billion in 2009 to €605 billion in 2018 (as shown in Figure 3). Germany exhibited the highest trade balance of goods with China in 2018 (Eurostat, 2019). Increasing trading volumes requires high-speed rail and well-equipped landbridges to transport cargos or containers through several countries. However, several scholars have highlighted a key problem in operating the Belt and Road framework: most trains from Europe to China are subject to empty repositioning and haulage (Smith, 2016). Moreover, carbon emissions from the rapid construction of infrastructure and economic development may harm the environment. Zhang et al. (2019) noted that the total CO_2 emissions generated by electricity increased from 4232.34 Mt to 4402.38 Mt between 2013 and 2015 in BRI nations. Jian et al. (2019) demonstrated that GDP growth related to economic development and potential carbon emissions related to energy consumption are two main factors influencing the level of carbon emissions. The continuous growth of GDP and population in BRI countries may considerably increase carbon emissions, and thus environmental impacts must be considered in the framework of the BRI.

With the increasing logistics and transportation activities along the BRI, the carbon emissions along the trading corridor have come into attention. Many researchers have examined the impacts of emissions from trade (imports and exports) between China and other BRI countries (Wu et al., 2021) and evaluated the factors influencing trade and emissions (Muhammad et al., 2020; Zhu & Gao, 2019). However, no previous studies have systematically analyzed the past trading freight flow of BRI countries in a designated corridor, with reference to key economic factors such as GDP, population and distance. Moreover, previous studies on trade and environment of BRI are mainly focused on historical performance and have less attempt in predicting the future impacts of carbon emissions from the trade flows among the BRI countries through a particular transportation mode (Jing et al., 2020; Kuik et al., 2019). Research on the impact of carbon emissions from railway freight along BRI corridors, in particular the Eurasian Landbridge, on nearby residents and cities is limited. Moreover, only a few studies have used the gravity model to analyze the relationship between trade activities and their environmental impacts (Jing et al., 2020; Kuik et al., 2019; Wang & Firestone, 2010). Most of the previous studies analyzed bilateral trade between BRI countries and ignored multilateral trade between these countries.

Thus, in this paper, a novel two-stage multilateral trade-based prediction model with a multilateral trade-based gravity model and nonlinear autoregressive neural network was developed to analyze the environmental impacts of the trade flow between BRI countries along the Eurasian Landbridge corridor. First, the feasibility of developing gravity models of bilateral trade between major locations along the Eurasian Landbridge was evaluated. By establishing the statistical relationship between freight and trade volumes of the locations, the future impact of carbon emissions from freight railways operating along the Eurasian Landbridge was estimated. It was shown that this analytical framework provides a novel and important approach for assessing the environmental impact associated with the development of transport and logistics between BRI countries along the landbridge corridor. The remainder of this paper is organized as follows. Section 2 presents the literature review on the trading and logistics flow of BRI, carbon emission from BRI countries and trading models. Section 3 explains the two-stage trade-based gravity model with a non-linear autoregressive neural network approach to forecast and analyze the impact of carbon emissions along the Eurasian Landbridge. Sections 4 presents the application of the developed model in analyzing the emission impact of the proposed Third Eurasian

Landbridge. In Section 5, the results on the use of the developed model in analyzing the emission impact of the extended Second Landbridge are discussed. Section 6 presents the conclusion and highlights the contributions of this study and the scope for future research.

2. Literature review

2.1. Emission impact of trade, logistics and transportation in BRI

Several groups of research have studied various aspects of the BRI since it was launched, focusing its impact on trade, the resulting paradigm shift in transportation modes, port and railway development, and its impact on the environment. Saeed et al. (2021), Lee et al. (2018) and Van der Putten and Meijnders (2015) focused on the changes in China's maritime development, such as port networks, infrastructure construction and zoning. These authors highlighted that the BRI provides a corridor between China and other countries that increases trade volumes. Huang (2016) and Shahriar (2019) investigated the economic relationships between China and other countries involved in the BRI, and several other researchers evaluated the impact of trade and logistics between BRI countries on carbon emissions. Wu et al. (2021) and Muhammad et al. (2020) analyzed the impact of trade and logistics between China and BRI countries on carbon emissions. In particular, Wu et al. (2021) analyzed the historical import figures of China, and Muhammad et al. (2020) focused on the effects of exports and imports on CO_2 emissions with reference to various income groups. The influence of trade and logistics between China and BRI countries is increasing, especially in terms of the impacts of carbon emissions from cargo flows between these countries.

The continuous growth in trading between China and BRI countries as well as the increase emphasis on the carbon-emission reduction targets set by several countries have pushed forward more research in analyzing the impact of carbon emissions from trade, logistics and transportation (Lin et al., 2023; Hussain et al., 2020; Li et al., 2015). With railway playing an important role in freight transportation along these countries, their impact to the environment has come to an attention. Li et al. (2019) constructed a multi-logit model for a competitive analysis on the railway transportation in the China Railway Express under the China-Europe Trade. Chen et al. (2020) explored the impact of the modal shift policy of China toward the carbon emissions and focused in evaluating various energy consumption and carbon emissions between the road freight transport and railways in China. Li and Zhang (2020) developed a hybrid optimization algorithm, combining the Non-dominated sorting genetic algorithm III (NSGA-III) and Descent algorithm, to increase the market share of railway freight and reduce carbon emissions. Lin et al. (2021) analyzed the impact of high-speed rail (HSR) on road traffic toward greenhouse gas (GHG) emissions and found that starting new HSR routes in China could reduce 11.183 million tons of CO_2e of GHG emitted from the vehicles in the highway, i.e. 1.33% of GHG emissions in the transport sector of China. Wang et al. (2023) also reviewed the factors of carbon emissions in railway transport based on the logarithmic mean divisia index (LMDI) decomposition method while Chen et al. (2021) assessed the carbon emissions of HSR with a focus on the Beijing-Shanghai corridor. Research on the impact of carbon emissions from railway freight along the Eurasian Landbridge is limited. There are studies adopting gravity models to analyze the relationship between trade activities and their environmental impacts, most of them analyzed bilateral trade between BRI countries without considering multilateral trade among these countries (Abbas & Waheed, 2019; Jing et al., 2020; Kuik et al., 2019). Wu et al. (2020) started to focus on multilateral trade path and network effects emerging from trade relations to formulate a general gravity model considering trade distances.

2.2. Trade interaction and prediction models

Regarding international trading volume prediction, gravity models, computable general equilibrium (CGE) models, and machine learning models are three common methods adopted in different studies. In the research on the trading interaction and networks between two countries, the gravity model has often been adopted to analyze influential factors. The gravity model measures the interactivity between various variables in a system in terms of entropy (Hallefjord & Jörnsten, 1986), and although the gravity model has been widely used for different purposes, it has been primarily used to examine economic relationships, such as the flow of goods between countries, and to realize transportation planning . Isard (1954) and Gatz (1964) first adopted the gravity model to analyze the effect of various factors on trade relationships between countries. Gatz (1964) applied the gravity model to analyze the trade relationship between six countries based on their GDP, population and distance. Zainal Abidin and Haseeb (2018) adopted the gravity model to examine the trade relationship and flow between Malaysia and the Organization of Islamic Cooperation member countries, considering factors such as exports, imports, GDP, direct investment flow and distance. Narayan and Nguyen (2016) applied the model to analyze the bilateral trade flow between Vietnam and 54 trading partners from 1986 to 2010. Dao et al. (2014) conducted similar research by analyzing the determinants of service-trade flow between Vietnam and EU countries. Grosche et al. (2007) used a model in an airline environment to estimate the passenger volume between cities by considering economic and social variables, such as GDP, population, catchment and average travel time. Gamassa and Chen (2017) evaluated the impacts of BRI policy on the development of Port of Abidjan on the Ivory Coast, which showed that population and GDP considerably influenced the trade relationship between China and the Ivory Coast.

CGE models provide another method to simulate the interactions among economic agents in different markets under numerous scenarios such as trade policy changes, shocks and the like. They are frequently used to analyze the effects of trade liberalization or integration on trade volume, welfare, income distribution across countries or regions (Bchir et al., 2002; Minford et al., 1997). These models are based on theoretical frameworks which rely on assumptions such as utility- and profit-maximisation, constant returns to scale, and fixed factor endowments (Bchir et al., 2002; Burfisher, 2021; DeRosa & Gilbert, 2006). In reality, the validity of these assumptions is subject to the fluidity of factors of production across countries or regions. Another critical property that makes CGE method inappropriate for some studies is its data intensive property (DeRosa & Gilbert, 2006). In some countries, for example, along BRI, where the variety of timely and reliable data is an issue, the identification of the relationship between multilateral trade and freight volumes may be difficult.

Machine learning regression models used various algorithms to learn from data and can support trading volume predictions (Batarseh et al., 2020; Gopinath et al., 2021; Jošić & Žmuk, 2022). They are data-driven and use algorithms to identify patterns and relationships in the data. As a result, they are good at capturing nonlinear and complex relationships between trade volume and factors that traditional models may not be able to capture. They can also handle larger and higher-dimensional data sets that may be difficult to process by gravity and CGE models (Gopinath et al., 2021). Nonetheless, this high-dimensional property of regression models may render interpretations difficult, and therefore hinder the understanding of the underlying mechanisms of the causal effects for trade policy changes (Jošić & Žmuk, 2022). Jošić and Žmuk (2022) noticed another limitation of machine learning algorithms in predicting trade flows in a horizon larger than one year. In case of structural changes or shocks such as the US-China trade conflicts and the COVID-19 pandemic, the predictive models derived may become harder for communication with policymakers in pressing time and poorer to derive longer term forecasts. In this respect, nonlinear autoregressive neural network regression models (NARX) can avoid such difficulty in communication. It has been known for its ability to capture nuanced autoregressive historical patterns in the response variable itself, especially when no known independent variables can be included in an obvious way in the regression models (De Giorgi et al., 2021; El Hamidi et al., 2020; Polson & Sokolov, 2019; Rossi & Allenby, 2003; Wang et al., 2021). For these reasons, gravity and NARX models are investigated for predicting multilateral trade volume and railway freight volume, respectively.

The input variables in gravity models are the main explanatory variables of international trade (Gurevich et al., 2018). Before using them for predicting trade volumes, the explanatory variables should be easily available and therefore this kind of approach is feasible in practical terms. In addition, the quality of data is imperative for the success in machine learning models (Nummelin & Hänninen, 2016). Jošić and Žmuk (2022) used GDP exporter, GDP importer variables, distance, and dummy variables, for instance, language, border, landlocked, and World Trade Organization (WTO) membership status, as input variables in the analysis of the international trade of Croatia. Other variables such as tariffs can also be considered (Gopinath et al., 2021). These variables are commonly used in the estimation of gravity models of trade but the decision of what factors to incorporate in fact depends on the availability, accuracy and explanatory ability of the data. For example, if historical variables, such as language, border, and WTO membership status, did not undergo a change during an investigation period, their inclusion in the gravity models cannot add much interpretation value to the prediction models so arrived during the study period. As a result, this paper relies on a list of representative input variables including the GDP and the population of, and the distance between different locations along the landbridges that guarantee good gravity models' prediction performances.

3. Two-stage multilateral trade-based prediction framework with modified gravity model and nonlinear autoregressive neural network

Railway freight volumes and the associated impacts of carbon emissions along the proposed Third Eurasian Landbridge and existing Second Eurasian Landbridge can be forecasted using gravity models of trade and volume regression models of trade and railway freight. Figure 4 illustrates the methodology used to forecast the impact of emissions from rail freight transported on these Eurasian landbridges. A multilateral trade forecasting is conducted through a series of trade correlation analysis, statistical performance review, and bilateral trade gravity model forecasting. The freight volume is further simulated through a regression model, statistical performance and multilateral freight regression model. The results are used for carbon emission impact analysis and determining the Landbridge railway freight carbon emission. Section 3.1 describes the gravity model developed to forecast the bilateral trade along the Third Eurasian Landbridge between three cities in China (Hong Kong (HKG), Shenzhen (SZN) and Kunming (KUM)) and three key countries on the landbridge (India (IND), Turkey (TUK) and The Netherlands (NET)), based on economic data over a 10-year period from 2009 to 2018. Under the assumptions that population, trade volume and distance the most significant factors for the multilateral trade and railway freight volume forecasting during the projection period, the model was also used to forecast the trade volume from 2019 to 2023. Moreover, the impact of carbon emissions from the predicted railway cargo transported between the cities was evaluated, as discussed in Sections 4 and 5.

3.1. Multilateral trade-based gravity model

A gravity model of international trade, which originates from the gravity model used in physics, treats bilateral trade flows between two economies as proportional to the sizes of the two economies and inversely proportional to the distance between them (Mátyás, 1998). The following gravity model proposed by Krugman and Obstfeld (2005) was adopted in this study:

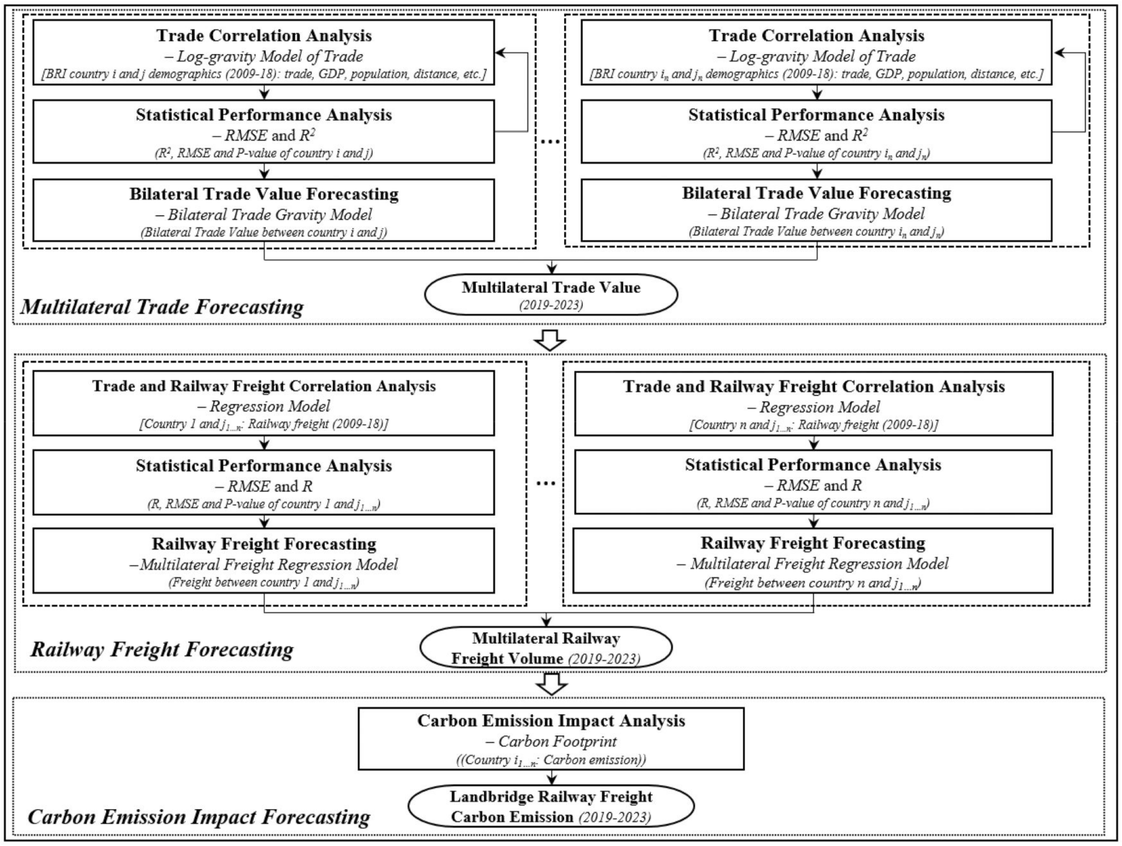

Figure 4. Multilateral trade-based gravity model framework for forecasting the impact of carbon emissions from rail freight transported on Eurasian Landbridges.

$$T_{ij} = A\frac{Y_i Y_j}{D_{ij}^2} \tag{1}$$

where T_{ij} is the bilateral trade between countries i and j; Y_i and Y_j represent the economic size of countries i and j, respectively; and D_{ij} is the distance between the two countries. To describe the trade flow along the proposed Third Eurasian Landbridge, a log-gravity model was developed (Equation (2)):

$$\ln\left(T_{ijt}\right) = \alpha_0 + \alpha_1 \ln\left(Y_{it} \times Y_{jt}\right) + \alpha_2 \ln\left(N_{it} \times N_{jt}\right) + \alpha_3 \ln\left(D_{ijt}\right). \tag{2}$$

i_n	analyzed locations along the proposed Third Eurasian Landbridge: i_1 = Hong Kong (HKG); i_2 = Shenzhen (SZN); i_3 = Kunming (KUM); i_4 = India (IND); i_5 = Turkey (TUK); and i_6 = The Netherlands (NET); analyzed locations along the extended Second Eurasian Landbridge: i_1 = Xinjiang (XIN), i_2 = Kazakhstan (KAZ), i_3 = Azerbaijan (AZE), i_4 = Georgia (GEO), and i_5 = Ukraine (UKR)
j_n	partner locations
t	2009 to 2018

The notations used in Equation (2) is defined as follows: Indices

T_{ijt}	trade flow from origin i to destination j in year t
Y_{it}	economic size of origin i, in terms of GDP, in year t
Y_{jt}	economic size of destination j, in terms of GDP, in year t
N_{it}	population of origin i in year t
N_{jt}	population of destination j in year t
D_{ij}	distance between origin locations i and j

Variables

Data spanning 10 years were collected from government reports and statistics provided by several organizations. As part of the data in some years were expressed in local currency, the values were converted to US$, based on the exchange rate at the end of the given year (31st December).

3.2. NARX-based railway freight regression models

To predict railway freight tonnage, LR and NARX regression models took actual or forecast trade figures from the gravity models developed as inputs. While LR is a basic regression method, NARX is a recurrent dynamic network generalizing simple ANNs (Benrhmach et al., 2020; Lin et al., 1996; Paul & Sinha, 2016; Sun et al., 2019). Its autoregressive property is reflected in the feedback that links some of the network layers. In this paper, the principal equation for the NARX model is nonlinear as follows:

$$F(t) = f\left(F_{i(t-1)}, F_{i(t-2)}, \ldots, F_{i(t-n_F)}, T_{i(t-1)}, T_{i(t-2)}, \ldots, T_{i(t-n_T)}\right) \tag{3}$$

where the predicted freight volume variable F at timestep t is computed based on its previous values delayed by n_F and the previous values of exogenous trade values T delayed by n_T. In this study, two NARX algorithms, namely, Bayesian regularization (BR) and Levenberg–Marquardt (LM) in MATLAB were deployed to train regression models, and the statistically best-performing model of each location was chosen for predictions.

While BR models generalize better as they have a penalty term to control the model complexity while avoiding overfitting (Polson & Sokolov, 2019; Rossi & Allenby, 2003), LM models are usually faster for formulation (Wang et al., 2021).

3.3. Measurement of forecasting errors

The accuracy of a regression model, whether gravity, LR, or NARX must be ensured to guarantee the quality of trade and railway freight forecasts. Three major indicators of regression error—and the coefficient of determination (R^2), the root-mean-square error (RMSE) and the mean absolute percentage error (MAPE)—were calculated and used to minimize the forecasting errors as shown in Equations (2) and (3). R^2 measures the degree to which actual outcomes can be replicated by a regression line, and therefore indicates the amount of variance in an original dataset that can be explained by the corresponding regression model. RMSEs represents the sample standard deviation of the differences between predicted and observed values. The RMSE calculation assigns a higher weight to errors, owing to its square operation, and thus highlights large errors in a regression model. RMSEs therefore enable effective evaluation of forecasting errors during the regression model development. MAPE is another common regression metric which shows the mean of all absolute percentage errors between the predicted and actual values. As a percentage of the actual value, this metric is known for its ease to understand and compare across cases. For instance, in predicting trade values, these indicators are defined as follows:

$$R^2 = \frac{\sum_{i,j=1}^{N}\left(\widehat{\ln T_{ijt}} - \overline{\ln T_{ijt}}\right)^{2^2}}{\sum_{i,j=1}^{N}\left(\ln T_{ijt} - \overline{\ln T_{ijt}}\right)} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i,j=1}^{N}\left(\ln T_{ijt} - \widehat{\ln T_{ijt}}\right)^2}{N}} \tag{5}$$

$$MAPE = \frac{1}{N}\sum_{i,j=1}^{N}\left|\frac{\ln T_{ijt} - \widehat{\ln T_{ijt}}}{\ln T_{ijt}}\right| \tag{6}$$

where N = the number of observations used in a regression model.

3.4. Computation of carbon footprint

After establishing the log-gravity models and regression models between the trade value and railway freight volume, as shown in Figure 4, future trade and railway freight volumes were forecast with the independent variables defined in Equations (2) and (3) as inputs. Subsequent projection of the amount of carbon emissions of a location in a year was realized using Equation (7), based on the activity (AD), emission factor (EF) and global-warming potential (GWP):

$$Total\ Carbon\ Emission = \sum_{x=1}^{n} AD_x \times EF_x \times GWP_x \tag{7}$$

where $x = x^{\text{th}}$ carbon-containing gas-emitting activity related to the combustion of diesel fuel in the engine of a train; and n = total number of carbon-containing gas-emitting activities. In more detail, AD_x, is defined mathematically as Equation (8) with the forecast railway freight tonnage, $F(t)$, as an input. Then the activity was calculated by converting such freight tonnage transportation into the diesel content required per kilometer. This method used was based on Wong et al. (2019), which includes the associated examples for carbon emission calculation.

$$AD_x = \frac{F_i}{Tonnage\ per\ train} \times Diesel\ Content\ per\ train\ per\ kilometre \tag{8}$$

Three global-warming gases CO_2, CH_4, and N_2O in diesel are considered in this paper. Their EF_x and GWP_x parameters were also based on Wong et al. (2019), with the assumption that the emission factors of diesel trains of other Landbridge locations similar to China's parameters. Table 1 below summarizes all data, including their variable notations and data sources, mentioned in Section 3.

4. Trade forecast and emission impact of the proposed Third Eurasian Landbridge

The trade forecast and corresponding carbon emission impact of the proposed Third Eurasian Landbridge were analyzed using the methodology described in Section 3. The GDP and trade of identified locations, shown in Figure 5, were input to the log-gravity model defined in Equation 2. The results of the log-gravity model of trade and trade forecasts of HKG, SZN and KUM in China and IND, TUK and NET along the proposed Third Eurasian Landbridge in 2019–2023 were analyzed. Subsequently, a railway freight volume regression model was established, and freight forecasts were modeled. Finally, the carbon emission forecasts in the same period were evaluated.

4.1. Log-gravity trade model of third Landbridge

To develop log-gravity trade models of the six locations, the populations and GDPs of these locations from 2009 to 2018 and the distances between them were obtained. Although HKG is no longer active in the railway freight business, its trade values were calculated to estimate the trade volumes of the other locations. The trade models derived for each location are summarized in Table 2. For example, the gravity model between HKG and KUM is given by

$$\ln\left(T_{ijt}\right) = 458.691 + 1.866\ln\left(Y_{it} \times Y_{jt}\right) - 16.925\ln\left(N_{it} \times N_{jt}\right) \tag{9}$$

where i = HKG, j = KUM, and the p-values of α_0, α_0, and α_0 are 0.001, 0.000, and 0.001, respectively, correct to 3 decimal places, and are smaller than 0.05 with 95% significance. The dependent variable $\ln\left(D_{ij}\right)$ is not shown as it was dropped during the regression model development. Its presence raised the P-values and made the regression model arrived insignificant.

Table 1. Data, their variables, uses and sources.

Actual/Forecast Data (Unit)	Variable	Data use	Data source	Website
Trade (USD)	T_{ijt}	Multilateral trade gravity model development and prediction	World Bank	https://wits.worldbank.org
			UN Comtrade Database	https://comtradeplus.un.org/data
			China Government	http://data.stats.gov.cn
			UNCTAD	https://unctadstat.unctad.org
			Eurostat	https://ec.europa.eu/eurostat/data/database
Population (people)	N_{it}		World Bank	https://wits.worldbank.org
Distance (km)	D_{ij}		Google Map	https://www.google.com/maps
GDP (USD)	Y_{it}		IMF public data	https://www.imf.org
			Hong Kong Government	https://www.hkeconomy.gov.hk
			China Government	http://data.stats.gov.cn
Freight volume (kilo Ton)	F_{it}	Multilateral freight regression model development and prediction	Eurostat	https://ec.europa.eu/eurostat/data/database
			OECD	https://data.oecd.org/
			Statista	https://www.statista.com
			China Government	http://data.stats.gov.cn
			Hong Kong Government	https://www.hkmpb.gov.hk
			India Government	http://www.indianrailways.gov.in/railwayboard
Carbon emitting activity data (kg/km)	AD_x	Carbon emission calculation of railway freight transportation of a particular type of global-warming gas in diesel	ISO Standard – ISO14064 ResearchGate	https://www.iso.org/standard/66453.html https://www.researchgate.net/figure/Average-fuel-consumption-by-train-type-per-kilometer_fig4_321058362
Emission factor (kg CO_2e/kg)	EF_x		Climate Change Research China	http://www.climatechange.cn/EN/1673-1719/home.shtml
Global warming potential (kgCO_2e per m^2 for a reference period of years)	GWP_x		The IPCC Fourth – Sixth Assessment Reports	https://www.ipcc.ch/assessment-report/ar6/ http://www.ipcc.ch/publications_and_data/ar4/wg1/en/ch2s2-10-2.html#table-2-14

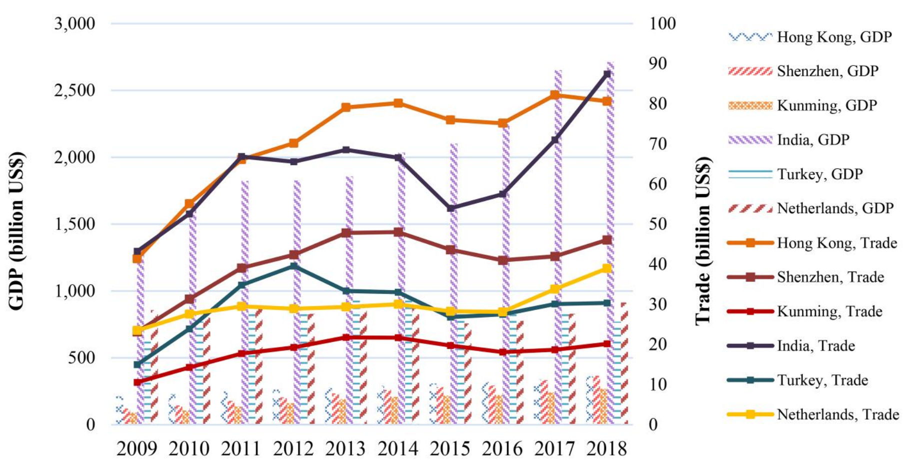

Figure 5. Economic performances of six locations on the proposed third Eurasian Landbridge from 2009 to 2018.

4.2. Error measurement of third Landbridge gravity models and trade forecast

Upon the trade values were estimated, the regression errors were determined to ensure the forecasts were good quality. As mentioned in Section 3.2, R2, RMSE, and MAPE were used to examine the suitability of the log-gravity trade models. The statistical performances of pairs of locations are summarized in Table 3. In general, the average R2 were 0.9, the maximum RMSE values were less than 0.3, and the MAPE is below 1%, which corresponds to an acceptable level of forecast quality. As an example, Figure 6 graphically shows a comparison of the trade forecasts with the actual trade volumes between TUK and NET from 2009 to 2018.

To obtain the 2019–2023 trade forecasts, the GDP and population forecasts were obtained from the International Monetary Fund, and then used in the equations listed in Table 2 to determine the trade volumes between locations i and j. The results are illustrated in Figure 7. IND is projected to have the largest increment in trade volume from 2019 to 2023, and the growths of most other locations will

Table 2. Results of log-gravity models of the proposed third Eurasian Landbridge locations.

	HKG			SZN			KUM			IND			TUK			NET		
	Location	Coefficient	*p*-value	Location	Coefficient	*p*-value	Location	Coefficient	*p*-value	Location	Coefficient	*p*-value	Location	Coefficient	*p*-value	Location	Coefficient	*p*-value
Intercept	TUK			TUK			TUK			TUK			HKG			TUK		
$\ln(Y_{it}*Y_{jt})$		0.389	.000		0.715	.000		0.609	.000								0.656	.002
$\ln(N_{it}*N_{jt})$					−0.500	.005		−0.359	.020		3.307	.001		3.667	.002		1.033	.005
$\ln(D_{ij})$											−12.824	.002		−11.665	.006		−6.254	.002
Intercept	KUM	458.691	.001	HKG	100.682	.000	HKG	459.194	.001	HKG			KUM	61.688	.017	HKG		
$\ln(Y_{it}*Y_{jt})$		1.866	.000		1.143	.000		1.861	.000		2.433	.002		0.811	.000			
$\ln(N_{it}*N_{jt})$		−16.925	.001		−4.274	.001		−16.932	.001		−12.918	.007		−2.494	.014		7.960	.000
$\ln(D_{ij})$											44.420	.008					−25.779	.000
Intercept	IND	191.899	.036	KUM			IND			KUM			IND			KUM		
$\ln(Y_{it}*Y_{jt})$		1.692	.004		0.316	.000		0.398	.000					0.404	.000		0.399	.000
$\ln(N_{it}*N_{jt})$		−7.087	.030								2.947	.003						
$\ln(D_{ij})$											−11.020	.010						
Intercept	NET	−123.128	.000	IND			NET			NET			NET			IND		
$\ln(Y_{it}*Y_{jt})$					0.412	.000		0.404	.000		1.921	.034		0.792	.010			
$\ln(N_{it}*N_{jt})$		4.504	.000								−8.566	.033		1.408	.014		0.600	.000
$\ln(D_{ij})$											27.162	.028		−8.909	.004			
Intercept	SZN	100.306	.001	NET			SZN			SZN			SZN			SZN		
$\ln(Y_{it}*Y_{jt})$		1.156	.000		0.417	.000		0.379	.000					0.321	.005			
$\ln(N_{it}*N_{jt})$		−4.284	.001								1.622	.003		1.225	.006		0.673	.000
$\ln(D_{ij})$											−4.609	.027		−4.288	.019			

Table 3. Results of forecast performance of the log-gravity trade models.

HKG				SZN				KUM				IND				TUK				NET			
Loc.	R^2	RMSE	MAPE	Loc.	R^2	RMSE	MAPE	Loc.	R^2	RMSE	MAPE	Loc.	R^2	RMSE	MAPE	Loc.	R^2	RMSE	MAPE	Loc.	R^2	RMSE	MAPE
TUK	1.000	0.121	0.490%	TUK	1.000	0.062	0.219%	TUK	1.000	0.072	0.288%	TUK	1.000	0.140	0.546%	HKG	1.000	0.087	0.308%	TUK	1.000	0.041	0.145%
KUM	0.903	0.073	0.268%	HKG	0.907	0.072	0.280%	HKG	0.901	0.073	0.269%	HKG	1.000	0.078	0.277%	KUM	0.904	0.064	0.282%	HKG	1.000	0.060	0.241%
IND	0.954	0.053	0.176%	KUM	1.000	0.186	0.942%	IND	1.000	0.100	0.378%	KUM	1.000	0.119	0.434%	IND	1.000	0.275	0.903%	KUM	1.000	0.131	0.484%
NET	0.970	0.026	0.096%	IND	1.000	0.097	0.362%	NET	0.079	0.079	0.263%	NET	1.000	0.162	0.573%	NET	1.000	0.064	0.249%	IND	1.000	0.162	0.638%
SZN	0.899	0.076	0.298%	NET	1.000	0.080	0.247%	SZN	0.130	0.130	0.519%	SZN	1.000	0.126	0.431%	SZN	1.000	0.101	0.406%	SZN	1.000	0.173	0.547%

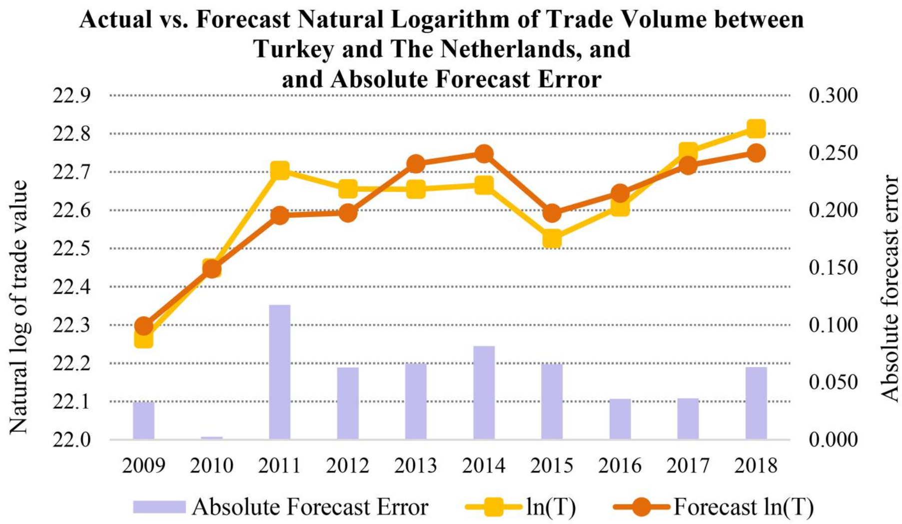

Figure 6. Actual and forecast natural logarithm of trade value (ln(T)) for the proposed third Landbridge.

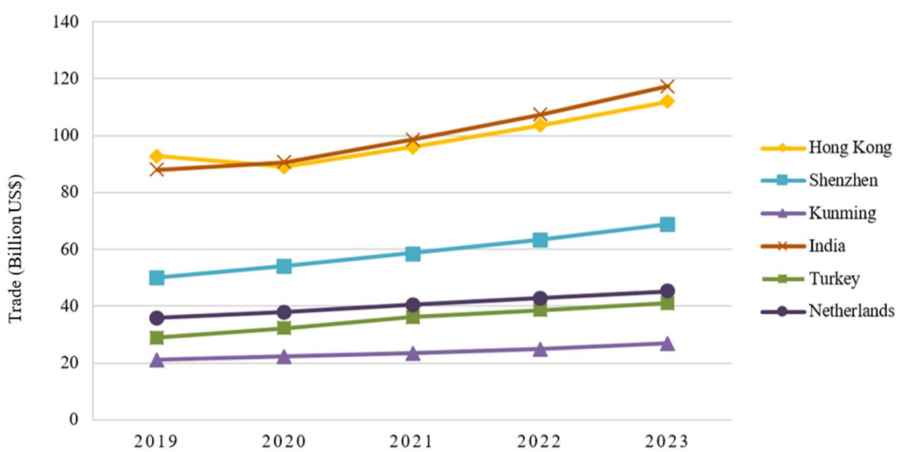

Figure 7. Multilateral trade forecasts of the proposed third Eurasian Landbridge locations from 2019 to 2023.

be steady. The five-year GDP and population forecasts collected from the IMF excludes the disruption factor of the COVID-19 pandemic. Thus, assuming the pandemic posing a negative effect on GDP in general, the trade volumes forecast represent the maximum trade potential among the locations.

4.3. Railway volume and carbon emissions of proposed third Eurasian Landbridge

The trade forecasts obtained as described in Section 4.2 were used as the inputs of linear regression (LR) and NARX regression models derived between the trade and rail-related freight volume of the five locations (excluding HKG). As a result, the railway freight volumes from 2019 to 2023 could be calculated. The R2, RMSE, and MAPE values of these regression models are presented in Table 4. During the research period, the 2019–2022 actual rail volumes of these locations have also become available. Therefore, they were compared with the forecasts from both types of regression methods (see Table 5). Except for Shenzhen, most NARX models provide a lower four-year average forecast % error and their forecast rail freight volumes are therefore used for the subsequent carbon emission projections. In Table 6, all locations exhibit a gradual increase in carbon emission levels owing to increasing railway freight volumes, no matter actual or forecast, on a year-on-year basis. As IND has the highest railway volume, the country is also predicted to have the maximum carbon emissions over these 5 years. A closer look also reveals the rapid growing carbon emission amount in Kunming, with a 3-year average year-on-year percentage change of 5%, which is the highest among all locations.

Table 4. Statistical performances of different third Eurasian Landbridge locations using LR and NARX prediction models.

	LR model training results			NARX model training results		
Location	R^2	RMSE	MAPE	R^2	RMSE	MAPE
Shenzhen	0.5601	0.0620	0.287%	0.9688	0.1897	2.739%
Kunming	0.9999	0.1795	0.863%	0.9386	0.7462	3.648%
India	0.4928	0.1128	0.451%	1.0000	0.0000	0.555%
Turkey	0.4322	0.0934	0.435%	0.9886	0.3691	3.936%
Netherlands	0.6016	0.0738	0.302%	0.8365	0.2553	2.033%

Table 5. Railway actual and forecast volumes and their accuracies of different locations of the proposed third Eurasian Landbridge using LR and NARX prediction models.

Location	Rail Freight Volume (Kilo Ton) and Statistical Performances	2019	2020	2021	2022	2023	4-year Average Forecast % Error
Shenzhen	Actual	102,820	96,490	118,440	117,070	N/A	
	LR Forecast	96,917	100,258	103,801	107,331	111,280	
	LR Forecast % Error	−5.74%	3.91%	−12.36%	−8.32%	N/A	−5.63%
	NARX Forecast	97,777	97,092	92,533	99,469	99,384	
	NARX Forecast % Error	−4.90%	0.62%	−21.87%	−15.03%	N/A	−10.30%
Kunming	Actual	48,860	49,190	53,420	60,090	N/A	
	LR Forecast	57,540	59,645	62,229	64,923	68,932	
	LR Forecast % Error	17.77%	21.26%	16.49%	8.04%	N/A	15.89%
	NARX Forecast	50,995	52,580	53,309	58,144	73,026	
	NARX Forecast % Error	4.37%	6.89%	−0.21%	−3.24%	N/A	1.95%
India	Actual	1,221,390	1,208,410	1,230,940	1,415,870	N/A	
	LR Forecast	1,338,380	1,370,331	1,464,578	1,568,017	1,682,187	
	LR Forecast % Error	9.58%	13.40%	18.98%	10.75%	N/A	13.18%
	NARX Forecast	1,234,368	1,284,097	1,308,536	1,331,234	1,309,825	
	NARX Forecast % Error	1.06%	6.26%	6.30%	−5.98%	N/A	1.91%
Turkey	Actual	33,285	34,374	38,155	38,670	N/A	
	LR Forecast	25,283	26,673	28,145	29,079	30,008	
	LR Forecast % Error	−24.04%	−22.40%	−26.23%	−24.80%	N/A	−24.37%
	NARX Forecast	34,213	34,816	38,750	38,643	39,416	
	NARX Forecast % Error	2.79%	1.28%	1.56%	−0.07%	N/A	1.39%
Netherlands	Actual	42,654	40,017	42,621	44,469	N/A	
	LR Forecast	45,293	47,257	49,839	52,009	54,213	
	LR Forecast % Error	6.19%	18.09%	16.94%	16.96%	N/A	14.54%
	NARX Forecast	42,382	43,293	43,261	43,590	43,252	
	NARX Forecast % Error	−0.64%	8.19%	1.50%	−1.98%	N/A	1.77%

Table 6. Railway carbon emission forecast and year-on-year % change of different regions associated with the proposed third Eurasian Landbridge.

	Shenzhen		Kunming		India		Turkey		Netherlands	
Projected volume (ton CO_2e/km)	Forecast	YoY % change	Forecast	YoY % change	Forecast	YoY % change	Forecast	YoY % change	Forecast	YoY % change
2019	1056	–	556	–	13,279	–	372	–	464	–
2020	1093	3%	573	3%	13,814	4%	378	2%	474	2%
2021	1131	4%	581	1%	14,077	2%	421	11%	473	0%
2022	1170	3%	634	9%	14,321	2%	420	0%	477	1%
2023	1213	4%	796	26%	14,091	−2%	428	2%	473	−1%
2020–2022 Average	1131	3%	596	5%	14,071	3%	406	4%	475	1%

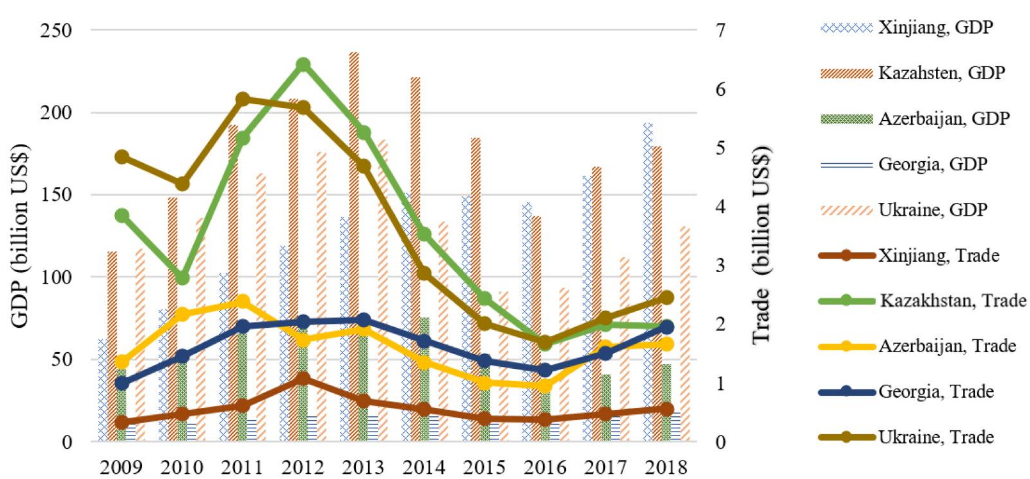

Figure 8. Economic performances of five locations in the proposed Second Eurasian Landbridge from 2009 to 2018.

5. Trade and emission levels of extended Second Eurasian Landbridge

The current Second Eurasian Landbridge will be expanded, as was announced by the Chinese government in its new plan (Lingliang, 2016). New countries such as Kazakhstan (KAZ), Azerbaijan (AZE), Georgia (GEO), and Ukraine (UKR) will become partners in the BRI and linked with Xinjiang (XIN). The economic performances of these countries, such as GDP values and bilateral trade volumes (shown in Figure 8) were used as inputs for the log-gravity model defined in Equation 2.

5.1. Log-gravity trade model of the Second Eurasian Landbridge

The log-gravity trade models of the five locations, populations and GDPs of these locations from 2009 to 2018, and the distances between them, were collected to derive the

Table 7. Results of log-gravity models of the Second Eurasian Landbridge locations.

	XIN			KAZ			AZE			GEO			UKR		
	Location	Coefficient	*p*-value	Location	Coefficient	*p*-value	Location	Coefficient	*p*-value	Location	Coefficient	*p*-value	Location	Coefficient	*p*-value
Intercept	AZE			AZE			GEO			AZE			AZE		
$\ln(Y_{it}*Y_{jt})$		0.328	.000					0.418	.000		0.702	.001		0.406	.000
$\ln(N_{it}*N_{jt})$					−3.873	.045					3.600	.044			
$\ln(D_{ij})$					18.719	.026					−19.177	.031			
Intercept	GEO			XIN			KAZ			XIN			GEO		
$\ln(Y_{it}*Y_{jt})$		0.332	.000		0.927	.000		0.380	.000		1.134	.000		0.627	.000
$\ln(N_{it}*N_{jt})$					−4.953	.000					−1.229	.000		5.395	.003
$\ln(D_{ij})$					18.831	.000								−25.009	.003
Intercept	KAZ			GEO			XIN			KAZ			KAZ	569.938	.000
$\ln(Y_{it}*Y_{jt})$		0.612	.005		1.1400	.0042					0.376	.000		0.613	.009
$\ln(N_{it}*N_{jt})$		−2.702	.014		−1.1939	.0284		3.706	.018					−16.923	.000
$\ln(D_{ij})$		10.766	.011					−13.149	.034						
Intercept	UKR			UKR			UKR			UKR			XIN		
$\ln(Y_{it}*Y_{jt})$		0.369	.000		0.738	.006		0.405	.000		0.413	.000		0.781	.000
$\ln(N_{it}*N_{jt})$					−9.349	.005								−0.616	.000
$\ln(D_{ij})$					37.124	.008									

Table 8. Results of forecast performance of the log-gravity trade models.

XIN				KAZ				AZE				GEO				UKR			
Loc.	R^2	RMSE	MAPE	Loc.	R^2	RMSE	MAPE	Loc.	R^2	RMSE	MAPE	Loc.	R^2	RMSE	MAPE	Loc.	R^2	RMSE	MAPE
AZE	1.000	0.276	1.27%	AZE	1.000	0.331	1.44%	GEO	1.000	0.062	0.27%	AZE	1.000	0.110	0.45%	AZE	1.000	0.419	1.70%
GEO	0.999	0.390	1.88%	XIN	1.000	0.429	1.16%	KAZ	1.000	0.345	1.51%	XIN	1.000	0.119	0.62%	GEO	1.000	0.052	0.22%
KAZ	1.000	0.137	0.58%	GEO	1.000	1.328	3.48%	XIN	1.000	0.285	1.20%	KAZ	0.999	0.443	2.16%	KAZ	0.923	0.178	0.69%
UKR	0.999	0.433	1.37%	UKR	1.000	0.194	0.64%	UKR	1.000	0.443	1.94%	UKR	1.000	0.085	0.33%	XIN	1.000	0.044	0.20%

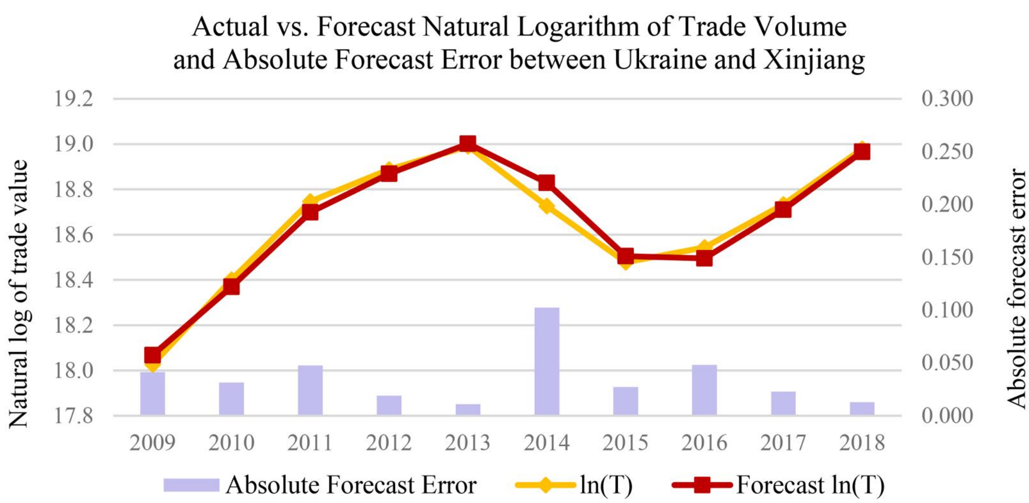

Figure 9. Actual and forecast natural logarithm of trade value (ln(T)) between Ukraine and Xinjiang *via* the Second Eurasian Landbridge.

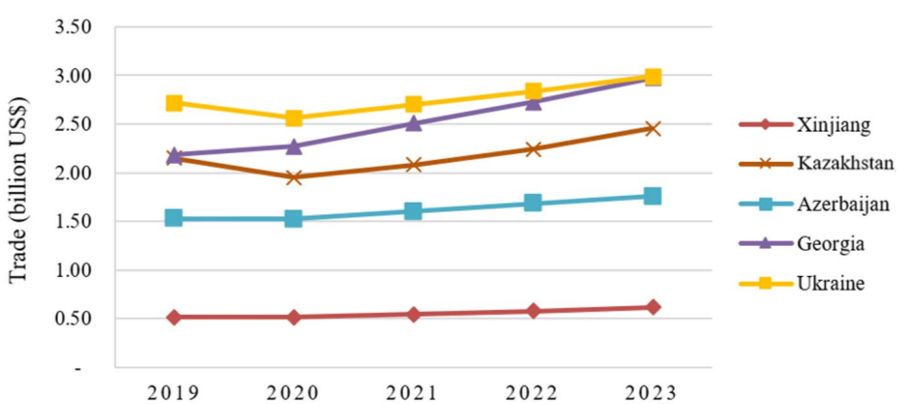

Figure 10. Multilateral trade forecasts of the extended Second Eurasian Landbridge locations from 2019 to 2023.

trade models summarized in Table 7. For instance, the gravity model between XIN and KAZ is given by

$$\ln\left(T_{ijt}\right) = 0.612\ln\left(Y_{it} \times Y_{jt}\right) - 2.702\ln\left(N_{it} \times N_{jt}\right) + 10.766\ln\left(D_{ijt}\right) \quad (10)$$

where I = XIN, j = KAZ, and the p-values of α_0, α_0, and α_0 are 0.005, 0.014, and 0.011, respectively, correct to 3 decimal places, and are smaller than 0.05 with 95% significance, meaning these variables hold a significant relationship with the trade variable. The intercept is not shown as it was dropped during the regression model development. Its presence raised the P-values above 0.05 and made the regression model arrived insignificant.

Table 9. Statistical performances of different extended Second Landbridge locations using LR and NARX prediction models.

	LR Model Training Results			NARX Model Training Results		
Location	R^2	RMSE	MAPE	R^2	RMSE	MAPE
Kazakhstan	0.999	0.592	2.040%	0.944	0.218	5.152%
Georgia	1.000	0.373	1.122%	0.955	0.201	6.533%
Xinjiang	1.000	0.333	1.451%	1.000	0.000	6.423%
Azerbaijan	1.000	0.295	1.173%	1.000	0.000	2.659%
Ukraine	0.749	0.057	0.161%	0.991	0.102	0.727%

5.2. Measurement of errors in Second Landbridge gravity models and trade forecasts

The R^2, RMSE, and MAPE values were calculated to evaluate the suitability of the log-gravity trade models presented in Table 7. The statistical performance values are listed in Table 8. In general, the average R^2 is close to 1, the average RMSE is approximately 0.3, and the maximum MAPE is no larger than 3.5%, which correspond to an acceptable level of forecasting accuracy. As an example, Figure 9 graphically presents the comparison of the trade forecasts with the actual trade volumes between UKR and XIN from 2009 to 2018.

The GDP and population forecasts collected from the International Monetary Fund were used to estimate the trade volume between the five locations from 2019 to 2023, using the equations presented in Table 7. The results are shown in Figure 10. GEO exhibits the most significant increase in its trade projection from 2019 to 2023, and the growths of the AZE and XIN are stable. Similar to the 2019–2023 trade volume forecasts of the Third Eurasian Landbridge, the projections here were based on IMF's GDP projections which excluded in the disruption of the pandemic.

Table 10. Railway actual and forecast volumes and their accuracies of different locations of the extended Second Eurasian Landbridge using LR and NARX prediction models.

Location	Rail Freight Volume (Kilo Ton) and Statistical Performances	2019	2020	2021	2022	2023	2 or 3-year Average Forecast % Error
Kazakhstan	Actual	289,174,000	302,156,100	N/A	N/A	N/A	
	LR Forecast	157,265,801	141,431,514	152,854,864	166,863,225	186,338,941	
	LR Forecast % Error	−45.62%	−53.19%	N/A	N/A	N/A	−49.40%
	NARX Forecast	275,852,705	288,117,765	289,349,519	293,185,733	296,565,297	
	NARX Forecast % Error	−4.61%	−4.65%	N/A	N/A	N/A	−4.63%
Georgia	Actual	2,935,100	2,925,600	3,322,145	N/A	N/A	
	LR Forecast	6,447,353	6,741,035	7,486,852	8,200,922	8,976,844	
	LR Forecast % Error	119.66%	130.42%	125.36%	N/A	N/A	125.15%
	NARX Forecast	3,010,440	3,224,588	3,479,847	3,935,070	4,024,272	
	NARX Forecast % Error	2.57%	10.22%	4.75%	N/A	N/A	5.84%
Xinjiang	Actual	151,330	175,090	191,990	210,680	N/A	
	LR Forecast	73,262	73,493	77,441	81,645	86,581	
	LR Forecast % Error	−51.59%	−58.03%	−59.66%	−61.25%	N/A	−57.63%
	NARX Forecast	167,673	165,168	154,635	138,456	123,527	
	NARX Forecast % Error	10.80%	−5.67%	−19.46%	−34.28%	N/A	−12.15%
Azerbaijan	Actual	5,152,000	4,861,000	5,316,000	N/A	N/A	
	LR Forecast	6,507,448	6,483,405	6,838,697	7,186,152	7,571,041	
	LR Forecast % Error	26.31%	33.38%	28.64%	N/A	N/A	29.44%
	NARX Forecast	4,770,464	5,090,515	4,722,820	5,249,479	5,256,260	
	NARX Forecast % Error	−7.41%	4.72%	−11.16%	N/A	N/A	−4.61%
Ukraine	Actual	181,844,000	175,587,000	N/A	N/A	N/A	
	LR Forecast	198,668,495	196,008,177	198,335,531	200,654,107	203,252,442	
	LR Forecast % Error	9.25%	11.63%	N/A	N/A	N/A	10.44%
	NARX Forecast	191,118,444	196,963,473	198,726,594	202,492,818	204,523,745	
	NARX Forecast % Error	5.10%	12.17%	N/A	N/A	N/A	8.64%

Table 11. Railway carbon emission forecast and year-on-year % change of different regions associated with the extended Second Eurasian Landbridge.

Projected volume (ton CO_2e/km)	Xinjiang		Kazakhstan		Azerbaijan		Georgia		Ukraine	
	Forecast	YoY % change	Forecast	YoY % change	Forecast	YoY % change	Forecast	YoY % change	Forecast	YoY % change
2019	1827	–	3,006,578	–	51,320	–	32,704	–	2,076,230	–
2020	1800	−1%	3,140,257	4%	54,763	7%	35,031	7%	2,139,728	3%
2021	1685	−6%	3,153,683	0%	50,808	−7%	37,804	8%	2,158,882	1%
2022	1509	−10%	3,195,494	1%	56,473	11%	42,749	13%	2,199,797	2%
2023	1346	−11%	3,232,329	1%	56,546	0%	43,718	2%	2,221,860	1%
2020–2022 Average	1665	−6%	3,163,145	2%	54,015	4%	38,528	9%	2,166,136	2%

5.3. Railway volume and carbon emissions associated with the extended Second Eurasian Landbridge

Similar to the Third Eurasian Landbridge, a set of LR and NARX regression models was developed to estimate the railway freight volumes from 2019 to 2023. The R^2, RMSE, and MAPE of these regression models are listed in Table 9. The fluctuations exhibited in railway freight volumes in all locations are largely explained by the variances in their trade volumes as reflected by the high values of R^2. The MAPEs of both LR and NARX models stay within an acceptable level (below 7%). To further compare the two regression approaches, the available actual rail freight volumes of the locations were compared with the forecasts in Table 10. Although all LR models have their P values much lower than 0.05 (95% confidence level) during the training stage, all NARX models show much lower two- or three-year average forecast % errors in predictions and were therefore used in subsequent carbon emission predictions. Figure 10 illustrates that the trade volume forecasts of all locations are growing steadily. However, actual railway freight volumes experienced fluctuations, for instance, in Azerbaijan and Ukraine, from 2019 to 2023, as indicated in Table 10. NARX models demonstrated a much better prediction performance due to its autoregressive property, which is able to capture nuanced perturbations in the dependent variable itself over the training period (El Hamidi et al., 2020; De Giorgi et al., 2021). In the projected carbon footprint along the proposed extension of the Second Landbridge (Table 11), Xinjiang shows relatively low forecast accuracy: while actual railway freight tonnage goes up over the prediction period, its NARX forecast goes down. Kazakhstan and Ukraine are predicted to have the largest amounts of emissions in the five years. Nevertheless, the prolonged period of war between Ukraine and Russia can add great difficulty to the emission forecast for the latter. Overall, most locations along this extended Second Landbridge, except for Xinjiang and Ukraine, can more safely confirm a rising emission trend in these five years. Despite the relative smaller amount of carbon emissions from Georgia, its 2020–2022 average year-on-year growth is high at 9%.

6. Conclusions and suggestions

The development of the BRI, the paradigm shift in transportation modes in the post-pandemic era and carbon emission reduction targets have led to continual growth in the amount of railway freight transported along Eurasian Landbridges. The expected extensive trading between cities and countries, such as HKG, SZN, KUM, IND, TUK, and NET along the proposed Third Eurasian Landbridge, and XIN, KAZ, AZE, GEO and UKR along the extended Second Eurasian Landbridge, are projected to show higher volumes of cargo flow *via* railway systems, especially when the aftermath of the pandemic subsides, and North and Central Asian countries intend to reduce their heavy dependence on road transport by rail and multimodal transports (Escap, 2020). Noteworthy is UKR, which is the only exception with its actual railway freight volumes dropping over 2019–2020. The carbon emissions associated with railway transport that are expected to adversely affect the environment in cities and lead to health concerns for residents should not be overlooked.

However, most previous studies did not focus on the impact of carbon emissions from railway freighting along a BRI corridor, such as the Eurasian Landbridges, on nearby residents and cities. Moreover, there has been little research on the use of gravity models to analyze the relationship between trade activities and their environmental impacts. Most of the previous studies primarily analyzed bilateral trade, rather than multilateral trade, between BRI countries. This paper addresses the knowledge gap regarding the sustainability impact of multilateral trading activities *via* railway transport on the Eurasian Landbridges, a novel two-stage multilateral trade-based prediction model framework was developed to first forecast railway freight based on multilateral trade data with a gravity model, then predict the railway freight volumes along the Eurasian Landbridges with a NARX model. The framework was used to analyze 10 years of demographic data and to conduct a 5-year forecast of the carbon emission impact of trading between BRI countries along the Eurasian Landbridges.

The 5-year trading figures of BRI locations along the proposed Third Eurasian Landbridge forecast through multilateral trade-based gravity models generally exhibit an increasing trend, with IND corresponding to the largest freight volume, followed by HKG, SZN and NET. Moreover, the carbon emissions for a 5-year period in these cities/countries were forecast. For instance, the projected volumes in 2023 for SZN, KUM, IND, TUK, and NET were calculated to be 1,213; 796; 14,091; 428; and 473 ton CO_2e/km, respectively. Despite the relatively small tonnage of carbon emissions of some locations, for instance Kunming, their faster year-on-year growth of 5% in the forecasts should still be monitored closely. Meanwhile, the 10-year trading volume of BRI cities/countries linked by the extended Second Eurasian Landbridge were also reviewed, and a 5-year trading forecast conducted. GEO and KAZ exhibit the second and the third highest trading volume forecasts in 2023, with UKR results being ignored due to the impact of the Russia-Ukraine war. The projected volumes of carbon emissions from railway freight along this landbridge for XIN, KAZ, AZE, and GEO were calculated to be 1,346; 3,232,329; 56,546; and 43,718 ton CO_2e/km, respectively, in 2023. The high year-on-year growth of carbon emissions is also observed in small locations along the second landbridge. For instance, Georgia has the 2020–2022 average high at 9%. This study demonstrates that a carbon emission forecast realized using the novel and structured two-stage model enabled quantitative analysis of the future environmental impacts of railway freight transport along these Eurasian Landbridges. With the use of the IMF's 2019–2023 GDPs which, when issued, had not taken into the possible disruption of COVID-19, future research could be carried out on the simulations of GDP impacts of a pandemic on the trade volumes as well as the railway freight volumes and carbon emissions. Nonetheless, the two-stage multilateral trade-based gravity and NARX model framework and its methodology demonstrated the feasibility of forecasting the carbon footprints of the Eurasian Landbridges associated with their rail freight activities. The results obtained in this way can provide policymakers guidance for the implementation of measures to meet carbon-emission mitigation targets and achieve carbon neutrality.

The carbon emission impacts of increased railway-freight transport along the Eurasian Landbridge must be addressed. Stronger government policy support, better transportation infrastructure, more promotion on the carbon emission mitigation guidelines, and the use of zero-carbon-emission rail vehicles along the landbridge will help enhance trading and business activities, and the living environment in China and other BRI countries. With the increasing freight transport along the landbridge corridor, governments and train manufacturers should explore and implement ways in lowering the adverse impact of railway toward the environment, through the use of renewable energy and technologies, like electric and hydrogen fuel cell. Freight forwarders can also explore methodologies in optimizing the cargo shifts among road, air and railway to reduce the overall transportation emissions. Put more science-based targets in designing and operating railways in achieving net zero emission targets. In this study, the development status of the three Eurasian Landbridges was reviewed, together with recent trends in trading using railway transportation. The impact of rail transportation-generated emissions on countries associated with the landbridge was forecast. Future work can be aimed at incorporating additional factors that influence the trade and logistics flow and considering additional potential countries located along the landbridges. The model also paves the way for further work to assess the sensitivity of carbon emissions in relation to trade flows and freight volumes with respect to policy factors.

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