Supporting Brazilian smallholder farmers decision making in supplying institutional markets

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Abstract

Smallholder farmers are among the most vulnerable communities in developing countries, lacking a stable income due to inconsistent access to markets. Aiming to tackle rural poverty, the Brazilian government established institutional markets for smallholder farmers to supply their produce to schools through a non-competitive bidding mechanism. However, participation of farmers is still limited due to the challenging decision-making process.

Aspiring to contribute towards increasing their participation, this study aims to support farmers into two key decisions they face during sequential stages of the bidding process, namely whether to bid for each available school and product combination and whether subsequently to accept the awarded bids once the bids' outcome is known. A decision support system, based on two sequential MILP optimisation models, was developed and applied to the case study of Canudos settlement, guiding farmers on the optimal bidding and contract acceptance strategy.

This study contributes to the decision support systems field by applying OR methods to a real-life problem within a new context. It is the first application of an OR-based decision support system in the non-competitive bid/no-bid literature, defining an optimal bidding strategy through the application of optimisation methods to maximise profitability while removing subjectivity from the decision-making process. Moreover, it is the first decision support system within the bid/no-bid decision-making field being applied to the agricultural and institutional market context. The proposed approach could have a significant social impact for smallholder farmers in Brazil, improving their living conditions by providing security of income and strengthening inclusive agricultural growth.

Keywords: OR in agriculture, Decision support systems, Bidding, OR in developing countries, smallholder farmers.

1 Introduction

Smallholder farmers are among the most vulnerable communities in developing countries due to poverty and social exclusion, often being marginalised from provisioning systems and relying solely on agriculture as a source of subsistence, income and employment (Grasseni, 2014; Medina et al., 2015; Moellers & Bîrhală, 2014; Ogutu & Qaim, 2019). This vulnerability stems from the several challenges smallholder farmers face in their daily life and activities.

These challenges include environmental aspects such as climate change and land degradation (Hazell et al., 2010; Stringer et al., 2008), social aspects, such as migration to urban areas and lack of generation renewal (Amekawa, 2016; Grasseni, 2014; Stringer et al., 2008), as well as the limited support offered through agricultural policies by governments (Graeub et al., 2016; Wilk et al., 2013). However, the main challenges faced by smallholder farmers fall within the economic domain. Capital constraints and limited access to credit affect their ability to invest which, coupled with the traditional agricultural techniques adopted (FAO, 2018; Graeub et al., 2016), prevent smallholder farmers from increasing their productivity (FAO, 2018;

Wiggins et al., 2010). This ultimately impedes their consistent access to markets for their produce due to the predominance of larger groups in the agri-food supply chain, which are able to offer lower prices (Graeub et al., 2016; Hazell et al., 2010). Low production volumes and subsequent lack of economies of scale, variable quality of produce, lack of planning skills and unavailability of remunerative distribution channels are additional factors which limit smallholder farmers' access to the market in developing countries (Hazell et al., 2010; Medina et al., 2015; Wilk et al., 2013). As a consequence, smallholder farmers face large uncertainty over whether their produce can be sold and at what price, with a detrimental effect on their family income and social security (Graeub et al., 2016; Tang et al., 2016; Wilk et al., 2013).

In some countries, public authorities, realising the extent and implications of this problem, have supported the emergence of institutional markets, in order to facilitate smallholder farmers' access to markets, promote rural development and reduce poverty (Getnet et al., 2018; Mossmann et al., 2017). Institutional markets can take the form of government feeding programs, which aim at providing an outlet for the smallholder farmer products, giving them priority in supplying public sector organisations. This allows the creation of a structured demand which "connects large, predictable sources of demand for agricultural products to small farmers", reducing risk and encouraging improved quality, as well as leading to increased income and reduced poverty for farmers (IPC-IG, 2013), who can benefit from operating in a protected market environment with limited competition.

The Brazilian PNAE program (Programa Nacional de Alimentação Escolar - National School Feeding Program) is an example of such an institutional market, where smallholder farmers can supply schools and is recognised as the largest institutional procurement program in the world that deliberately prioritises purchasing from smallholder farmers (IPC-IG, 2013). First launched in 2009, it creates an institutional market in the primary sector for socially disadvantaged groups in order to support their transition from subsistence agriculture to commercial agriculture and to improve their living conditions.

The PNAE works through a two-stage process. First, public calls are published by public authorities and farmers express their interests by bidding for specific schools and products to supply. Second, once the bids are submitted and evaluated, the outcome of the bids is revealed and a priority ranking for supplying is generated, based on a distance criterion - i.e. giving preference to local suppliers -, and a social exclusion criterion, i.e. prioritising agrarian reform settlements, indigenous traditional communities and *quilombola* communities (a self-declared ethno-racial group consisting mainly of descendants of Afro-Brazilian slaves who escaped from slave plantations). Then, farmers who were awarded the bids can select whether to take on each awarded bid.

According to Brazilian law, public schools have to spend at least 30% of the budget allocated from the National Fund for the Development of Education (FNDE - Fundo Nacional de Desenvolvimento da Educação) for meals to purchase food produced from socially disadvantaged groups, such as smallholder farmers, thus creating a protected institutional market for such groups. Despite the support created from public authorities through the secure demand of PNAE, many public calls remain unattended, with the

Midwest region lagging behind and certain states such as Distrito Federal, Amapá, Piauí, Rio Grande do Norte, Amazonas, Tocantins, Goiás and Mato Grosso still being far away from the 30% threshold budget allocation to socially disadvantaged groups identified from the federal government, as can be seen in Figure 1 (Fundo Nacional de Desenvolvimento da Educação, 2019; Grisa et al., 2014).

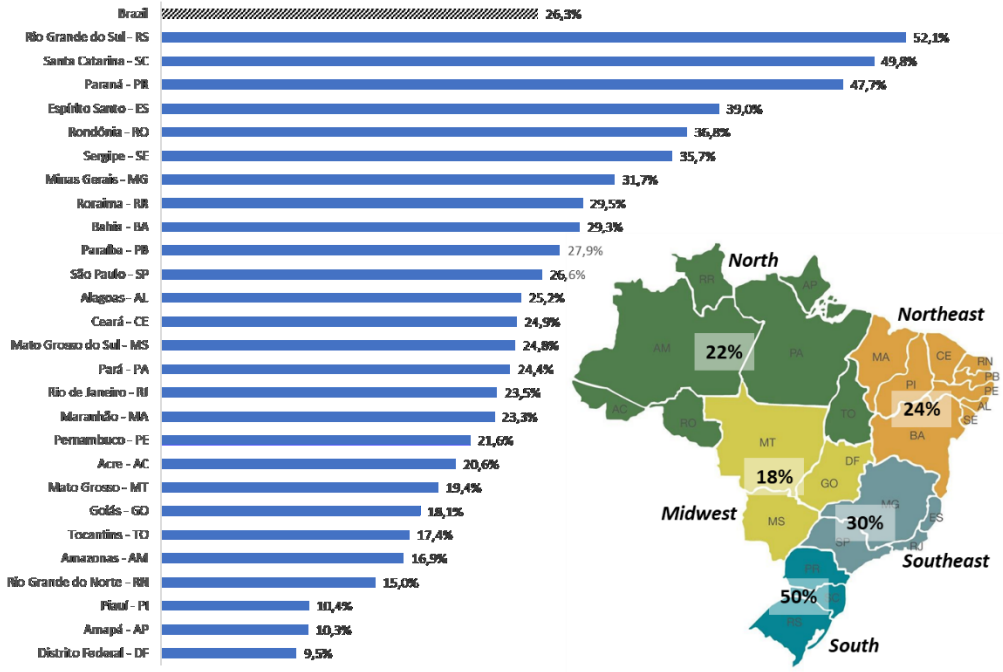

Figure 1: Percentage of the allocation of PNAE resources to socially disadvantaged groups by state and region in 2017

The apparent lack of interest from smallholder farmers for participating in PNAE calls is motivated by the challenges they face to access the program on a regular basis. The public procurement process is perceived as cumbersome by farmers, who struggle to deal with the relevant administrative workload and cost, due to their lack of management skills (Mossmann et al., 2017; Triches & Grisa, 2015). This appears particularly critical in two stages of the PNAE process: the evaluation of the profitability of participating in each call (Machado et al., 2018; Reis, 2016; Triches & Grisa, 2015) and the organisation of the transport and distribution of their produce (Mossmann et al., 2017; Reis, 2016). This study aims to support smallholder farmers in the first set of decisions, namely (a) the decision whether to bid or not to bid for each specific school and product combination and (b) the decision whether to accept or not the awarded bids once the outcome of the bids is revealed. Both decisions, which are currently made on the basis of intuition, require a more structured approach in order to improve the profitability of the participation of farmers in PNAE and ultimate contribute positively to the improvement of their living conditions.

The novelty of this study lies in the use of established operational research (OR) methods, such as mixed integer linear programming (MILP), to develop a novel decision support system (DSS) that aims to facilitate decision-making of smallholder farmers in a developing countries context when participating in institutional markets through non-competitive bidding mechanisms, with the ultimate objective of maximising their profitability from this participation and thus improving their living conditions.

The remaining part of this paper is structured as follows. Section 2 reviews the literature related to decision-making in agriculture and identifies existing quantitative methodologies to support the bid/no-bid decision. Section 3 illustrates the decision support system developed, first by providing an overview of the problem, then illustrating the mathematical models of the DSS and finally introducing the details about the case study application, based on primary data sourced from actual practice. Results arising from the application of the DSS in the settlement of Canudos in Brazil are presented and discussed in Section 4, while Section 5 concludes this paper by highlighting the main contribution to knowledge and to society, as well as by identifying directions for future research.

2 Literature Review

2.1 Decision Support for Farmers

Decision support models have been applied in agriculture for various types of decisions, that can be linked to the key functional areas in the agricultural supply chain, such as production, harvest, storage and the decision of amounts to sell in each planning period (Ahumada & Villalobos, 2009; Soto-Silva et al., 2016). Decision makers can be farmers, but also policy makers and other stakeholders in agricultural supply chains (Hayashi, 2000; Jonkman et al., 2019).

Farmers face decisions at strategic, tactical and operational levels, i.e. which products to grow, how to rotate crops, how to manage their land, and which channels to use to bring their product to the market (Biswas & Pal, 2005; Mauri, 2019). In this respect, various types of approaches have been proposed to support farmers in diverse decision-making processes. Income-related objectives within the farm planning context have been used in many cases, expressed as maximising gross margins, income, expected returns, net revenues or trading surplus (Hayashi, 2000). Selling decisions have also been analysed as a two-stage recourse model with the objective to minimise the expected nutrient deficits during the planning period (Maatman et al., 2002). Contract arrangements for multi-echelon agricultural supply chain coordination have also been investigated, in the context of developed countries (Anderson & Monjardino, 2019).

Despite the broad coverage of OR-based decision support methods in the literature, their transfer to the practitioners' community within agricultural supply chains has remained somehow limited (Higgins et al., 2010; Plà et al., 2014) and this is especially the case for decision support systems targeted to farmers (Plà et al., 2014). Misalignment between models and decision makers requirements, cost-effectiveness, capital investment requirements, lack of transparency, data requirements, and risk aversion, coupled with "the educational level of the producers and their lack of familiarity with model-based quantitative methods" were mentioned among the factors determining the low adoption of such methods by farmers (Higgins et al., 2010; Plà et al., 2014).

2.2 Bid/No-Bid Literature

Investigating the literature at the interface of OR and agriculture, there is no evidence of decision support systems aimed at farmers when they are participating in bidding processes, as in the application-oriented problem of this study, despite the widespread adoption of bidding across several sectors both in the private and public domain (Fanzeres et al., 2019). The majority of existing research in the 'bid/no-bid' literature is in the construction sector, aiming to support contractors to decide whether to bid or not for specific projects (Leśniak & Plebankiewicz, 2015; Wanous et al., 2003). Due to the relevance of the topic, and the lack of relevant literature in the agricultural sector, the 'bid/no-bid' literature analysis herein is focused on the construction sector, which is characterised by competitive bidding features. Hence, two sequential decisions are usually involved, the bid/no-bid decision and the mark-up level definition for the shortlisted bids.

Bidding is the act through which two or more actors compete for the right to perform a contract by submitting independent bids (Curtis & Maines, 1973). The first decision such actors face in the bidding process is whether to submit a bid or not (Engwall, 1975). Traditionally, the common practice was to base the 'bid/no-bid' decision on subjective intuitions, derived from a combination of gut feelings, experience and guesses (Cheng et al., 2011; Egemen & Mohamed, 2008; Irtishad, 1990; Polat & Bingol, 2017; Sonmez & Sözgen, 2017; Wanous et al., 2003). However, as such decisions increased in complexity, with additional items factored into the decision-making process, the need for more structured and objective approaches emerged (Egemen & Mohamed, 2008; Irtishad, 1990; Wanous et al., 2003), as systematic models are likely to improve the quality of decision-making (Polat & Bingol, 2017).

Two dominant approaches to the 'bid/no-bid' decision support exist, namely model-driven decision support systems and knowledge-driven decision support systems (Mohemad et al., 2018). Model-driven DSS build on information emerging from historical bids to analyse the decision to bid or not to bid through statistical analysis. As an example, a logistic regression method to support the 'bid/no-bid' decision based on the outcomes of previous bids was proposed in Hwang & Kim (2016). Establishing a correlation between certain variables and the outcomes of past bids, they identify critical success factors for future bids. However, such approaches have been targeted with criticism as they assume that competitors will present the same bidding behaviour as in the past (Lin & Chen, 2004).

On the other hand, knowledge-driven DSS build on both structured and unstructured data, incorporating qualitative information from decision makers, usually expressed in a linguistic scale, and transforming them into quantitative values through different techniques. A variety of knowledge-driven DSS have been developed, with the dominant approach being multi-criteria decision-making methods. Multiple criteria have been proposed, though these are typically clustered among internal criteria, also known as firm-related (Chisala, 2017; Egemen & Mohamed, 2008), and external criteria, divided among project-related and macro-environment criteria, which consider market and demand considerations (Chisala, 2017; Egemen & Mohamed, 2008). The criteria are typically aggregated based on various weighted sum mechanisms generating a bid/no-bid score or index (Chisala, 2017; Egemen & Mohamed, 2008; Hassanein & Hakam,

1996; Irtishad, 1990; Wanous et al., 2000), while in certain instances fuzziness is introduced to take into account the vagueness associated with experts' opinions (Cheng et al., 2011; Leśniak & Plebankiewicz, 2015; Lin & Chen, 2004). Additionally, neural networks have been adopted in isolation (Wanous et al., 2003), in combination with rough sets (Shi et al., 2016) or in combination with linear regression (Sonmez & Sözgen, 2017). However, knowledge-driven DSS suffer from a common drawback, which is the influence of the subjective judgement of decision makers on the final outcome of the decision (Lin & Chen, 2004).

Mathematical programming DSS have therefore emerged in the 'bid/no-bid' literature as an alternative option, with a large predominance of data envelopment analysis (DEA) based methods. DEA is a non-parametric linear programming method, which is widely used for benchmarking and performance measurement. DEA is able to incorporate qualitative and quantitative measures in a single efficiency score for each potential bid, automatically attributing weights to different measures in order to reduce ambiguity and subjectivity (El-Mashaleh, 2013). While embedded in mathematical programming, DEA still requires the definition of multiple variables, with the most common approach prescribing the identification of factors affecting the bid positively and negatively (El-Mashaleh, 2010; Polat & Bingol, 2017). This requirement of identifying positive and negative impacts of the factors has been simplified in a piece of work separating the 19 criteria adopted simply into inputs to be minimised and outputs to be maximised, according to the general framework of DEA (El-Mashaleh, 2013). Finally, a fuzzy goal programming technique was used by Tan and Shen, (2010), who developed a linear programming method with two objectives, namely the maximisation of the technical score of the bid and the minimisation of the tender price (Tan & Shen, 2010). Nevertheless, the method relies on the knowledge and experience of decision makers to rate parameters such as internal technical ability, management skill and financial ability that influence the values of the objective functions, thus sharing some of the weaknesses of knowledge-driven DSS.

As a result, there is currently no method in the existing literature, which does not rely on outcomes of past bids only, while basing its support to the 'bid/no-bid' decision on objective, quantitative factors that are not affected by the subjective judgement of decision makers.

While the PNAE process follows a "many bidders strategy" similarly to most bids in the construction sector, i.e. number and identity of competitors are not known (Gates, 1967), it is different from such bids as it guarantees a structured demand (IPC-IG, 2013), i.e. the price of the bid is known and fixed, thus eliminating the competitive bidding element (IPC-IG, 2013; Mossmann et al., 2017), which is largely investigated in the construction sector literature.

This eliminates concerns regarding the mark-up level decision, as prices and costs are deterministic and known to farmers ahead of bidding with the only exception being transport costs, which are dependent on the number of bids the farmers will be awarded and will accept. As a result, the expected profit may be estimated beforehand with a reasonable confidence level and farmers are expected to bid to any school where they can obtain an estimated profitability after production and distribution costs have been accounted for, as competition factors cannot be forecasted.

Summarising, the PNAE features lower uncertainties and associated risks compared to the bids in the construction sector (IPC-IG, 2013) and allows farmers to focus exclusively on the economic dimension of the bid, rendering the other criteria typically considered in construction bidding strategies irrelevant. Therefore, the decision support system has substantially different requirements than the approaches developed for the construction sector, due to the specificities of the institutional markets bidding process, which favour the use of objective criteria. This study therefore introduces a novel DSS for the 'bid/no-bid' decision, based on mathematical programming, which is applied within a new context, namely an institutional market for smallholder farmers in Brazil.

3 Materials and Methods

3.1 Problem Statement and Decision Support Overview

The PNAE program aims to support smallholder farmers, also referred to as family farmers, identified by the Brazilian law as those who do not have availability of an area greater than four fiscal modules[1], predominantly use family to manage their agricultural business and as a source of labour in their agricultural activities. Moreover, the Brazilian government identifies a maximum threshold of income farmers can generate through agricultural activities to qualify them as a socially disadvantaged group and thus categorise them as family farmers.

Figure 2 outlines the PNAE process and connects it to key farming activities on a timeline for a typical semester starting end of January (with indicative dates). The PNAE process can be summarised into seven main steps:

1. Data collection about production capability in the local smallholder farmers' community: farmers have to identify the produce mix they are able to produce within the settlement.
2. Communication to school nutritionists about production capability: farmers inform local schools about the produce available for the following planning period, to ensure that the menus will be designed, as much as possible, to include local varieties of fruits and vegetables and to guarantee the produce freshness.
3. Release of public calls for products: based on the menus developed by school nutritionists, public calls are released by the state (for state schools) and municipalities (for municipal schools). Calls by state schools are released twice a year, with each covering one school semester, while calls by municipal schools are released once a year, covering the entire school year. Each state school publishes an independent call for bids, while each municipality publishes one call for all municipal schools within its city council.
4. Bidding for products: farmers can decide whether to bid to supply a specific product to a specific school. This means that farmers can bid for one product in certain schools and not in others and can bid to supply

[1] Fiscal module is a unit of measurement whose value is fixed by the National Institute for Colonization and Agrarian Reform, a federal government authority of the public administration of Brazil. The size of a fiscal module varies across the country depending on the municipality and the predominant use of land in the area, spanning from 5 to 110 hectares. In the case study presented in this work, the value of a fiscal module is approximately 20 hectares.

to each school only a subset of the products required by the school. For the purposes of this study, a 'bid' is defined as the participation in the call of one specific school/municipality, for one or more of the products required by the school/municipality. Farmers are forbidden from bidding in a particular school if they have failed to deliver the agreed produce to that school in previous years. DSS1 supports the bidding decisions at this step.

5. Bid selection: bids are evaluated by public authorities, ranked and selected on the basis of the distance from schools, in order to favour locally sourced food, and of other social criteria, which aim to give priority to more socially disadvantaged groups. On the production side, planning for planting activities commences, together with actual planting of the products that need to be supplied at the beginning of the semester.
6. Signing of delivery contracts: once the bids are awarded, farmers can decide whether to take on the delivery, thus signing the contract, or reject specific supplies (e.g. specific school-product pairs), in which case the contract is offered to the farmers following in the ranking. Contracts are valid for one school semester (state schools) or a year (municipal schools). DSS2 supports the contract signing decisions that happen within a short time period from receiving the outcomes of step 5. On the production side, planning of planting activities is finalised, based on the outcomes of DSS2.
7. Delivery of produce to schools: each month schools provide to farmers the schedule for delivery for each week of that month. Typically, harvested produce is delivered once a week to each school with no fixed date of delivery. The timings are usually informally arranged between farmers and schools.

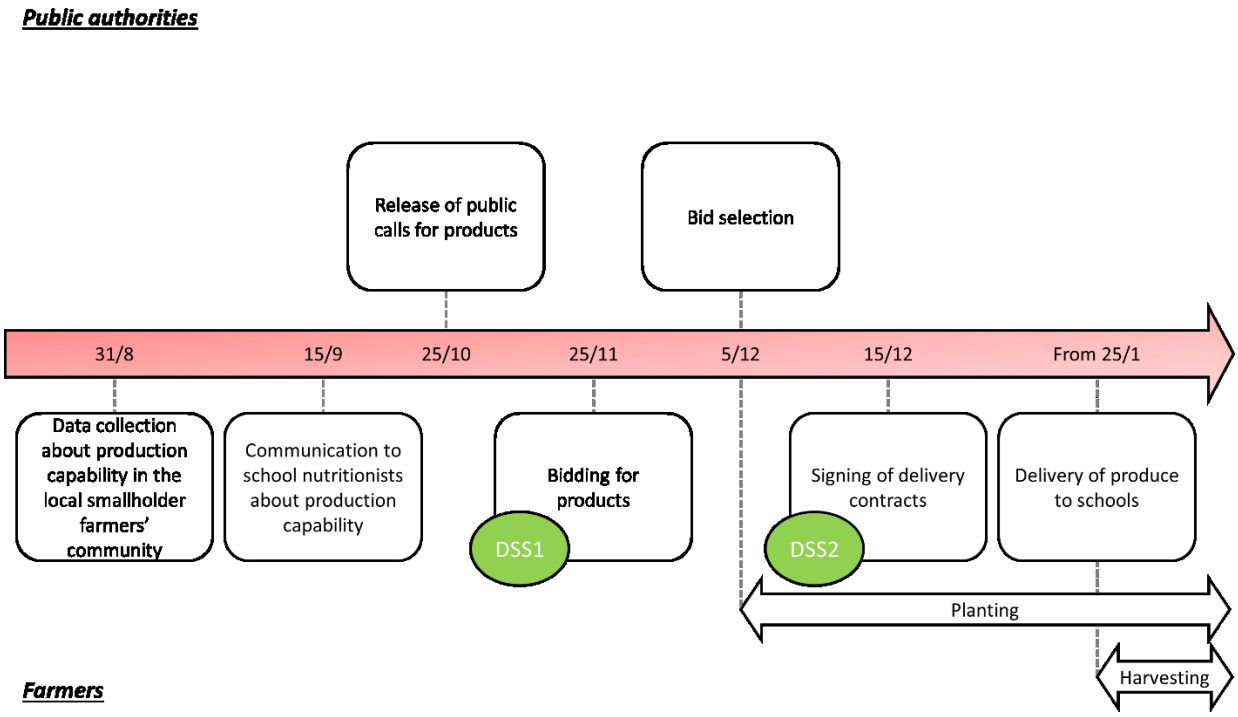

Figure 2: Overview of the PNAE process, key farming activities and positioning of the proposed Decision Support Systems (DSS) on a timeline for a typical semester starting end of January (with indicative dates)

The participation rate of smallholder farmers in PNAE calls is still low and the majority of Brazilian states still struggle to meet the 30% threshold of food purchases from socially disadvantaged groups as defined by the Brazilian law (Grisa et al., 2014), meaning that large amounts of resources dedicated to improve social conditions of marginalised groups are left unused. The main reason for this lies in the difficulty smallholder farmers and other socially disadvantaged groups face to take part to the PNAE program (Machado et al., 2018; Mossmann et al., 2017).

Aspiring to contribute towards the increase in the participation of smallholder farmers in the PNAE program, this study aims to support the farmers into two key decisions they face during the PNAE process, namely the bid/no-bid decision (DSS1, Section 3.2.2) and the decision whether to sign the contract for each school/product pair (DSS2, Section 3.2.3), as highlighted in Figure 2. Both decision support systems are modelled as MILP models, aiming to identify the optimal strategy for farmers. The decision support systems can enhance the profitability farmers are able to achieve through the participation in PNAE with the ultimate objective to improve their living conditions.

3.2 DSS Optimisation Models Description

The mathematical formulation of the two DSS optimisation models is presented in this section. First, the notation of common parameters adopted for both DSS is introduced in Section 3.2.1, then the two DSS are presented individually. DSS1 aiming to support the bid/no-bid decision is introduced in Section 3.2.2, followed by the description of DSS2 to support the decision which of the awarded bids to accept or not in Section 3.2.3. The illustration of both DSS follows the same pattern: first decision variables are outlined, then the objective function is presented and finally the constraints are listed.

3.2.1 Notation

Indices

i: Set of products ($i = 1, \dots, n$) [DSS1&2]

j: Set of groups of products: products based on the same agricultural produce, e.g. peeled and unpeeled ($j = 1, \dots, ng$) [DSS2]

k: Set of calls – equal to set of schools ($k = 1, \dots, m$) [DSS1&2]

r: Set of school clusters ($r = 1, \dots, nclus$) [DSS1&2]

Parameters

a_j: Land productivity: area required to produce one kilogram of group of products j [DSS2]

$Area_j$: Area available for planting group of products j - only for annual crops [DSS2]

$AreaTot$: Total area available for planting all annual crops [DSS2]

c_i^{prod}: Production cost per kilogram of product i [DSS1&2]

c_r^{bur}: Bureaucracy cost per school cluster r [DSS1]

c^{km}: Transport cost per km [DSS1&2]

Cap_j^{prod}: Production capacity for the products of group j per planning period in weight (kg) [DSS2]

$cluster_{kr}$: Linkage between schools and clusters (binary, 1 if school cluster r contains school k, 0 otherwise) [DSS1&2]

Cpb_i: Capability to produce product i (binary, 1 if product i can be produced by the farmers and 0 otherwise) [DSS1]

CV_{avg}^{volume}: Average capacity of the vehicles in volume (number of crates) [DSS1&2]

CV_{avg}^{weight}: Average capacity of the vehicles in weight (kg) [DSS1&2]

$dist_r$: Distance from farmer settlement to school cluster r (km) [DSS1&2]

f_j Product category (binary, 1 if the products of group j are from a perennial crop and 0 if the products of group j are from an annual crop) [DSS2]

fbd_k: Penalty forbidding farmers to attend the call at school k (binary, 1 if call at school k is forbidden and 0 otherwise) [DSS1]

g_{ij}: Product grouping linkage (binary, 1 if the product i belongs to product group j and 0 otherwise) [DSS2]

M: A very large number [DSS1&2]

$maxcalls$: Maximum number of calls to bid for per planning period [DSS1]

$ncycle_j$: Number of cycles the group of products j can be harvested per planning period [DSS2]

$ntrip_r$: Number of trips from the settlement to school cluster r [DSS1&2]

$nweeks$: Total number of weeks in the planning period [DSS1&2]

p_{ik}: Price of product i in the call of school k [DSS1&2]

q_{ik}: Quantity of product i requested in the call of school k (kg/planning period) [DSS1&2]

v_{ik}: Volume of products i requested in the call of school k (number of crates/planning period) [DSS1&2]

y'_{ik}: Bid selection outcome (binary, 1 if the call for product i at school k was successful and 0 otherwise) [DSS2]

3.2.2 DSS1: Bid/No-Bid

The aim of DSS1 is to determine whether to bid or not for each school-product pair, in order to maximise the potential profit for the farmers through the participation in the PNAE program should all bids be successful. From an administrative perspective, the farmers have to submit one single application per school (state schools) or municipality (municipal schools), for any number of products they wish to bid for. A finite number of schools exist in an area compatible with the local sourcing criterion defined by PNAE and each school proposes a finite number of products in the calls, each of whom with a specified quantity and unitary price per kilogram. Usually prices offered for the same product by different schools differ. At this stage, farmers need to select their strategy on which calls to attend and within each call what products to bid for based on the maximum potential profitability.

DSS1 operates in an uncertain environment, as farmers do not know at this stage in which bids they will be successful, or what competition they will face. As such, DSS1 aims to select all economically profitable bids with an upper limit of potential bids being defined to avoid overloading farmers with bureaucratic work. Accordingly, production capacity is assumed unlimited at this stage. On the other hand, some basic constraints in terms of transport to schools exist, consistently with the limited and uncertain information available about transport requirements at this stage of the PNAE process.

The following assumptions were made in the development of DSS1:

1. The planning horizon is equal to a Brazilian school semester for state schools and to a Brazilian school year for municipal schools.
2. Each school belongs to a single cluster, which can include one or more schools.
3. Each municipality represents a cluster of schools, meaning that certain costs that are related to trips from the farmers' settlement to the cluster are not allocated directly to a single school but are shared among different schools within the cluster. These include bureaucracy cost c_r^{bur} and transport costs.
4. Bureaucracy cost to submit a bid is calculated as the travel cost associated with a return trip from the farmers' settlement to the cluster r using an average vehicle. This is accounted for only once per cluster, assuming the farmers submit all bids to schools within one cluster during the same trip.
5. Transport costs are assumed linear with distance and can be obtained by multiplying the transport cost per km c^{km} by the distance from the settlement to the cluster r, $dist_r$(expressed in km).
6. An average vehicle is used to estimate the transport cost per km c^{km} as well as the average product transport capacity both in weight and in volume, as the details regarding the transport schedule are not known at this stage and are released on a monthly basis during each school semester.

The decision variables of DSS1 are:

x_k	binary, equal to 1 if farmers bid for any number of products in the call of school k and 0 otherwise
y_{ikr}	binary, equal to 1 if a bid for product i of the call at school k in the cluster r is submitted and 0 otherwise
z_r	binary, equal to 1 if farmers bid in any school in cluster r and 0 otherwise

The objective function aims to maximise the potential profit for the farmers by taking part in the PNAE program, which is defined as the net profit before transport, minus the cost of bureaucracy to bid in the different clusters, minus an estimated average cost associated with the transport for the winning bids, as expressed in Equation (1). The first term expresses the product profit per unit as the difference between sales price minus production cost, the second term is the cost associated with bidding bureaucracy and the third is the product transport cost. Since the bids that will be ultimately won and the schedule of transport to schools are not known at this stage, an approximation of the transport costs is used based on the amounts of products farmers bid for in each cluster, which is assumed as an upper bound of the related costs.

$$Max \sum_{r=1}^{nclus}[\sum_{i=1}^{n}\sum_{k=1}^{m}(p_{ik} - c_i^{prod})q_{ik}y_{ikr} - c_r^{bur}z_r - 2dist_r ntrip_r c^{km}] \quad (1)$$

The objective function is subject to a number of constraints. Equation (2) ensures that farmers bid only for products that they are able to produce at the settlement. Equation (3) limits the number of calls to schools below a maximum threshold to limit the bureaucracy workload on farmers at the stage of bidding. Equation (4) guarantees that bids are submitted only for products i, for which a demand exists. Constraint (5) prevents farmers from bidding for calls at schools they are not allowed to supply due to failure to deliver products according to the specifications of contracts in previous years. Constraints (6), (7) and (8) are linkage constraints: equation (6) prevents farmers from bidding for products at schools they do not present a bid for, equation (7) links schools and clusters, while equation (8) links products and clusters. The following constraints are related to the number of trips travelled in a planning period. Equations (9) and (10) ensure that the number of trips for product delivery to each cluster are consistent with the capacity constraints of the average vehicle both in terms of weight and volume. Additionally, equation (11) refers to the frequency of trips to each cluster r defining the lower limit to one trip per week to each cluster where a bid is presented, consistent with the average delivery schedule requirement of schools for fresh produce in previous school years. The combination of constraints regarding the number of trips ultimately prevents bidding for very small quantities/volumes within a certain cluster due to transport costs, which is desirable in the practical setting. Finally, equation (12) defines all decision variables as binary.

$$y_{ikr} \leq Cpb_i,\ i = 1, ..., n,\ k = 1, \ldots, m,\ r = 1, ..., nclus, \tag{2}$$

$$\sum_{k=1}^{m} x_k \leq maxcalls, \tag{3}$$

$$\sum_{r=1}^{nclus} y_{ikr} \leq M.q_{ik},\ i = 1, \ldots, n,\ k = 1, \ldots, m, \tag{4}$$

$$x_k \leq 1 - fbd_k,\ k = 1, \ldots, m, \tag{5}$$

$$\sum_{i=1}^{n} \sum_{r=1}^{nclus} y_{ikr} \leq M.x_k,\ k = 1, \ldots, m, \tag{6}$$

$$\sum_{k=1}^{m} x_k cluster_{kr} \leq M.z_r\ \ r = 1, ..., nclus, \tag{7}$$

$$\sum_{i=1}^{n} y_{ikr} \leq M.cluster_{kr}\ k = 1, \ldots, m,\ r = 1, ..., nclus, \tag{8}$$

$$ntrips_r \geq \frac{\sum_{i=1}^{n} \sum_{k=1}^{m} q_{ik} y_{ikr}}{CV_{avg}^{weight}},\ r = 1, ..., nclus, \tag{9}$$

$$ntrips_r \geq \frac{\sum_{i=1}^{n} \sum_{k=1}^{m} v_{ik} y_{ikr}}{CV_{avg}^{volume}},\ r = 1, ..., nclus, \tag{10}$$

$$ntrips_r \geq nweeks.y_{ikr},\ i = 1, \ldots, n,\ k = 1, \ldots, m,\ r = 1, ..., nclus, \tag{11}$$

$$x_k, y_{ikr,} z_r \in \{0,1\},\ i = 1, ..., n,\ k = 1, ..., m,\ r = 1, ..., nclus. \tag{12}$$

3.2.3 DSS2: Contract Signing

The second decision the farmers face, and require support with, arises at a later stage, when the results of the bids are released. The farmers may have been selected to supply certain school-product pairs and missed others as other farmers may have had higher priority. At this stage, farmers face the option for each bid they were awarded whether to sign the contract for each school-product pair or not. In the former case they are formally obliged to deliver the quantities mentioned in the contract over one planning period.

This decision is based on a more accurate set of information compared to DSS1. While full details about the transport cost over the whole planning period are not known yet, as the schedule of deliveries is revealed by the schools only on a monthly basis, farmers are at this stage aware of the mix of products they have been awarded in each school and in each cluster, allowing a more precise estimation of the real transport cost based on the amount of products that are going to share this cost and being able to infer on the economic viability of serving each cluster. Moreover, while DSS1 aimed to maximise the potential profit in a full uncertain spectrum of bids prospectively being awarded, DSS2 has to consider production capacity constraints in terms of land availability for production, based on exact demand figures from schools where bids were won.

Therefore, beyond the assumptions guiding the development of DSS1, the following assumptions were additionally made in the development of DSS2:

1. Products are divided into two categories, namely perennial and annual crops, as highlighted by the parameter f_j. Perennial crops are allocated a specific land surface, which can be only used to produce this specific crop. This is typically the case of bananas or tree crops (e.g. lemons). Annual crops are not allocated a specific land surface, but can be planted or not each planning period based on the demand (e.g. cassava). A share of land in the settlement is therefore available to plant any annual crop.
2. Groups of products are created. Each group of products includes all products which are obtained from the same crop, hence they are alternative products in terms of land occupation that differentiate themselves on the level of post-harvest processing (e.g. product unpeeled or peeled). Each product belongs to a single group of products, whereas a group of products can include one or more products.
3. Each annual crop can be planted on a maximum land surface based on the characteristics of the soil, water requirements and need for diversification. The maximum surface is defined per group of products ($Area_j$).
4. All annual crops combined can be planted on a maximum land surface ($AreaTot$), based on the land available at the settlement.
5. Each group of products can be harvested a number of times during a planning period, as represented by the parameter $ncycle_j$.

The decision variables of DSS2 are:

y_{ikr} binary, equal to 1 if the contract for product i of call at school k in the cluster r is signed and 0 otherwise

The objective of DSS2 is also to maximise the potential profit for the farmers based on the awarded bids they sign a contract for. The profit is here defined as the net profit before transport, minus an estimated average cost associated to the transport for the winning bids, as detailed in Equation (13).

$$Max \ \sum_{r=1}^{nclus}[\sum_{i=1}^{n}\sum_{k=1}^{m}(p_{ik} - c_i^{prod})q_{ik}y_{ikr} - \ 2dist_r ntrip_r c^{km}] \quad (13)$$

The objective function differs from DSS1 as it does not consider the cost of bureaucracy, which is an expense the farmers have already experienced at the stage of bidding and is at this stage a sunk cost. At the

same time, the transport cost is still at this stage an estimation as the horizon of planning of the contracts is either a semester or a school year, whereas the detailed delivery plans are released on a monthly basis, as detailed in Section 3.1. Therefore, an exact transport cost estimation covering the whole planning period is not possible. However, at this stage the transport costs can be calculated based on the exact amounts of products the farmers will commit to deliver.

The objective function of DSS2 is also subject to a number of constraints. Constraints (14) and (15) are related to the production capacity. Constraint (14) delimits the maximum production capacity per crop per planning period: this is calculated in pre-processing (Supplementary material, equation A1) and is ultimately determined by the available land for each crop, the land productivity and the number of cycles each annual crop can be harvested in a planning period. The available land for each crop is pre-allocated for perennial crops, hence cannot be modified by short- and medium-term decisions, as in the case of planted trees, for example. Conversely, the available land for each crop is not pre-allocated for annual crops; nevertheless, crop-specific maximum land availability limits exist depending on the water and soil requirements of each crop. As certain plots of land can be used to cultivate different crops, constraint (15) identifies the overall maximum land available to cultivate all annual crops. Constraint (16) guarantees that only school-product pairs with an existing demand are selected to be supplied, whereas equation (17) is a linkage constraint. Finally, constraints (18) throughout (20) are related to the number of trips. Equations (18) and (19) determine the minimum number of trips required to each cluster r to fully satisfy the demand based on the capacity of the average vehicle, in terms of weight and volume respectively, whereas equation (20) determines the lower bound for the number of trips to clusters being supplied based on the number of weeks in each planning period, similarly to constraint (11) introduced in DSS1. Finally, equation (21) ensures that farmers can select only from school-product pairs they were awarded following the decision of public authorities and equation (22) defines the binary decision variables.

$$\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{r=1}^{nclus} q_{ik} g_{ij} y_{ikr} \leq Cap_j^{prod}, j = 1, ..., ng, \tag{14}$$

$$\sum_{j=1}^{ng} \frac{\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{r=1}^{nclus} a_j q_{ik} g_{ij} y_{ikr}(1-f_j)}{ncycle_j} \leq AreaTot, \tag{15}$$

$$\sum_{r=1}^{nclus} y_{ikr} \leq M.q_{ik}, i = 1, \ldots, n, k = 1, \ldots, m, \tag{16}$$

$$\sum_{i=1}^{n} y_{ikr} \leq M.cluster_{kr}, k = 1, \ldots, m, r = 1, ..., nclus, \tag{17}$$

$$ntrips_r \geq \frac{\sum_{i=1}^{n}\sum_{k=1}^{m} q_{ik} y_{ikr}}{CV_{avg}^{weight}}, r = 1, ..., nclus, \tag{18}$$

$$ntrips_r \geq \frac{\sum_{i=1}^{n}\sum_{k=1}^{m} v_{ik} y_{ikr}}{CV_{avg}^{volume}}, r = 1, ..., nclus, \tag{19}$$

$$ntrips_r \geq nweeks.y_{ikr}, i = 1, \ldots, n, k = 1, \ldots, m, r = 1, ..., nclus, \tag{20}$$

$$\sum_{r=1}^{nclus} y_{ikr} \leq M.y'_{ik}, i = 1, \ldots, n, k = 1, \ldots, m, \tag{21}$$

$$y_{ikr} \in \{0,1\}, i = 1, ..., n, k = 1, ..., m, r = 1, ..., nclus. \tag{22}$$

3.3 DSS Application: Canudos Case Study

3.3.1 Case study Overview

The decision support systems were applied to the case study of the smallholder farmers' settlement of Canudos, which lies in the state of Goiás, in the Centre-West Region of Brazil. The settlement is located between the towns of Palmeiras de Goiás, Campestre de Goiás and Guapó and is around 100 km away from Goiania, the capital of the state of Goiás, and 300 km away from the capital city Brasilia (Figure 3).

The agrarian reform settlement, founded in 1997, is facing an increased number of challenges threatening its survival, including rural exodus of younger generations, difficulties to access credit, volatility of prices of agricultural produce, lack of infrastructure, and environmental degradation in the areas surrounding the settlement. However, the main current challenge for farmers is to switch from subsistence agriculture towards commercialisation of produce.

Challenges are associated with most of the produce distribution pathways available to farmers. Large retailers require large volumes of produce, whose demand smallholder farmers are not able to meet, and pay low prices, which barely cover the production costs of the smallholder farmers, who have limited access to mechanised agriculture and do not have large scale production. Moreover, agri-food supply chains of large retailers require a stable supply over time and not only during the period of the harvest, meaning that farmers are required to store the produce, which is not currently a viable option at Canudos. Local fairs and markets are an alternative opportunity; however, the profit margin for individual sellers is small, as the costs associated with marketing and self-organised distribution have to be considered.

Farmers have tried to react to such challenges by creating a number of cooperatives within the settlement in order to boost collaboration among families of farmers and to take advantage of economies of scale, in order to move towards commercialisation of their produce in a more efficient way. One such cooperative is specifically dedicated to the distribution of the produce through the PNAE program, in order to get access to the structured demand generated through the program. Hence, this cooperative within the settlement of Canudos was adopted as the unit of analysis in this case study. As a single unit of analysis is adopted with a single case design, the study can be considered as a holistic single case study (Yin, 2003).

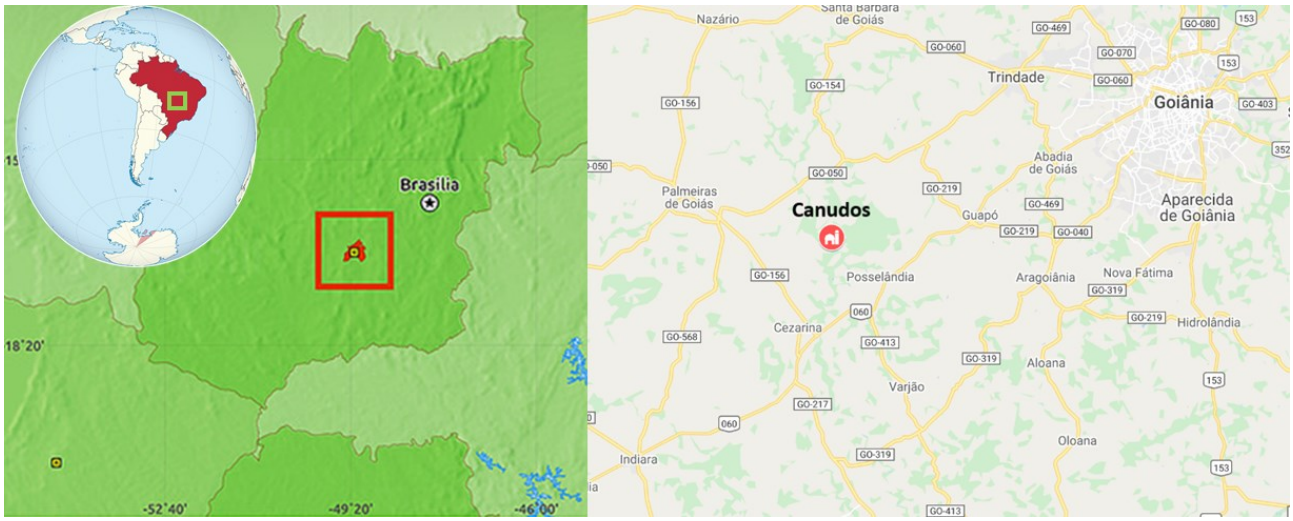

Figure 3: Geographical location of Canudos settlement within Goiás state

3.3.2 **Input Data**

The researchers have been supporting Canudos smallholder farmers in the processes of production planning, organisation of the cooperative and bidding to PNAE since January 2017. Regular face-to-face meetings between the researchers and the farmers have taken place since then, approximately every 20 days. Additional regular communication has included telephone contacts and social network messages. During this period, it was possible to understand in-depth the dynamics of the PNAE from the farmers' perspective and the challenges faced by Brazilian smallholder farmers in Canudos. This information allowed the definition of the key variables of the models, in order to cover the main challenges in terms of decision making faced by smallholder farmers in relation to their participation in the PNAE. The specific data inputs to carry out the case study were obtained from several sources.

The calls chosen as inputs for the case study matched the calls that were shortlisted by the farmers during the meetings of the months of November and December 2018 for the preparation of bids for the first semester of academic year 2019. The information of the calls is publicly available. As a result, a set of 24 state schools in the Goiania metropolitan region was considered in the case study as schools where the Canudos farmers could possibly bid within PNAE. Schools are located in seven municipal clusters, as detailed in Table 1. For each municipal cluster, the distance from the Canudos settlement to the centre of each municipal council was retrieved from geographic information systems (GIS), and the bureaucracy cost c_r^{bur} associated with the delivery of the bids to each cluster, are displayed. Most clusters are located within 100km from Canudos, thus increasing the chances of farmers being selected according to the priority rules for local suppliers. The only exception is the cluster of Posse, which was shortlisted by farmers due to the high number of schools it includes and the large quantities of demand (Supplementary material, Table A.2). The bureaucracy cost for each cluster is calculated as the cost of a return trip from Canudos to each municipal council using an average vehicle and corresponds to the second term of the objective function of DSS1 (Equation 1). All

clusters, with the exception of Varjão, include at least two schools within the municipal boundaries. As all schools are state schools, the planning period is set to one Brazilian school semester (22 weeks).

Table 1: Information about municipal clusters and schools

Municipal Cluster	Distance from Canudos [km]	Bureaucracy cost [BRL]	School	School code
Campestre de Goiás	17	21.76	Col. Est. Castelo Branco	1
			Esc. Estadual Nossa Sra. Das Graças	2
Cezarina	34	43.52	Col. Est. Prof. Maria Apresentação	3
			Esc. Est. Maria do Carmo Franco	4
Guapó	35	44.80	Col. Est Dep. José de Assis	5
			Col. Est. De Posselândia	6
			Col. Est. Prof. Lidosia Serra Ramos	7
			Esc. Est. Dr. Jose Feliciano Ferreira	8
			Esc. Est. Valdivino Serafim	9
Indiara	64	81.92	Col. Est. De Indiara	10
			Esc. Est. Valeriano de Barros	11
Palmeiras de Goiás	36	46.08	CEPI Barão do Rio Branco	12
			CEPI Dona Maricota	13
			CEPMEG - Palmeiras de Goiás	14
			Col. Est. Polivalente de Palmeiras de Goiás	15
			Esc. Est. Lourival Bueno de Oliveira de Palmeiras	16
Posse	580	742.40	CEPI - Argemiro Antônio de Araujo	17
			CEPI - Prof. Francisca Pinto Fernandes Rosa	18
			Col. Est. Coronel Ernesto Antônio de Araújo	19
			Col. Est. Do Povoado Barreiro	20
			CPMG - Dom Prudêncio	21
			Esc. Est. Do Povoado Nova Vista	22
			Esc. Est. Dr. João Teixeira Júnior	23
Varjão	35	44.80	Col. Est. José Cipriano	24

The characteristics of the vehicle considered are displayed in Table 2 and include the capacity of the vehicle both in terms of weight and volume as well as its average cost per km travelled.

Table 2: Average vehicle characteristics

Characteristic	Variable	Unit	Value
Capacity in weight	CV_{avg}^{weight}	[kg]	650
Capacity in volume	CV_{avg}^{volume}	[crates]	23
Transportation cost	c^{km}	[BRL/km]	0.64

Data about the production dynamics in Canudos were collected using a questionnaire with all smallholder farmers active in the cooperative dedicated to PNAE in the period between the months of March and April 2019. Moreover, visits were made to rural properties and each member of the cooperative was interviewed. There were overall 21 interviews lasting approximately 2 hours each. Table A.1 (in supplementary material) summarises the information about the products cultivated at the Canudos settlement, which are part of the PNAE demand in the Goiania metropolitan region. Overall, there are 28 product groups, which corresponds to 31 products. Grouping of products exist only for cassava, corn and garlic as multiple products demanded by schools are obtained from these crops, with different levels of post-harvest processing. For each of the 31 products, information includes the type of crop (annual or perennial), the maximum area theoretically available for the production of each annual crop, the land productivity for each product, which is the inverse of the yield, as well as the number of cycles the product can be harvested per semester, thus leading to the production capacity per semester. This is obtained as the ratio of the area available per product divided by the land productivity, times the number of cycles per semester of the product (Supplementary material, equation A.1). Moreover, the last two columns display the weight-to-volume ratio and the production cost for each product. The total area available for all annual crops is equal to 10.5 hectares. It should be noted that production costs are subject to uncertainty, due to potential variation of the production inputs cost or the actual yield. This uncertainty has been minimised by using timely data based on local conditions and the past experience of the farmers.

Finally, Table A.2 and Table A.3 (in supplementary material) show the quantities demanded and the prices paid by each school for each product. Farmers are allowed to bid for all calls, with no forbidden calls and after discussion with the farmers, the maximum number of calls was set at 24. To reduce size, only information related to products that farmers in Canudos are able to produce is reported in the tables. A peculiar feature of the PNAE program is that different schools pay different prices to farmers for the same product, thus increasing the complexity of the decision-making process both at the stage of the bid/no-bid decision and at the stage of contract selection and signing.

4 Results and Discussion

The DSS for both optimisation models was applied in the settlement of Canudos using information on past bids attended by Canudos farmers referring to the first school semester of the Brazilian academic year 2019. Section 4.1 shows results from the DSS1 application related to the bid/no-bid decision, whereas Section 4.2 on DSS2 builds on the outputs of DSS1 and the additional information about the outcome of the bids and the school-product pairs farmers from Canudos were awarded in order to determine which contracts for supply they should accept. Finally, Section 4.3 discusses the results.

Both mathematical optimisation models were implemented in the syntax of the Julia language using the environment JuliaPro version 1.2.0-0 and were solved using the branch-and-cut algorithm included in the GUROBI MILP solver version 8.1.1. All computational experimentations were run on a Pentium Intel Core i7 with 1.99 GHz processor, 16 GB RAM memory and Windows Operating System.

4.1 DSS1 Results

The DSS1 case study problem was solved to optimality in an acceptable computation time, i.e., all results were obtained in 101.00 seconds, including procedures for reading input data and outputting into files.

The identified optimal solution achieves an overall expected profit of 51,153.26 BRL (Brazilian Reals) over the course of a school semester should all bids be successful. The generated expected revenue (product price paid minus production costs) through PNAE of 73,704.30 BRL is reduced by 980.48 due to bureaucracy costs and by 21,570.56 BRL due to overall transport costs, as illustrated in Table 3. Interestingly, Posse is the cluster generating more expected revenues, which are equal to 29,731.37 BRL, and is being selected despite the large distance from Canudos due to its largest demand; however, Palmeiras de Goiás is the most profitable cluster once the bureaucracy costs and the transport cost are deducted, benefiting from much lower transport costs thanks to the more proximate position to the settlement of Canudos.

Table 3: DSS1 breakdown of expected profits

Municipal Cluster	PNAE expected revenues [BRL]	Bureaucracy cost [BRL]	Transport Cost [BRL]	Expected profit [BRL]
Campestre de Goiás	1,656.71	21.76	478.72	1,155.69
Cezarina	7,868.21	43.52	957.44	6,867.25
Guapó	14,322.47	44.80	985.60	13,292.07
Indiara	5,762.88	81.92	1802.24	3,878.72
Palmeiras de Goiás	14,363.20	46.08	1013.76	13,303.36
Posse	29,731.37	742.40	16,332.80	12,656.17
Varjão	0	0	0	0
Total	**73,704.30**	**980.48**	**21,570.56**	**51,153.26**

The overall potential profit is achieved thanks to the expected delivery of 23,385 kg of produce to 23 schools, belonging to 6 municipal clusters. Table 4 illustrates the school-product pairs which have been selected for bidding (any non-zero, non-strikethrough product quantity numbers), whereas no bid is to be submitted for pairs displayed with strikethrough numbers. Varjão is the only cluster for which a complete no-bid decision is taken, according to the model. The low demand of this cluster, which includes only a single school, coupled with potentially 22 trips to the municipality determines that transport cost would not be covered by the profits generated through PNAE, thus discouraging farmers to bid for it. Moreover, five pairs of school-product were not selected for schools that the model proposed to bid in anyway. The reason for this may be traced on the grounds that the price paid is actually lower than the production cost: this is the case of carrot (schools 5, 15, 19) and lettuce (schools 17, 20).

Table 4: School-product pairs selected for bidding

Product/School [kg/semester]	School 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total [kg]
Pumpkin – Cabotia	40	0	90	12	80	0	100	0	0	25	15	30	10	74	100	50	100	400	~~150~~	210	300	75	~~140~~	~~8~~	1,711
Courgette	40	0	60	0	0	0	90	0	0	25	0	0	0	0	0	20	100	0	0	0	0	45	0	0	380
Saffron	2	0	8	2	0	3	19	0	2	10	4	0	1	0	15	4	20	25	4	10	20	1	15	0	165
Chard	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50
Cress	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40
Lettuce	0	0	50	0	0	0	90	0	0	30	0	50	10	30	100	0	~~60~~	0	0	~~36~~	0	0	0	0	360
Garlic - peeled	6	4	20	6	50	25	40	0	20	30	13	0	10	65	40	20	0	40	3	63	50	6	40	0	551
Garlic - unpeeled	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20
Banana - Prata	50	50	500	100	189	0	150	100	70	100	140	250	120	57	200	60	450	800	200	860	~~300~~	160	450	0	5,056
Sweet Potato	40	0	90	20	0	0	70	10	0	25	10	0	0	112	100	50	200	0	100	170	0	25	50	0	1,072
Beetroot	40	0	10	15	90	40	130	15	40	30	10	0	0	20	60	0	100	0	100	0	0	20	80	0	800
Onion	30	12	100	15	0	50	150	50	50	50	140	0	40	200	200	50	100	0	0	0	400	0	0	0	1,637
Chive	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20
Carrot	30	9	100	96	~~170~~	80	160	50	40	50	200	0	60	313	~~150~~	50	~~150~~	~~400~~	~~180~~	~~100~~	~~200~~	~~50~~	~~180~~	0	1,238
Parsley	0	0	10	0	50	0	0	0	0	10	0	30	0	0	0	0	~~20~~	0	0	~~24~~	~~10~~	~~6~~	0	0	100
Coriander	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30
Kale	0	0	10	0	0	0	50	0	0	20	4	50	12	30	80	4	~~40~~	0	0	~~60~~	0	0	0	0	260
Mint	0	0	0	0	0	0	15	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	20
Lemon	0	0	0	0	0	0	50	0	0	0	0	0	0	50	0	0	0	0	0	0	100	0	0	0	200
Papaya – Formosa	0	40	400	100	200	0	150	100	100	40	0	0	60	0	100	50	0	0	0	0	0	0	0	0	1,340
Cassava - unpeeled	0	0	0	0	400	0	0	0	0	0	200	0	0	0	0	100	0	0	150	220	0	55	100	0	1,225
Cassava- peeled	60	60	201	19	0	60	100	200	40	200	0	70	80	200	300	0	300	400	0	360	250	0	0	0	2,900
Corn - crystal	0	0	0	0	0	0	150	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	150
Corn - green	0	14	200	18	0	0	0	60	0	90	15	50	70	75	150	50	100	0	0	0	0	0	0	0	892
Cucumber	0	0	0	0	0	0	40	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	80
Cabbage	0	25	99	25	150	40	160	60	20	100	80	0	46	200	90	50	~~100~~	0	60	0	200	0	0	0	1,405
Cabbage - Purple	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50
Rocket	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30
Tangerine	0	0	180	0	0	0	0	0	0	0	0	0	0	86	0	0	0	0	0	0	0	0	0	0	266
Tomato	0	10	90	19	150	30	60	80	78	50	50	0	30	70	60	50	80	0	80	0	250	30	0	0	1,267
Green bean	0	0	0	0	0	0	30	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	70
Total [kg]	**338**	**224**	**2218**	**447**	**1359**	**328**	**2024**	**745**	**460**	**885**	**881**	**530**	**549**	**1622**	**1640**	**608**	**1550**	**1665**	**697**	**1893**	**1570**	**417**	**735**	**0**	**23,385**

Finally, additional products were not selected for bidding within the cluster of Posse (schools 17-23), which is the furthest from Canudos. Posse is also the cluster with the largest demand: the minimum number of trips, which is equal to the number of weeks within one semester as per Equation (11), would not be sufficient to cover the entire demand due to the vehicle capacity constraint. In this case, the volume capacity is the active constraint compared to weight capacity, therefore the model selects the products whose profit per unit of volume is higher until the 22nd trip to the Posse cluster is loaded to fill its entire volume capacity. After investigation, it was identified that a 23rd trip to Posse would not be profitable as the marginal revenues generated through any mix of the excluded products would not cover the transport cost of one extra trip.

The selected school-product pairs in non-zero, non-strikethrough quantities in Table 4 constitute the best-case scenario for farmers in terms of profitability, as it is unlikely that all submitted bids are going to be successful following the selection process by public authorities. Ultimately, the DSS1 model proposes that farmers bid for 23 out of the 24 schools (Table 4), but not for all products in each school.

4.2 DSS2 Results

4.2.1 **Bid Outcomes**

Once the public authorities have ranked the bids on the basis of the distance and social exclusion criteria, farmers face the second decision, which is whether to accept to supply the produce for the awarded bids or reject to supply specific school-product pairs. The time difference between the decisions made in DSS1 and DSS2 is typically less than one month.

In the case study examined, out of the 23 schools they submitted a bid for, Canudos' farmers were successful in the bids to 15 schools, while they were unsuccessful in the bids to 8 schools, due to the distance criterion. These eight schools are all those located within the clusters of Indiara and Posse, where other local suppliers were given priority. Moreover, Canudos' farmers were unsuccessful everywhere for the product 'Tangerine', due to the social exclusion criterion. As a result, the range of options following the bids selection by public authorities is reduced, as shown in Table 5, where the unsuccessful clusters of Indiara and Posse have been omitted, in addition to the cluster of Varjão, where farmers did not bid for any product. School-product pairs that are depicted in bordered cells in Table 5 cannot be supplied either because farmers did not bid for them in the first stage of the process, as in the case of carrots at schools 5 and 15, or because farmers did not get selected, as in the case of tangerines.

Table 5: Final selection of school-product pairs for supplying

Product/School [kg/semester]	**School 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**12**	**13**	**14**	**15**	**16**	**Total [kg]**
Pumpkin – Cabotia	40	0	90	12	80	0	100	0	0	30	10	74	100	50	**586**
Courgette	40	0	60	0	0	0	90	0	0	0	0	0	0	20	**210**
Saffron	2	0	8	2	0	3	19	0	2	0	1	0	15	4	**56**
Chard	0	0	0	0	0	0	50	0	0	0	0	0	0	0	**50**
Cress	0	0	0	0	0	0	40	0	0	0	0	0	0	0	**40**
Lettuce	0	0	50	0	0	0	90	0	0	50	10	30	100	0	**330**
Garlic - peeled	6	4	20	6	50	25	40	0	20	0	10	65	40	20	**306**
Garlic - unpeeled	0	0	0	0	0	0	0	20	0	0	0	0	0	0	**20**
Banana - Prata	50	50	500	100	~~**189**~~	0	~~**150**~~	100	~~**70**~~	~~**250**~~	~~**120**~~	~~**57**~~	200	~~**60**~~	**1,000**
Sweet Potato	40	0	90	20	0	0	70	10	0	0	0	112	100	50	**492**
Beetroot	40	0	10	15	90	40	130	15	40	0	0	20	60	0	**460**
Onion	30	12	100	15	0	50	150	50	50	0	40	200	200	50	**947**
Chive	0	0	0	0	0	0	20	0	0	0	0	0	0	0	**20**
Carrot	30	9	100	96	170	80	160	50	40	0	60	313	150	50	**988**
Parsley	0	0	10	0	50	0	0	0	0	30	0	0	0	0	**90**
Coriander	0	0	0	0	0	0	30	0	0	0	0	0	0	0	**30**
Kale	0	0	10	0	0	0	50	0	0	50	12	30	80	4	**236**
Mint	0	0	0	0	0	0	15	0	0	0	0	0	5	0	**20**
Lemon	0	0	0	0	0	0	50	0	0	0	0	50	0	0	**100**
Papaya – Formosa	0	40	400	100	200	0	150	100	100	0	60	0	100	50	**1,300**
Cassava - unpeeled	0	0	0	0	400	0	0	0	0	0	0	0	0	100	**500**
Cassava- peeled	60	60	201	19	0	60	100	200	40	70	80	200	300	0	**1,390**
Corn - crystal	0	0	0	0	0	0	150	0	0	0	0	0	0	0	**150**
Corn - green	0	14	200	18	0	0	0	60	0	50	70	75	150	50	**687**
Cucumber	0	0	0	0	0	0	40	0	0	0	0	40	0	0	**80**
Cabbage	0	25	99	25	150	40	160	60	20	0	46	200	90	50	**965**
Cabbage - Purple	0	0	0	0	0	0	50	0	0	0	0	0	0	0	**50**
Rocket	0	0	0	0	0	0	30	0	0	0	0	0	0	0	**30**
Tangerine	0	0	180	0	0	0	0	0	0	0	0	86	0	0	**0**
Tomato	0	10	90	19	150	30	60	80	78	0	30	70	60	50	**727**
Green bean	0	0	0	0	0	0	30	0	0	0	0	0	40	0	**70**
Total [kg]	**338**	**224**	**2038**	**447**	**1170**	**328**	**1874**	**745**	**390**	**280**	**429**	**1479**	**1640**	**548**	**11,930**

[ ] **Contract unavailable for signing** xx **Contract signed** ~~**xx**~~ **Contract not signed**

4.2.2 Signing Decision by Farmers

The DSS2 case study was solved to optimality in an acceptable computation time, i.e., all results were obtained in 106.07 seconds, including procedures for reading input data and outputting into files.

The identified optimal solution achieves an expected overall potential profit of 32,156.81 BRL over the course of a school semester by signing the shortlisted contracts to supply 171 school-product pairs. The generated potential revenue (product price paid minus production costs) through PNAE of 35,592.33 BRL is further reduced by 3,435.52 BRL due to the estimated transport costs, as illustrated in Table 6. Similarly to DSS1, the transport cost is an estimation as the full information about the delivery schedule to schools is not available at this stage.

Table 6: DSS2 breakdown of expected profits

Municipal Cluster	PNAE expected revenues [BRL]	Transport cost [BRL]	Profit [BRL]
Campestre de Goiás	1,656.17	478.72	1,177.45
Cezarina	7,268.81	957.44	6,311.37
Guapó	13,527.90	985.60	12,542.30
Indiara	0	0	0
Palmeiras de Goiás	13,139.45	1,013.76	12,125.69
Posse	0	0	0
Varjão	0	0	0
Total	**35,592.33**	**3,435.32**	**32,156.81**

The potential revenue decreased by a remarkable 37%, compared to the outcomes of DSS1. This is largely due to the fact that farmers were not successful in any bid in the clusters of Indiara and Posse, hence reducing sources of potential income. Another consequence of the bid selection process by public authorities is that, following DSS2 optimisation, Guapó becomes the cluster expected to generate more profits, standing at 12,542.30 BRL, followed closely by Palmeiras de Goiás cluster, which was the most profitable cluster following DSS1 optimisation.

The overall potential profit is achieved thanks to the expected delivery of 11,930 kg of produce to 14 schools, belonging to 4 municipal clusters. This marks a sharp decrease by 49% in the amount of produce to be delivered compared to DSS1, which is largely caused by the number of schools included in the delivery program dropping by 39% due to unsuccessful bids. Table 5 illustrates the school-product pairs which have been selected for signing the contract (in any cell with non-zero, non-strikethrough, non-bordered cell numbers), whereas no contract is to be signed for pairs displayed with strikethrough numbers.

Out of all school-product pairs available for selection, Banana-Prata is the only produce for which DSS2 prescribes not to sign contracts in certain schools. This is due to the production capacity limit for Banana-Prata, which is equal to 1,000 kg. As Banana-Prata is a perennial crop, this production capacity is fixed and cannot be expanded in the short term. Therefore, DSS2 elects to sign the contracts for Banana-Prata according to the combination that provides the maximum profit, thus prioritising schools where the price

paid per kilogram of produce is higher. On the other hand, no other product or group of products was restricted by crop-specific production capacity constraints. Case study solutions were also not restricted by the overall production capacity constraint, as Canudos settlement has enough land availability to cultivate all annual crops to satisfy the demand of signed contracts through DSS2. Finally, the lack of inclusion of specific products due to the bid selection process by public authorities (e.g. Tangerines) or due to the contract signing decisions by farmers (e.g. Banana-Prata) did not cause the profitability of any cluster to drop below the threshold where the profits generated through other products are not sufficient to cover the transport costs to the cluster, hence determining that contracts for the whole cluster would not be signed.

Finally, it is worth noting that the expected overall profit obtained through DSS2 does not consider the cost of bureaucracy, which is a sunk cost at this stage of decision-making regarding signing the contracts. Nevertheless, as DSS1 and DSS2 are applied sequentially, the real final overall profit of the farmers would further drop by 980.48 BRL due to bureaucracy costs faced at the bidding stage, thus decreasing to 31,176.33 BRL. Thus, the bureaucracy cost is a real cost even though sunk at this stage.

4.3 Discussion

In DSS1, the support provided in terms of guidance on where to bid is critical, as the time window of applications for bidding is narrow, the farmers may have concurrent in-farm obligations, and in many cases, they do not understand whether they would actually make a profit from specific products and/or schools, leading them to decisions based on intuition or simply on proximity. These are not always to their benefit, as shown by the results of DSS1, where certain school-product pairs were discarded as the price paid by such schools was lower than the production cost faced by farmers. Vice versa, products with a low profit margin are still included if they are part of larger supplies to a cluster, as they take on a share of the transport cost to that cluster. This is especially the case of products in more distant schools, which may be not be selected for bidding by farmers despite being profitable options. Moreover, the contribution of DSS1 was also demonstrated for the cluster of Varjão which was not proposed for bidding, despite the fact that the profit per unit of product before transport (price minus production cost) is highly positive. Therefore, the farmers could benefit from using the proposed DSS1 to prioritise their limited resources to maximise their potential for profit, since the bidding decision is very complex.

To validate the model outcomes against real farmer decisions, the case study application of the proposed model was compared against the reality, by applying the model in parallel to a real bidding process and comparing the outcomes. In terms of DSS1-related decisions, the farmers' intuitive strategy was to bid in all schools of clusters Campestre de Goiás, Cezarina, Guapó, Indiara and Palmeiras de Goiás (schools 1-16 in Table 1), their sole criterion being proximity, and for all products of each school. The model outcomes differed in two aspects: firstly, the model proposed submitting a bid also in the cluster of Posse (schools 17-23), where the farmers did not consider bidding as they thought the increased distance would make this unprofitable; secondly, the model suggested not to bid for specific products in some schools (e.g. carrots in

schools 5 and 15, 17-23 and other product-school combinations marked as strikethrough in Table 4), contrary to the farmers' intuitive strategy of bidding for all products of each school they would submit a bid in. The expected profit following the farmers' intuitive strategy would be 38,356.99 BRL whereas the proposed model outcomes lead to an expected profit of 51,152.26 BRL, both due to the inclusion of the additional profitable cluster of Posse, and due to eliminating some non-profitable product-school combinations. This indicates the difficulty of understanding the potential for profit generation based on intuitive and simplistic rules.

Similarly, DSS2 can support further complex decisions. There is particular value in providing an understanding on which school-product pairs of the successful bids farmers should commit to supply, which can ultimately maximise the profit they make from the supply through PNAE. Based solely on intuition, farmers may decide to sign contracts for all school-product pairs where they have been successful, neglecting any production capacity or land availability constraint, since considering them would require a detailed overview knowledge and calculations for different produce mixes. This could lead to potential serious consequences for farmers in the case where they are not able to deliver the quantities agreed in the contracts, as they may be excluded from participation in PNAE calls of specific schools in the following years. Moreover, certain schools may not be profitable for the available product mix at this stage of the decision-making process due to the exclusion of certain products from the submitted bids during DSS1. In the case that farmers have not been selected to supply certain products by public authorities, the remaining product mix may not be sufficient to cover the transport cost and generate a profit. The decision-making problem that farmers are facing at the stage of signing contracts is a very complicated one, especially considering the transport cost, which is usually not considered by the farmers, leading to suboptimal solutions when they base their decisions on intuition only.

DSS2 was also validated against the farmers' real decisions by inputting in the model case study application the schools and product bids where the farmers were successful. The farmers' intuitive strategy was to sign the contract for all successful schools and all products awarded, including the carrots in schools 5 and 15 that are unprofitable. The additional profit by following the model solution would be 140.1 BRL, due to not supplying the carrots. Additionally, the model suggested not to sign contracts for one product (Banana – Prata) in several schools (5, 7, 9, 12-14, 16 as seen in Table 5). In this case the specific product is only supplied to some schools due to production capacity constraints rather than it not being profitable. The intuitive strategy adopted by the farmers entails significant risk in this case as not honouring the contracts in certain schools leads to exclusion from future bids in such schools. The value of the model in this case lies firstly in clearly highlighting and considering the capacity constraints; and secondly in identifying the optimal allocation of the products with limited availability to the schools with the maximum potential for profit, while considering the transportation costs too. This indicates the complexity of the problem at hand and the difficulty of making the most effective decisions based on intuitive rules.

Utilising the proposed DSS models, farmers can take more timely and effective decisions and spend effort only on administrative tasks that are actually beneficial for them, allowing them to spend more time on their core activities of farming and maximising the returns from their participation in the PNAE program.

5 Conclusions and Further Research Directions

This study aimed to support smallholder farmers in decisions relating to participation in institutional markets for school feeding programs in Brazil. There were two stages of decisions supported, the decision whether to bid or not for each specific school and product combination and the decision whether to accept or not the awarded bids once the outcome of the bids is known. For this reason, two MILP optimisation models were developed to support these decisions. The DSS models were applied to a case study with primary data sourced from actual practice for the smallholder farmer settlement of Canudos in Brazil, and their utility was demonstrated; however, they can be applied for any similar case of farmers aiming to bid in institutional markets.

This study contributes to the knowledge in the field of decision support systems by applying established OR methods, such as MILP, to a real-life problem, within a new context. It enhances the knowledge base in the scarce non-DEA OR-based bid/no-bid DSS literature and is the first DSS application for non-competitive bidding. Since DEA focuses on ranking of strategies or bids whereas the proposed DSS define an optimal bidding strategy through application of optimisation methods, the proposed DSS has a different scope than the existing DEA literature. Within the bid/no-bid decision-making area, this is also the first DSS applied to the agricultural and institutional markets context, aiming to facilitate decision-making of smallholder farmers in a developing country context when participating in institutional markets.

In terms of contribution to practice, the development of both DSS models was driven by the needs of smallholder farmers, with the objective to provide them with tools that can effectively facilitate their real-life decisions and increase their participation in a governmental support program specifically designed for them. The use of the proposed DSS models can remove subjectivity and intuition from the decision-making process, leading to more effective bidding strategies. At the same time, it removes the obstacle of disagreements within the farmers' cooperative on where to bid and which successful bids to select, due to an objective strategy being defined. The two DSS models support the farmers through the different phases of the bidding process, incorporating the available information at each stage to provide more accurate solutions. The use of these DSS models allows farmers to disengage from the complicated process behind bidding and leaves them with more time to focus on their core farming and land management activities.

There are also wider social implications, relevant for the policy makers. As the developed DSS models can contribute towards the increase in the participation of farmers to PNAE, by facilitating their participation-related decision-making process, this can lead to more schools reaching the 30% threshold of spending from socially disadvantaged groups identified by FNDE, thus minimising the amount of unused funds by schools. Also, the proposed DSS defines efficient school supply regimes for the farmers, in the sense that

transportation costs are considered; meaning that more of the revenue can stay with smallholder farmer communities instead of being spent directly in more transport activities. Both previous arguments mean more funds can eventually reach the smallholder farmers as intended and support vulnerable rural communities, maximising the impact of the relevant policies. Finally, this study could also indirectly benefit schools and pupils, as the PNAE funds would not be returned to FNDE, but could remain within the schools, which would thus better care for the nutritional needs of pupils.

The limitations of the proposed approach are primarily linked to the level of available information at each stage of the decision process. For example, the lack of visibility over the requested amounts of products at each school each week does not allow for a more accurate calculation of the distribution costs at the early decision stages, and leads to assumptions made in the models. Another limitation is that the deterministic nature of the proposed approach does not allow consideration of the impact of input factors uncertainty, such as the production cost. Despite limiting this uncertainty by using the farmers' experience and local data inputs, the optimal solution could potentially change for some marginally profitable or unprofitable product-school combinations if the actual production cost changed. Moreover, since the DSS has been applied to a single case study; it would be interesting to validate the DSS with more farming communities in order to strengthen the external validity of the case study through replication logic (Yin, 2003) to further validate the model outcomes against the farmers' real decisions.

Beyond further applications of the DSS models to additional PNAE institutional markets, it would be interesting to explore the potential for additional applications to other institutional markets showcasing different features, or even in other types of markets or combinations of markets. In addition, the proposed DSS models could be further developed as stochastic, to be able to consider parameter uncertainty. Other directions for future research include converting the DSS models in a social technology application, adopting a user-friendly format, such as a mobile phone application using simplified language, to allow farmers to use them independently. In this respect, knowledge transfer is required to train farmers in order to better understand the use of the proposed DSS models and exploit their potential. It would also be relevant to study ways of ensuring an equitable distribution of the profit generated at the cooperative level, to the individual farmer level. Finally, it would also be interesting to study the impact if the DSS models were applied at a large scale, i.e. whether many competing smallholder farmers and cooperatives using this tool simultaneously could distort their bidding behaviour, perhaps using a game-theory approach. However, the key idea behind the DSS development that there is a fixed amount of resources, i.e. budget of PNAE, to be shared among all farmers and that there are efficient ways to share this fixed resource by minimising the transport costs and avoiding economic losses, always holds true.

Ultimately, the DSS models proposed in this study could have a substantial social impact in the livelihoods of smallholder farmers in Brazil, as they can maximise the returns from participation in programs that are designed to support the farmers, such as institutional markets, and secure a stable source of income. The idea of making efficient use of the limited resources that are available to support them enhances the potential for

profit staying within the smallholder farmer families, which could subsequently lead to better living conditions, healthcare, sanitation, education and re-investment in their agricultural production and ultimately contributes to inclusive agricultural growth.

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Declaration of Interest

Declarations of interests: none.

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