10 Methods for Evaluating Food-Energy-Water Nexus: Data Envelopment Analysis and Network Equilibrium Model Approaches

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Abstract

Understanding the food, energy, and water nexus (FEW Nexus) and more broadly the environment and socioeconomic impact of the food supply chains has become an important topic on policy-makers' agendas all over the world. Particularly in Brazil, this analysis is of great value because of the country's importance in world food production, and it's expected that Brazil will be among the main players in supplying the additional food demand that will be requested because of the world population expansion. In this chapter, our objective is to present a model and describe modeling frameworks that can be used to measure the FEW Nexus performance in production and transportation, among other systems, and present cases of the utilization of this kind of tool in Brazil. We present a dual-step procedure that combines the Data Envelopment Analysis (DEA) method with the Network Equilibrium Model (NEM). This approach is used to evaluate the cost and energy from transportation and its expansion, at the same time promote food production and productivity growth, considering the occurrence of proper water balance promoted by natural rainfall, for a sustainable agricultural frontier expansion in Brazil under the FEW Nexus context. We also include the mitigation of CO_2emissions in our model.

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10.1 Introduction

Agriculture in the twenty-first century faces multiple challenges (FAO, 2009, 2017). The population is estimated to reach 9.7 billion people in 2050 (United Nations, 2019), while urbanization is expected to increase, accounting for 70 percent of the world population. Simultaneously, the world will still be managing the issue of economic deprivation and malnutrition of significant parts of the population (FAO, 2009). Demand for cereals – for both food and animal feed uses – is projected to reach about 3 billion tonnes by 2050 (European Comission, 2019). These trends mean that food security will continue to be a key driver of sociopolitical priorities at the global, regional, and national levels (European Comission, 2019).

Together, these movements in the world food market imply many challenges, such as increasing total food availability; sustainably improving agricultural productivity; satisfying the increasing diversification of consumers' basket; meeting quality, safety, environment, welfare, and ethical standards; ending hunger and malnutrition; addressing climate change; and keeping food affordable (European Comission, 2019; FAO, 2017).

Some studies analyze how production would respond to these trends and challenges. The pressure on natural resources, such as arable land and water use, will necessarily increase. FAO (2009) and Alexandratos and Bruinsma (2012) point out that the problem is that these natural resources are very unevenly distributed, with an increasing number of countries or regions reaching alarming levels of land and water scarcity (FAO, 2009).

In general, the FAO (2009) remarks that 80 percent of the growth in crop production in developing countries is expected to come from higher yields and increased cropping intensity, with the remainder coming from land expansion. Crop yields would continue to grow but at a.

slower rate than in the past (FAO, 2009). Resource constraints for agricultural production have become relatively more stringent than in the past, while the growth of yields is slowing down (Alexandratos & Bruinsma, 2012).

The expansion in food production will occur mainly in developing countries, especially in sub-Saharan Africa and Latin America (FAO, 2009). Brazil figures as an important world food supplier, being the world leader in the exports of soybeans, beef meat, poultry, sugar, orange juice, and coffee (USDA, 2018; apud Calil et al., 2019).

Soybeans and corn are the main grains produced in Brazil. Their production was about 210 million tonnes in 2019 and is expected to reach 266 million tonnes in 2029. To address this expansion, the cropland area used for soybean and corn production should increase from 23 million ha in 2019 to 34 million ha in the next 10 years (MAPA, 2019).

More resources, such as land, energy, water, and fertilizer, will be requested for increasing food production in Brazil. Moreover, distances between production areas and consumers (urban centers or ports, in the case of exports) have been increasing due to the expansion of the agricultural cropland frontier to more remote areas in the last decades. This expansion is advancing without a good planning for improving the sustainability performance of the supply chains. Providing integrated planning including production land use, transportation, processing, and distribution until the final consumer, aiming at minimizing the use of natural and energy resources, can make the food system more efficient and sustainable.

The best regions for expanding the soybean and corn production in Brazil depend on the availability of suitable cropland area without legally protected natural forests and the occurrence of a good water balance promoted by natural rainfall and will be affected by the configuration of the transportation system. There is an important trade-off that must be considered: there are regions that have good agriculture eco-performance but present higher distances and higher transportation costs and emit higher levels of greenhouse gases (GHG). In view of those characteristics regarding land use and transportation, it is desirable that the planning of the Brazilian grain production expansion goal at balancing this trade-off.

In this chapter, our overall objective is to present modeling frameworks that could be applied to evaluate and improve the FEW Nexus performance of various agriculture systems, including the Brazilian food supply chains.

Based on the modeling results, we intend to present an analysis of the most efficient regions to produce soybeans and corn in Brazil, considering criteria such as rainfall availability, yield, energy consumed, and CO_2 emissions in the transport.

This chapter will present a dual-step procedure using a Data Envelopment Analysis (DEA) and a Network Equilibrium Model (NEM). While DEA classifies suitable regions for a production growing according to their agriculture eco-performance, NEM finds the optimal spatial distribution of the soybean and corn production expected in the future and the optimal interregional transportation flows of cargo between the supply and demand regions.

We show two case studies to illustrate the application of this procedure for planning future corn and soybean production in Brazil.

Our approach can be used to guide strategies aiming at the expansion of the food production. The results obtained with our model reveal an efficient set of policies that can be used to reach the expected future food demand while improving supply chain sustainability. The model formulation avoids that production expansion occurs in areas covered with natural forests, reduces the GHG emission by land use and transportation, minimizes the energy from transportation, and reduces the need of water via supplemental irrigation, benefiting lower and competitive costs.

10.2 Data Envelopment Analysis (DEA) and Network Equilibrium Model (NEM): Some Insights About the Models and Applications

10.2.1 Data Envelopment Analysis (DEA)

According to Lampe and Hilgers (2015) and Chen et al. (2015), usually stochastic frontier analysis (SFA) is applied to the economic field, while usually DEA is applied to the operations research field. And comparing these methods, generally, common SFA models consider one output and multiple inputs and it needs a functional form, while DEA always allows multiple outputs and multiple inputs, besides not requiring a specific functional form.

According to Farrell (1957), one of the types of efficiency is technical efficiency. T echnical efficiency reflects obtaining the maximum outputs with the minimum inputs, i.e., obtaining the optimal efficiency (best weights) for each DMU. Data Envelopment Analysis (DEA) was developed by Charnes et al. (1978) for efficiency analysis based on the concept of technical efficiency from Farrell (1957).

Data Envelopment Analysis (DEA) models are widely applied in various areas for multicriteria efficiency level assessment, comparison, and ranking across decision-making units (DMUs). According to Stewart (1996), DEA is a satisfactory method for grading systems or DMUs' performance, by comparing how efficiently these DMUs convert inputs to outputs. DEA is a non-parametric method, based on mathematical programming, which makes it possible to minimize or maximize functions with or without restrictions.

The main advantage of this method is that it allows measuring the performance of systems with multiple inputs and outputs, without requiring a production function specification nor the prior definition of inputs and outputs weights, making the weighting process less subjective. When compared to other methods, such as econometric models that depend on the estimation and tests of several parameters, the flexibility given by DEA models is often preferable. However, the formulation of DEA models results in a separate linear program for each DMU, and their solution may require large computational capacity when the problem comprehends a large number of DMUs (Raju & Kumar, 2006).

Several studies have used DEA to evaluate performance in agriculture, focusing mainly on the analysis of efficiency, often measured by the total factor productivity (TFP). According to Fare et al. (1994), TFP is an index widely used to measure the economic efficiency of agricultural production. The index embodies the average productivity of all inputs with market value, such as land, labor, and capital (tractors, machinery, fertilizers, livestock, etc.), measured in terms of market value. The main objective of efficiency analysis is to understand whether a production unit is delivering the maximum yield from a given set of inputs (Kalirajan et al., 1996).

DEA method is also applied to measure the eco-efficiency of agri-food supply chains. This type of analysis has become more popular given the increasing concerns about the possible damage to the environment caused by agriculture (Masuda, 2016; DeSimone & Popoff, 2000; Mwambo et al., 2020). The assessment of irrigation efficiency is another popular application of DEA in agriculture and has been studied by Kibirige et al. (2019), Yilmaz et al. (2009), Raju and Kumar (2006), and Rodrigues-Díaz et al. (2004), for example.

There is a lack of studies applying DEA to evaluate FEW Nexus systems. Li et al. (2016) and Zhang and Xu (2019) developed DEA-Malmquist models to compare the Nexus efficiency for Chinese cities or regions. While Ibrahim et al. (2019) evaluated the efficiency of Organization for Economic Co-operation and Development (OECD) countries in terms of land-FEW Nexus at a transnational level. Results showed that the outcome obtained from the land-FEW Nexus efficiency scores is more related to an adequate use of resources than the scores obtained using the minimum land-FEW Nexus resources.

10.2.2 Network Equilibrium Model (NEM)

According to Alves Junior et al. (2021), NEM applications in green and sustainable cargo transportation are increasing, but they are still rare. Since the mid-nineteenth century, the researchers and urban and transportation planners recognized the importance of developing tools for modeling the interaction of land use and transportation, with a special contribution of Carey (1858), who proposed a macroeconomic model to predict people and commodity spatial flows (Nijkamp, 2007).

According to Holguín-Veras et al. (2001), the conditions of the transport supply and costs influence the business and production location decisions. At the same time, there are other aspects influencing the land-use configuration and thus impacting indirectly the transportation system. For this reason, scientific researchers perceived the necessity for developing strategic planning models that take into account the mutual relation between land use and transportation. More recently, other aspects, such as environmental impacts and energy consumption on transportation, are being frequently considered in this kind of modeling.

The freight transportation models have the as main purpose to reproduce the transportation system consciously, including the main components of the system and their interrelationships, and it is desirable they take into account spatial variations of the supply and demand levels, allowing the planners to assess the impacts of policies, infrastructure improvements, and management actions upon the current and future transportation performance (Holguín-Veras et al., 2001).

The modeling of spatial production and transportation models are analytical tools of freight movement patterns and economic interaction over geographic space. The methods and models developed for evaluating these phenomena have been improved since the second half of the nineteenth century in order to support the transportation and land-use planners. The initial foundations of multiregional goods interchange modeling are based on the gravitational force theory consolidating a category named gravity models (Batten & Boyce, 2007). The gravity models are widely applied in the distribution phase of the traditional four-step method used in transportation planning: (i) trip generation, (ii) distribution, (iii) mode split, and (iv) traffic assignment.

Holguín-Veras et al. (2001) based on an extensive review of regional freight models (RFM) classified them into three main families: Input-Output models, Spatial Interaction models, and Origin-Destination synthesis formulations.

The Input-Output (I-O) models are analytical formulations representing the interrelation among economic sectors, based on functions that describe the number of inputs required by a sector to produce a given economic output. The I-O models are derived from the initial concepts proposed by Leontief (1936), and generally, they predict the intersectoral flows of the economic production when the equilibrium between total supply and total demand occurs, considering that the products are homogeneous and assuming the average technology of the production sectors. The single-region I-O model does not allow assessing the commodity or monetary regional flows, as a consequence of its natural structure. However, improved methods like the Multiregional Input-Output Models (MRIO) overcome this limitation. The literature indicates that I-O models can be well applied for interregional freight transportation forecasting. One negative aspect of this method is that it requires a significant amount of data, and the estimation of the different technical coefficients can be difficult.

Spatial Interaction models are a family of models that try to estimate the commodity interregional flows as a function of the interactions among supply and demand regions in space, and this model's category includes gravity, direct demand, and equilibrium models.

In the case of the direct demand models, the transportation flows and the mode split are determined using an econometric model that predict the interregional freight flows based on a set of regions and transportation network aspects, such as population, production, income, travel time, transportation costs, and others (Holguín-Veras et al., 2001).

The equilibrium models are based on "Wardrop's principle," assuming that all cargo shippers are identical, non-cooperative, and rational and that they select the shortest (or lowest cost) route for delivering their cargo. Considering that all shippers select the routes according to this principle, the flows through the transportation network reach an equilibrium. Generally, the equilibrium models are classified into two main categories: the spatial price equilibrium (SPE) model and the network equilibrium model (NEM).

Since the Harvard Model (Kresge & Roberts, 1971) proposed a method for finding the optimal distribution of freight flows from suppliers to consumers that minimize total transportation cost over a simplified transportation network, the world's researchers have developed other equilibrium models that permit a more detailed simulation of logistics operations and transportation network aspects.

As an example of these advances, specialized models are presented in the literature proposing – among others – the use of nonlinear transport cost functions sensitive to economies of scale, a multimodal transportation network with capacity constraints, delay functions reproducing the effect of congestions, and the traffic of empty or specialized vehicles, allowing a more detailed and realistic representation of transportation systems (Branco et al., 2020; Branco et al., 2019; Caixeta-Filho & Macaulay, 1989; Crainic et al., 1990; Crainic & Laporte, 1997; De La Cruz et al., 2010; Friesz et al., 1983; Friesz and Harker, 1983; Gédéon et al., 1993; Guélat et al., 1990; Labys & Yang, 1991).

According to Holguín-Veras et al. (2001), it is expected that a transportation planning tool provides a good estimative of commodity interregional flows and freight traffic, supporting the analysis of the impacts caused by capacity enhancement or new multimodal transport infrastructures upon the freight transportation system as a whole. In view of that, the authors highlight two important aspects of freight transportation models:

- It should take into account the interrelationship between transportation activity and the economy as a whole because the typical use of a regional freight model is on the analyses of how the level of economic activity could impact the transportation demand and vice versa.
- It should simulate the shippers' choice about the different transportation modes, being able to model as real as possible the complex freight transportation systems. So, it could be applied to the analyses of multimodal projects.

10.2.3 Data Envelopment Analysis (DEA) and Network Equilibrium Model (NEM)

The traditional interregional freight models allow finding the optimal spatial distribution of the production and the optimal interregional flows through the multimodal transportation network, resultant of the supply and demand levels in each region, that minimize the total cost. However, it does not consider other important aspects that can affect the production spatial distribution, like the agriculture performance of the production regions. In other words, normally this kind of modeling did not take into account the productivity of the supply regions when choosing the best regions that could increase their production for supplying the expected future demand.

In view of that, over time, transportation models have become progressively fused with models that allow describing and predicting economic production behavior (Batten & Boyce, 2007).

In this context, we used a dual-step procedure for determining the optimal future grain production and its interregional transportation flows into the multimode network. First, we applied a Data Envelopment Analysis (DEA) aiming to classify suitable regions for soybean growing according to their agriculture yield. In the second step, we applied a Network Equilibrium Model (NEM) to find the optimal spatial distribution of the soybean and corn production expected by 2050 and the optimal interregional transportation flows of cargo between the supply and demand regions. The application is detailed in the next sections.

10.3 A Dual-Step Procedure Using Data Envelopment Analysis (DEA) and Network Equilibrium Model (NEM): An Application to Few Nexus Performance Evaluation

The Brazilian freight transportation system is highly dependent on trucks, even for large distance routes. Around 60% of the Brazilian corn and soybean production is transported by road, 30% by rail, and 10% by waterway (BRASIL, 2018). However, the total public investment in freight transport infrastructure fell to 37% between 2010 and 2017, almost freezing the expansion of waterways, railways, and roads in the country (BRASIL & EPL, 2019). During the same period, Brazilian corn and soybean production increased 61% (IBGE, 2020), occupying new cropland located even farther from the main grain exporting ports terminals. Consequently, the eco-efficiency of freight transportation in Brazil weakened, increasing costs, diesel consumption, and GHG emissions. The Brazilian transport sector is responsible for about 35% of the total fossil fuel consumption and for over 48% of the GHG emissions in the country (BRASIL and EPL, 2019).

In 2020, the Brazilian government scheduled the next steps of the railway concession plan, aiming to attract private companies to build and operate the following railway projects: Ferrogrão railway (FG), West-East Integration Railway (FIOL), and Center-West Integration Railway (BRASIL, 2020; VALEC, 2020).

Due to the importance of Brazilian agriculture, especially the production and exports of soybean, the case goals to determine the efficient locations where production should be expanded to reach the estimated oilseed production in 2050. The analysis prioritizes production in suitable areas located in the most efficient producing regions and only allowing the use of pasture areas, without additional deforestation. Therefore, a holistic and integrated perspective is applied, considering the interaction between the transport system and the land use.

The developed model consists of a two-step process, in which we describe the interaction between transportation and land use. Other models that integrate those two variables often consider the association between production location and transport. With that said, the level of transport accessibility affects the decision regarding the production location, and each production location generates different travel demands. As the changes in the transport system can cause long-term effects on the spatial distribution of production and transportation demands, the connection between land use and transport (and vice versa) is a pillar to the transportation modeling (Mackett, 1985).

In this section, we describe the application of a Data Envelopment Analysis (DEA) and Network Equilibrium Model (NEM) models used to evaluate the FEW Nexus performance in various regions and to direct cropland area expansion in Brazil. This model is used to find the best transportation flows, considering the trade-off between environmental and economic gains. In our FEW Nexus approach, we use the average soybean yield and soybean yield risk to represent "food," the average temperature to represent "energy," and the reduction of potential soybean yield due to water deficit to represent "water." In addition to the FEW variables, we include the energy consumed in soybean transportation in a Network Equilibrium Model (NEM).

After applying the DEA model to determine the most appropriate spatial distribution for the current production, we use the Network Equilibrium Model to find the optimal spatial distribution for future production. We considered as total cost the sum of the following individual costs: (i) the loss of productivity due to water deficit in each region, (ii) the cost of corn and soybean production, and (iii) the transportation cost from the producing regions to the exporting ports.

10.3.1 DEA Model Formulation

DEA model was used to determine soybean production efficiency in Brazilian microregions, the decision-making units (DMUs). The method implementation returns efficiency scores for each DMU that are used to represent performance composite indicators. The formulation of a DEA model depends on a set of characteristics, such as the assumptions regarding the returns to scale (variable, VRS; or constant, CRS) or its orientation (output, input, or non-oriented) (Charnes et al., 1978; Banker et al., 1984). The slack-based measure (SBM) model (Tone, 2001) allows DMUs to simultaneously maximize their output and minimize their inputs (Cook et al., 2014). Several studies have used DEA models to solve agricultural and logistic problems (Gómez-Limón et al., 2012; Toma et al., 2017; Melo et al., 2018; Melo et al., 2020). Equations (10.1) through (10.6) represent the slack-based measure (SBM) model developed by Tone (2001), assuming variable returns to scale (VRS):

$$Minimize\,\tau = t - \left(\frac{1}{m}\right)\left(\sum_{i=1}^{m}\frac{S_i^-}{x_{i0}}\right) \quad (10.1)$$

$$t + \left(\frac{1}{n}\right)\left(\sum_{j=1}^{n}\frac{S_j^+}{y_{j0}}\right) = 1 \quad (10.2)$$

$$\sum_{k=1}^{z} {}_{k}x_{ik} + S_i^- - tx_{i0} = 0 \qquad i = 1,2,\ldots,m \quad (10.3)$$

$$\sum_{k=1}^{z} {}_{k}y_{jk} - S_j^+ - ty_{j0} = 0 \qquad j = 1,2,\ldots,n \quad (10.4)$$

$$\sum_{k=1}^{z} {}_{k} - t = 0 \quad (10.5)$$

$${}_{k} \ge 0, S_i^- \ge 0, S_j^+ \ge 0, \text{and}\, t > 0 \quad (10.6)$$

Where τ is the efficiency level, t is the model linearization variable, S_i^- is the slack variable for the i-th input, S_j^+ is the slack variable for the j-th output, Λ_k is the contribution of the k-th DMU to the DMU$_0$ (under analysis), x_{i0} is the amount of i-th input used by DMU$_0$ (under analysis), y_{j0} is the amount of the j-th output produced by DMU$_0$

(under analysis), x_{ik} is the amount of the i-th input used by the k-th DMU, y_{jk} is the amount of the j-th output produced by the k-th DMU, m is the number of inputs used in the model, n is the number of outputs considered in the model, and z is the number of DMUs in our analysis.

The model represented with Eqs. 10.1 through 10.6 is the standard SBM model under VRS assumptions and is formulated considering desirable inputs, simply deemed as inputs, and desirable outputs, simply deemed as outputs. However, according to Liu et al. (2010), in real-world situations, the DMUs also face both undesirable inputs (UI) and undesirable outputs (UO). Since the DMUs aim to minimize inputs and UO as negative factors (Rentizelas et al., 2019; Seiford & Zhu, 2002), we can consider UO as inputs in the model. Moreover, because the DMUs aim to maximize outputs and UI as positive factors (Liu et al., 2015), we can use UI as outputs in the model. In our approach, the reduction of potential yield due to water balance deficit and yield risk is an example of UO, and the average temperature is an example of UI.

We use our model to estimate individual scores for each DMU (region), which correspond to their relative efficiency levels. DMUs with estimated score equal to one ($\tau^* = 1$), the maximum value, are considered efficient. Because more than one DMU can be assigned with the maximum efficient score, we use the double frontier composite indicator (CI) tiebreaking method, suggested by Leta et al. (2005), to avoid ties in the first position of our rank. The CI (Eq. 10.7) is the arithmetic average calculated using the inverted (handling outputs as inputs and vice versa) and the standard efficiency scores. We standardize each score dividing it by the maximum value.

$$t_k^{\text{composite}} = \frac{\left[t_k^{\text{standard}} + \left(1 - t_k^{\text{inverted}}\right)\right]/2}{\max\left\{\left[t_k^{\text{standard}} + \left(1 - t_k^{\text{inverted}}\right)\right]/2\right\}} \quad k = 1, 2, 3, \ldots, z \tag{10.7}$$

Where τ_k^{inverted} is the inverted efficiency score estimated for the k-th DMU and τ_k^{standard} is the standard efficiency score calculated for the k-th DMU.

Based on the efficiency score rank obtained from the DEA model results, the DMUs (regions) were split into three groups: (i) high-performance regions, consisting of the first tertile of the most efficient production regions accordingly to DEA; (ii) regular-performance regions, consisting of the second tertile; and (iii) the low-performance regions, consisting of the last tertile. The estimated cost reflects the reduction of the maximum soybean potential yield due to the water balance deficit for each group of regions. This cost was included in the total cost of the NEM.

10.3.2 Data and Variable Description

Our analysis uses data from all Brazilian microregions (Brazilian Institute of Geography and Statistics – IBGE, 2020) which were considered suitable for soybean production and the expansion areas identified by the territorial intelligence decision-making support system provided by AGROIDEAL (2019). Figure 10.1 summarizes the analyzed microregions and their current soybean production. This approach indicates the available cropland areas, considering the locations that are currently used for pasture and could be used for agricultural production expansion. As all forest areas are out of the scope of the current investigation, the expansion necessary occurs only on pasture areas.

We consider the average soybean yield as a positive performance factor in our model, because this variable shows how efficiently a DMU converts land into soybean production. The standard deviation of yields is calculated to represent yield risk and is considered a negative performance factor. We used the soybean yield data, from 2014 through 2018, for each microregion, from the Brazilian Institute for Geography and Statistics (IBGE, 2020).

The potential reductions in soybean yield due to water balance deficit were obtained from the National Institute of Meteorology (INMET, 2019). The INMET (2019) developed

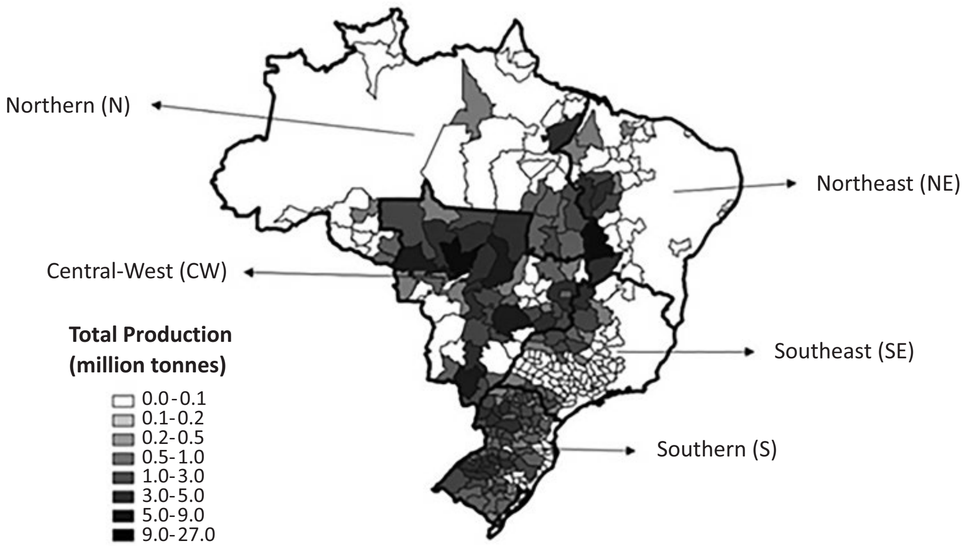

Fig. 10.1 Brazilian regions and current soybean production per microregion

a forecast model that uses weather information from many climate stations to estimate this potential reduction in production. The estimated values obtained from this model were used as negative performance factors. Our assumption is that producers located in areas with higher expected yield reduction will be more likely to use irrigation in their crop. The data set from INMET (2019) covers the period between 2014 and 2018.

According to EMBRAPA (2013), temperatures lower than 20 °C can reduce germination, and temperatures lower than 10 °C may severely stunt the growth of the soybean plant. The ideal temperature for soybean cultivation is around 30 °C. Despite temperatures higher than 40 °C also being harmful to the growth and flowering, the average temperature range of the selected microregions was between 20 °C and 30 °C. Therefore, within this temperature range, there is a positive relationship between temperature and soybean yield, justifying the use of the average temperature as a positive factor of performance in our model. The average temperature within microregions was obtained from (INMET 2019), between 2014 and 2018.

10.3.3 Network Equilibrium Model Formulation

The goals of our NEM model are to:

(i) Find the optimal distribution of corn and soybean production forecast for 2050.
(ii) Use results from (i) to minimize the total cost of a multimodal transport network used to model the transportation flows among producing and demand regions.
(iii) Calculate CO_2 emissions originated from the transportation flows in (ii).
(iv) Measure the possible impact of the inclusion of planned railways in our transport intermodal network, in terms of cost and CO_2 emission reduction.

Our model was built under the assumption that soybean and corn producers choose where to grow their crops, considering the distribution of transportation flows that provides the minimum total cost.

Figure 10.2 summarizes the transportation network and its connection between supply and demand regions, as well as the main variables, used in our model.

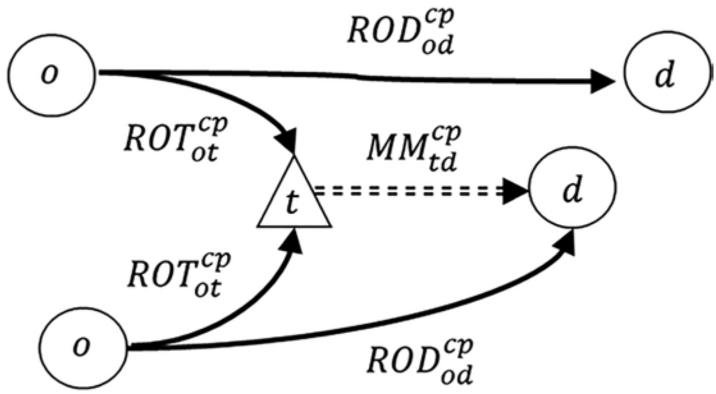

Fig. 10.2 Transportation network and main variables of the model. (Source: Adapted from Branco et al., 2020)

where:

o: Supply regions (origins).

d: Demand regions (destination) – domestic demand region or an export terminal.

c: Demand market, which can be a domestic market (dm) or international market (im).

t: Transshipment terminal, which loads cargo into different transportation modes including rail and inland waterways, but not roadways.

p: Product: soybean (s) or corn (co).

The transportation nodes are connected through network arcs, which represent the available transportation infrastructure, utilized in interregional freight flows between producing and demand regions. We use the following variables to represent interregional flows:

ROD_{od}^{cp} : Road transportation flow of product p between origin o and destination d, in the market c.

ROT_{ot}^{cp} : Road transportation flow of product p between origin o and transshipment point t, in the market c.

MM_{td}^{cp} : Multimodal transportation flow of product p between transshipment point t and destination d, in the market c.

Our goal is to minimize the total supply cost (C) represented in the following objective function (Eq. 10.8):

$$C = \sum_o \sum_d \sum_c \sum_p \mathrm{ROD}_{od}^{cp}.\left(YC_o + PC_o^p + TC_{od}\right)$$

$$+\sum_o \sum_t \sum_c \sum_p \mathrm{ROT}_{ot}^{cp}.\left(YC_o + PC_o^p + TC_{ot}\right) \quad (10.8)$$

$$+ \sum_t \sum_d \sum_c \sum_p MM_{td}^{cp}.TC_{td}$$

where:

C: Total cost ($US\$/tonne$), including the maximum yield reduction cost and production and transportation costs.

TC: Transportation cost (US$/tonne of cargo) between an origin and a destination ($\mathrm{TC}_{\mathrm{od}}$), between an origin and a transshipment terminal ($\mathrm{TC}_{\mathrm{ot}}$), and between a transshipment terminal and a destination ($\mathrm{TC}_{\mathrm{td}}$).

PC_o^p : Production cost (*US$*/tonne of corn and soybean) in each origin o (origins suitable for corn and soybean production) for product p (soybean or corn).

YC_o: Yield cost (*US$/tonne* of soybean) representing the soybean maximum yield reduction of each suitable production region o due to the water balance deficit.

We only consider soybean yields in our analysis because we assume that corn is taken as a secondary crop in most of the country. Our assumption is that corn is mainly used for soil rotation after soybean harvest, planted as the winter crop. Moreover, the soybean crop represents the largest part of farming revenue, while corn revenue is secondary. With that said, we assume that the spatial distribution of the future production regions will be mainly guided by the soybean regional growing performance.

We use Eq. (10.9) to represent the total CO_2 emissions from transportation:

$$CO_2 = \sum_o \sum_d \sum_c \sum_p \mathrm{ROD}_{od}^{cp}.ECO_{2od} + \sum_o \sum_t \sum_c \sum_p \mathrm{ROT}_{ot}^{cp}.ECO_{2ot} + \sum_t \sum_d \sum_c \sum_p MM_{td}^{cp}.ECO_{2td} \quad (10.9)$$

where:

$\mathrm{ECO_2}$: Emissions of CO_2 (tonnes of CO_2/tonne of cargo) by transportation between an origin and a destination ($\mathrm{ECO_{2od}}$), between an origin and a transshipment terminal ($\mathrm{ECO_{2ot}}$), and between a transshipment terminal and a destination ($\mathrm{ECO_{2td}}$).

The variable "$\mathrm{ECO_2}$" represents the CO_2emission from each network link. Emissions were calculated multiplying the amount of CO_2 emission per kilometer and tonne, by the distance between the nodes of the network.

Equation (10.10) represents a set of constraints regarding the total amount of soybeans and corn shipped to supply domestic demand and exports. The total amount of shipped oilseed and grains must be lower than or equal to the total production (PRO_o^p) of each product p and origin region o plus their respective future production. Future production is obtained multiplying the size (in hectares) of the future area (FA_o) used for corn and soybean production expansion, in each origin o, by the respective expected yield $\left(\mathrm{YL}_o^p\right)$ for each product p in the origin o (tonnes/hectare).

$$\sum_d \sum_c \mathrm{ROD}_{od}^{cp} + \sum_t \sum_c \mathrm{ROT}_{ot}^{cp} \le \mathrm{PRO}_o^p + \left(FA_o.\mathrm{YL}_o^p\right), \forall o \text{ and } p \quad (10.10)$$

Equation (10.11) shows that the future production area in each origin o must be lower or equal than the maximum suitable area for corn and soybean production in that same region (SA_o).

$$FA_o \le SA_o, \forall o \quad (10.11)$$

We use Eq. (10.12) to cover the supply of domestic demand ($c = dm$). The following equation states the total amount of products moved to each demand region must be equal to the domestic demand (DEM_d^p) for each product in that region:

$$\sum_o \mathrm{ROD}_{od}^{cp} + \sum_t MM_{td}^{cp} = DEM_d^p, \forall d, p \text{ and } c = dm \quad (10.12)$$

Equation (10.13) is used to determine that the total amount of each commodity transported to each destination node addressed as an exporting terminal ($d \in \{sp\}$) is equal to the international demand ($c = im$):

$$\sum_o \mathrm{ROD}_{od}^{cp} + \sum_t MM_{td}^{cp} = EXP_d^p, \forall d \in \{sp\}, p \text{ and } c = im \quad (10.13)$$

Equation (10.14) determines that the sum of transportation flows arriving in each transshipment terminal t must be equal to the sum of transportation flows that departs from each terminal:

$$\sum_o \mathrm{ROT}_{ot}^{cp} = \sum_d MM_{td}^{cp}, \forall t, c \text{ and } p \quad (10.14)$$

Equation (10.15) is used to add a limitation for the total quantity of cargo assigned to each transshipment terminal t. This total must be equal to or less than the load capacity of each terminal (TCAP_t):

$$\sum_o \sum_c \sum_p \mathrm{ROT}_{ot}^{cp} \le \mathrm{TCAP}_t, \forall t \quad (10.15)$$

10.3.4 Transportation Network and Scenarios

We built the multimodal transportation network and determined the capacity for each node in the model based on information regarding the total amount of soybeans and corn shipped in 2017 (ANTAQ, 2017; ANTT, 2017).

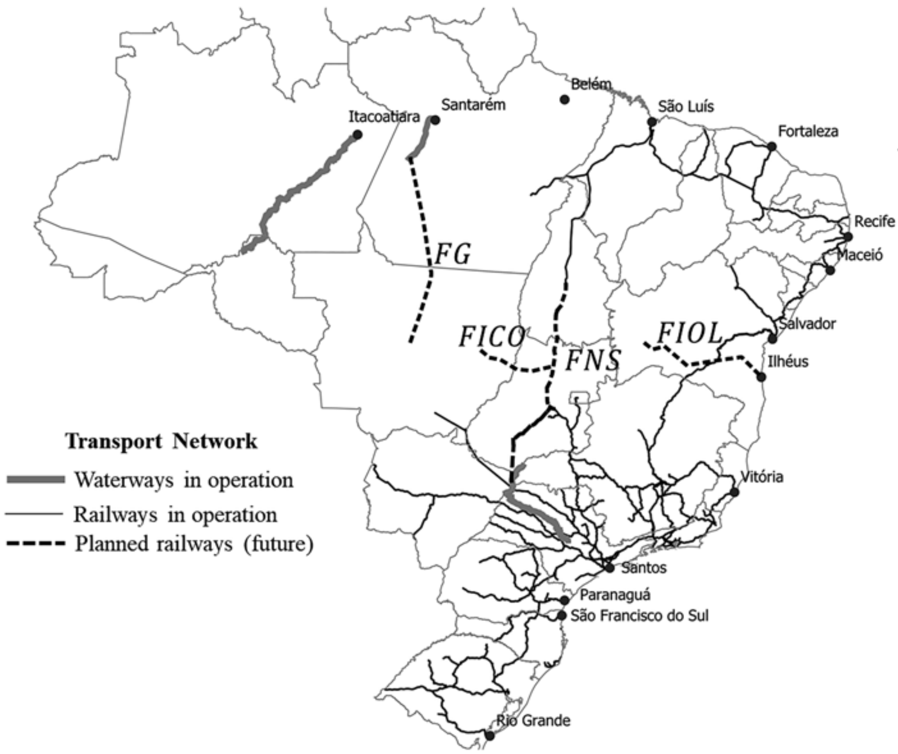

Fig. 10.3 Brazilian current transportation network, planned railways, and export ports. (Source: Elaborated by the authors)

The future scenarios consider the following planned projects: West-East Integration Railway (FIOL), South stretch of North-South railway (FNS), Center-West Integration Railway (FICO), and Ferrogrão railway (FG). We assumed unconstrained capacities. Figure 10.3 shows the current and planned infrastructure (railways, waterways, and ports).

We analyze the following scenarios in our model:

(i) Current production: The objective is to reach the minimum total cost using the current multimodal network – MTC (CP/CMN). The costs are minimized considering the 2018 corn and soybean production.
(ii) Forecasted production: The objective is to reach the minimum total future cost using the current multimodal network – MTC (FP/CMN). The costs in 2050 are minimized costs, using the constraints established in the current multimodal network, i.e., using the current availability for grain transportation and capacities.
(iii) Planned infrastructure and forecasted production: The objective is to reach the minimum total cost with future multimodal network – MTC (FP/FMN). The total cost in 2050 is minimized, considering that transportation will occur in the future multimodal network, including planned railways, and assuming no capacity constraints.
(iv) CO_2 emission minimization: Assuming the Forecasted Production with Future Multimodal Network – MCO_2 (FP/FMN). The total CO_2 emissions in 2050 are minimized, considering that transportation will occur in the future multimodal network, including planned railways, and assuming no capacity constraints.

10.4 Results and Discussion

10.4.1 DEA Approach

The relative efficiency scores for a total of 107 microregions were calculated using Eqs. (10.1) through (10.7). We only considered microregions that are suitable for soybean production in our analysis. Figure 10.4 shows all microregions used in our analysis, which are combined in nine groups of similar efficiency scores, according to the DEA model results. The more efficient the microregion, the darker the color in the map.

The FEW Nexus approach resulted in a spatial distribution with the best-ranked microregions in the central-west and northern regions. After applying the DEA model, we ranked microregions accordingly to their scores and analyzed them, considering three efficiency groups: high (position 1 through 35), average (position 36 through 72), and low position 73 through 107).

According to our results, the microregions (DMUs) in the central-west (CW) and in the north (N) presented relatively high scores. We found that 53.7% (22 out of 41) of the microregions in the CW and 75% (6 out of 8) in the north are classified within the high-efficiency group. Only 12.2% (5 out of 41) of the CW microregions and none in the north are within the low-efficiency group. On the contrary, our results reveal that microregions in the southeast (SE) and northeast (NE) have relatively low scores, with respectively 57.5% (23 out of 40) and 37.4% (6 out of 16) of the microregions within the low-efficiency group. Only 5% (2 out of 40) of the microregions in the SE and 31.3% (5 out of 16) in the NE are within the high-efficiency group. Because all high-efficiency areas in the south (S) were already occupied, we could analyze only two microregions that presented suitable areas to

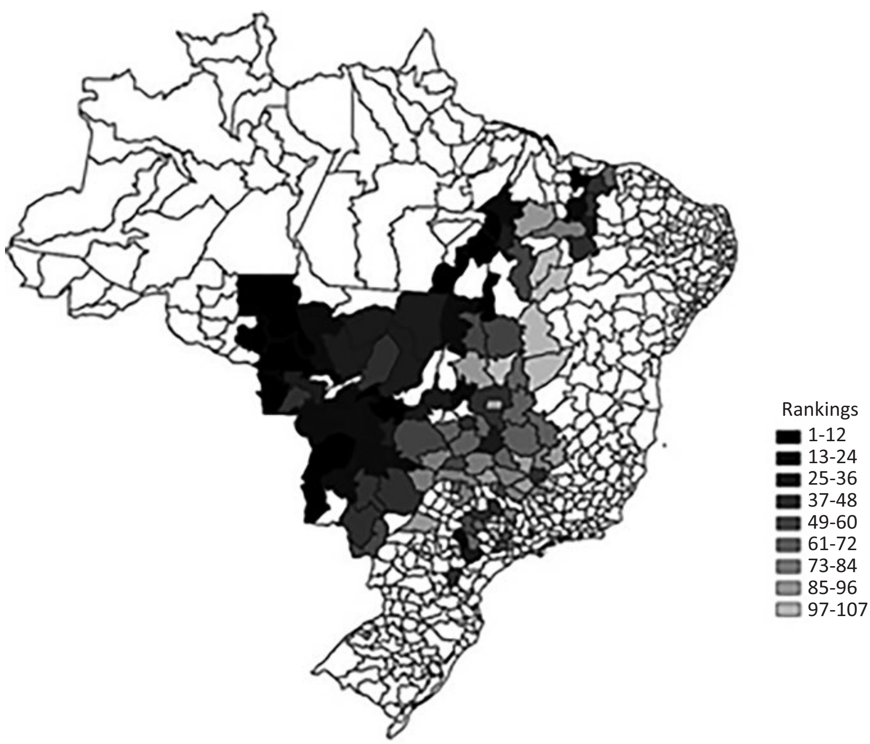

Fig. 10.4 Microregions suitable for soybean growing, classified according to their efficient scores

expand production: one is classified in the average-efficiency group and the other in the low-efficiency group.

We forecasted the future production in 2050 using the estimated efficiency scores to rank the availability of suitable areas for soybean production, in each microregion. We then assigned additional production to suitable areas, starting with the most efficient microregions. For those areas with no suitable land to expand the production, we used the same 2018/2019 production for 2050. We additionally assumed that the production expansion can only occur in released pasture suitable areas (PA). The expected soybean spatial production distribution, in 2050, is shown in Fig. 10.5.

The expansion of soybean production in Brazil (over PA) was calculated based on FAO (2017) and MAPA (2019). Our results indicate that the country can potentially produce a total of 192 million tonnes in 2050 (expanding only over PA). When compared to the 115 million tonnes of soybeans produced in the 2018/2019 crop year (IBGE, 2020), the expected production represents an increase of 67%.

The results in Fig. 10.5 show that deforestation for agriculture production can be avoided since Brazil does not need to use forest areas to achieve the expected production in 2050. Our findings suggest that the exclusive use of pasture areas is sufficient to meet 100% of the production goals. This outcome is achievable if future soybean production occurs only in areas located in the most efficient microregions in the country. This result is in line with previous studies in literature, such as Stabile et al. (2020), that demonstrated that it is possible to increase production (also in the Amazon region) and simultaneously decrease deforestation. The same authors suggested investments in increasing productivity and public policies to avoid deforestation.

According to the results obtained from our DEA models, the 2050 expected soybean production could be reached using part of the areas currently used as pasture and reducing the water balance deficit. With expansion occurring only in pasture areas (PA), our results indicate yield reductions due to water balance deficit in comparison to the current scenario from 35.1% (average between 2014 and 2018) to 31.7% (2050).

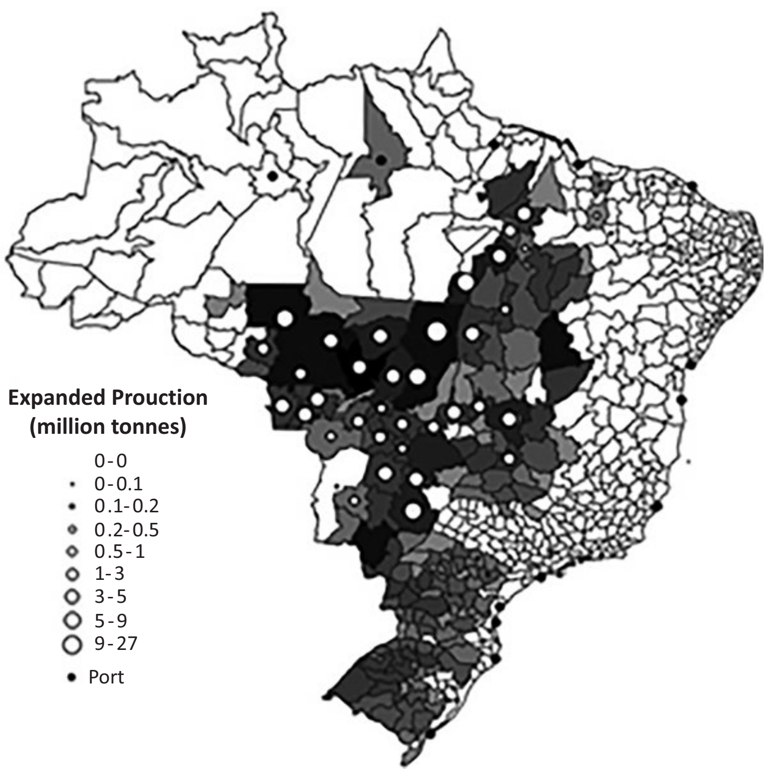

Fig. 10.5 Expected soybean production for 2050, considering the expansion only over PA

In summary, incentives aiming to improve production and transportation efficiency should encourage soybean production in areas with lower water deficit, where irrigation is less necessary, as well as where there are near routes connecting the production areas to export terminals. Since the most efficient regions (considering the number of microregions and the production volume) are located far from the main ports, in the central-west, policymakers are recommended to prioritize infrastructure investments.

Whether future investments, technological evolution, and public policies promote the improvement of crop yields and, at the same time, the increase of soybean production in areas with lower water deficit, it will be possible to reduce even more the projected need of irrigation, improve energy efficiency, and reduce CO_2 emissions transporting corn and soybeans. It is fundamental to highlight that, even for the current scenario, our findings demonstrate that it is possible to achieve a cleaner production for the next 30 years using only pasture area and no deforestation is needed. Moreover, the development of alternative routes to transport grains and oilseeds (including waterways and railroads in green transport corridors), the improvement of road pavement conditions, and the encouragement of cargo fleet renewal will also result in positive environmental and economic impacts.

10.4.2 NEM Approach

Table 10.1 shows the current and the future (2050) production by state. The results indicate that the spatial distribution of future production in the MTC (FP/CMN) scenario points out to an

Table 10.1 Current and future (2050) corn and soybean production by state (thousand tonnes)

	2018	2050		
Brazilian state	MTC (CP/CMN)	MTC (FP/CMN)	MTC (FP/FMN)	MCO_2 (FP/FMN)
Mato Grosso (MT)	60,763	69,149	75,754	68,454
Mato Grosso do Sul (MS)	18,937	54,157	49,438	49,891
Goiás (GO)	21,614	39,717	50,413	45,085
Minas Gerais (MG)	11,977	42,402	33,892	42,402
Paraná (PR)	36,777	41,875	41,875	41,875
Rio Grande do Sul (RS)	26,251	28,181	28,181	28,181
Maranhão (MA)	4056	21,830	20,384	21,830
Bahia (BA)	7431	14,545	14,545	14,545
São Paulo (SP)	8267	13,548	11,497	13,548
Tocantins (TO)	3432	12,721	12,299	12,721
Piauí (PI)	3537	6381	6227	6381
Santa Catarina (SC)	5424	5775	5775	5775
Pará (PA)	2596	2511	2511	2511
Rondônia (RO)	1849	1978	1978	1978
Distrito Federal (DF)	683	1268	1268	860
Sergipe (SE)	759	844	844	844
Ceará (CE)	336	374	374	374
Amazonas (AM)	8	298	298	298
Roraima (RR)	99	147	147	147
Acre (AC)	81	91	91	91
Pernambuco (PE)	54	60	60	60
Amapá (AP)	62	55	55	55
Espírito Santo (ES)	33	37	37	37
Alagoas (AL)	32	37	37	37
Paraíba (PB)	24	26	26	26
Rio de Janeiro (RJ)	7	8	8	8
Rio Grande do Norte (RN)	4	4	4	4
Total	215,092	358,018	358,018	358,018

increase in corn and soybean production in the states of Mato Grosso do Sul/MS (35 million tonnes of additional production), Minas Gerais/MG (30 million tonnes), Goiás/GO (18 million tonnes), Maranhão/MA (18 million tonnes), Tocantins/TO (9 million tonnes), Mato Grosso/MT (8 million tonnes), Bahia/BA (7 million tonnes), São Paulo/SP (5 million tonnes), and Paraná/PR (5 million tonnes). Together, these states can potentially represent about 87% of the expected production expected in 2050.

The results for the analysis of scenarios MTC (CP/CMN) and MTC (FP/CMN) are shown in Fig. 10.6a, b, respectively. Figure 10.6b shows where production should be located considering the total cost minimization and that the 2050 transport network will remain the same as in 2018. In this scenario, there is no change in the current railway network.

The spatial distribution of the expected 2050 production according to scenarios MTC (FP/FMN) and MCO_2 (FP/FMN) is shown in Fig. 10.7. The results do not indicate any significant difference between these scenarios in terms of improvements in the future spatial production distribution when we minimize costs and emissions. According to it, the future railway network will simultaneously improve the competitiveness and efficiency of transport in terms of CO_2 emissions.

Since we could only find relatively small changes in the production spatial distribution using the scenarios that aim to minimize total costs, we can conclude that the routes designed for the planned railways are efficient. The planned railways cross regions with high efficiency for grain production and are in line with the optimal corn and soybean interregional transportation flows for the expected production, in 2050.

When we focused on the cost minimization using the MTC (FP/FMN) scenario, our models indicate an additional production of 11 million tonnes in Goiás/GO and 7 million tonnes in Mato Grosso/MT. Our results also suggest a reduction in the production in Minas Gerais/MG (−9 million tonnes), Mato Grosso do Sul/MS (−5 million tonnes), São Paulo/SP (−2 million tonnes), Maranhão/MA (−1 million tonnes), and Tocantins/TO (−1 million tonnes). Therefore, we can conclude that the planned railways will play an important role in improving the competitiveness of grain production in the more central states, such as Mato Grosso/MT and Goiás/GO.

Considering the CO_2 emission minimization in scenario MCO_2 (FP/FMN), our results suggest

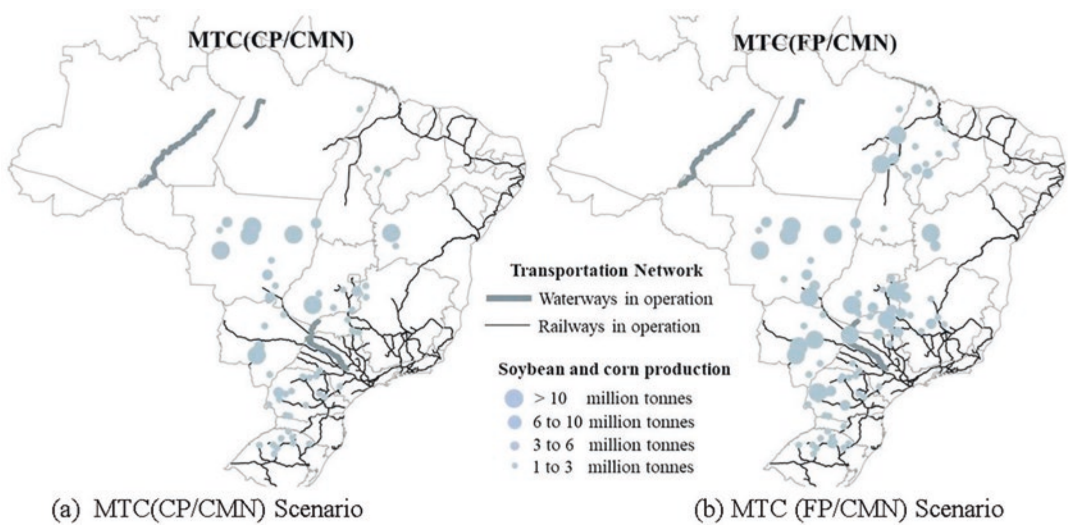

Fig. 10.6 Spatial distribution of current (2018) and future (2050) production maintaining the current multimodal network. (**a**) MTC(CP/CMN) Scenario. (**b**) MTC (FP/CMN) Scenario

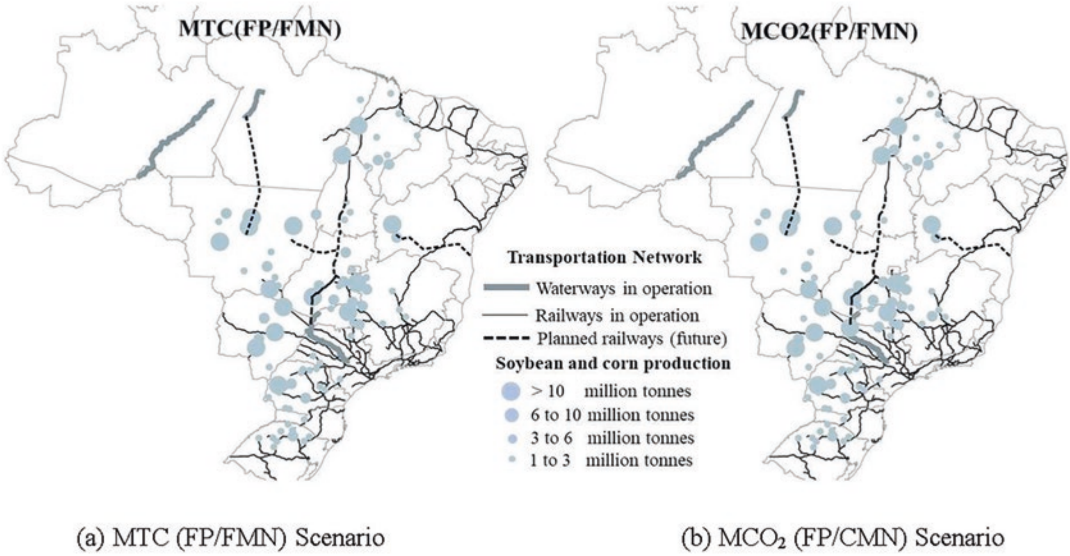

Fig. 10.7 Spatial distribution of future (2050) production including new planned railways. (**a**) MTC (FP/FMN) Scenario. (**b**) MCO_2 (FP/CMN) Scenario

Table 10.2 Total CO_2 emissions and total cost for each scenario

	Total CO_2 emissions		Total cost	
Scenario	Million tonnes	$kgCO_2$/tonne	Billion US$[a]	US$/tonne
MCO2 (FP/FMN) (2050)	5.9	17	239.4	668.6
MTC (FP/FMN) (2050)	6.3	18	237.2	662.6
MTC (FP/CMN) (2050)	7.2	20	241.9	675.8
MTC (CP/CMN) (2018)	4.7	22	144.1	669.9

Source: Results of the modeling
[a]It was considered the following exchange rate: @ US$ 4.3/R$ (April 2020, Brazilian Central Bank)

production increase in Minas Gerais/MG (9 million tonnes), São Paulo/SP (2 million tonnes), and Maranhão/MA (1 million tonne). Additionally, the model results suggest production reductions in Mato Grosso/MT (−7 million tonnes) and Goiás (−6 million tonnes). With these results, we can conclude that model was able to assign smaller shares of the additional production to further regions and higher shares to regions closer to the export terminals, aiming to minimize the CO_2 emissions with transportation.

As presented in Table 10.2, MTC (FP/FMN) scenario indicates a decrease of 0.9 million tonnes of CO_2 emissions compared to scenario MTC (FP/CMN). This result indicates that the implementation of the planned railways could decrease approximately 13% of the current CO_2 emissions, from 20 $kgCO_2$ by tonne of corn and soybean transported to 18 $kgCO_2$ by tonne. Using the minimization of CO_2 emission levels, the MCO2 (FP/FMN) scenario indicates a potential reduction of 18% on emissions, reaching 17 $kgCO_2$ by tonne.

The minimum total cost resultant from the spatial optimization of the future production and the interregional transportation flows is around US$ 663 per tonne in the MTC (FP/FMN) scenario and increases to US$ 669 per tonne when the model minimizes the CO_2 emissions, in the MCO_2 (FP/FMN) scenario. However, the latest scenario promoted a reduction in CO_2 emissions from 18 to 17 $kgCO_2$/tonne. It is important to highlight that when compared to the current total cost, scenarios MTC (FP/FMN) and MCO_2 (FP/FMN) present lower average total costs (US$). This result indicates that, under the following conditions, the planned railways could foster a cost reduction by 2050: (i) when agriculture production and planning of transportation flow goals are related to a minimum CO_2 emission and (ii) when agriculture expansion and planning of transportation flow planning reach the minimum total cost.

10.5 Main Conclusions

There is a lack of studies applying DEA to evaluate FEW Nexus systems. As shown before, some authors applied DEA to evaluate the efficiency of OECD countries, Chinese cities, or regions, based on FEW Nexus variables, and one of them showed that adequate use of resources is related to the Land-FEW-Nexus efficiency rather than simply using the minimum Land-FEW-Nexus resources. And the CO_2 emission is a common undesirable output in DEA applications in climate change studies that could be more explored in FEW Nexus in city studies. One of the advantages of applying DEA to evaluate FEW Nexus is that it does not need to assume a complex functional form to evaluate it, and it can be easily integrated to other methods, but one of the limitations is the lack of information on the dynamics of the system and its networks.

In this chapter, we showed how to apply a dual-step model, based on DEA and NEM, to minimize total crop production costs and CO_2 emissions with transportation; at the same time, we promote sustainable production expansion in Brazil. The analysis using our model considers four scenarios that account for the possible expansion of the transportation system in the country. The results indicate that it is possible to reach minimal costs and emissions by 2050, considering several constraints, including the production expansion only in pasture areas, with no need for additional deforestation. At last, our results proved to be the optimal configuration of the multimodal transportation network.

Our model could be used as an important tool, once is a powerful toll for policymakers planning the future agriculture production and the transportation network simultaneously, considering the mutual relation between transportation and land use. The results provided important thoughts regarding the environmental and economic impacts of the planned railways. Additionally, our model provided results regarding the dimension of transportation infrastructure capacities, such as roads, railways, waterways, and ports, for the location of transshipment terminals.

The results of this type of analysis are useful for guiding and coordinating public policies and private initiatives, aiming to optimize the selection and prioritization of future investments in transport infrastructure and, at the same time, establish incentives (programs, actions, rules) to conduct agricultural production to more interesting areas from an agronomic, economic, and environmental points of view.

The model can be replicated in other regions and countries, as well as considering other types of agricultural products.

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