Data-driven Planning in the Face of Supply Disruption in Global Agricultural Supply Chains

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***Abstract*—The intricacies of global food networks have been exacerbated by increased globalization, advances in farming/logistics technology, and a rising agricultural exchange between countries. Certain economies, especially regions with low agricultural yield, rely on food imports and are susceptible to food insecurity due to potential negative disruptions to the global food network. These rising complexities in global food networks result in increased dependencies between countries, rendering the overall network extremely vulnerable. Local disruptions to production levels could entirely cripple the food network and lead to long-term reduced food access worldwide. Understanding the impact of different disruptions and potential mitigation strategies at the country level on agricultural supply chains becomes important in the analysis of the global allocation of agricultural products. We model a stochastic resource allocation problem with non-linear connectivity costs to capture trade dynamics between countries. We compare model recommendations to historical trade flow data including coffee import/export between countries, unveiling the value of centralized planning under potential disruption scenarios against the current practices.**

***Index Terms*—Global Agriculture Networks, Stochastic Optimization, Supply Chain and Risk**

I. INTRODUCTION

Many service systems experience failures or capacity reductions due to intentional disruptions, natural disasters, or accidental failures [1]. Advancing technology and increased globalization in recent decades have seen supply chain vulnerability to disruption rise and demand in most sectors become increasingly volatile [2, 3]. If not properly considered, uncertainty in supply chains can manifest itself in many forms of disturbances, such as deviations in demand patterns, supply side disruptions, and limited response capability to natural disasters [4]. This is particularly relevant for agricultural supply chains (ASCs) that already face high levels of stochasticity due to their inherent characteristics including long lead-times, seasonality, perishability, and even sanitary emergencies (e.g., diseases), among several others [5]. Unexpected shocks to key production-heavy regions could entirely cripple the ASC networks and reduce food access globally [6]. Certain economies, especially regions with low agricultural yield, rely on imports for food and are susceptible to food insecurity and negative disruptions to the global food network.

Understanding and modeling network disruption within ASCS is an essential analysis of the performance of supply chains. Several researchers have studied supply chain network disruptions via simulations [7–9]. Optimization models have also been employed by researchers to explore disruption also design supply chains that are robust and/or resilient to these disruptions [10–15]. However, the works intersecting ASCs and risk analysis rarely analyze supply chains at the global scale or even include measures distinctive to the Agricultural Supply Chains such as trade connections.

Our research aims to comprehend how production capacity disruptions at the country level affect food distribution and access globally, and how can we create systems to mitigate these disruptions. To address these questions, we model a stochastic resource allocation problem with non-linear connectivity costs that accounts for the trade connections between countries. We use historical coffee trade data from a World bank database to illustrate the use of the proposed framework. The model provides information about how suppliers should optimally allocate agricultural products, based on supply/demand, connectivity costs, and the potential disruptions between nodes in the network. In addition, we discuss some limitations in existing models and plans to extend the formulation to accommodate these limitations, including implementing a risk-averse formulation where planners will be able to explicitly evaluate the risk associated with each solution.

II. METHODOLOGY

A. Uncertainty: Node Disruption

We utilize a global ASC network, consisting of the exchange of single or multiple agricultural products between countries to analyze the worldwide impact of disruptions to agricultural products. The global ASC network is abstracted into a graph, with nodes representing countries and edges denoting the quantity of material moving between the nodes. To incorporate uncertainty in our optimization framework, we generate a series of scenarios capturing potential disruptions in the global supply chain (at a node level). We define a disruption as a fractional loss in the production/supply capacity of a node during a single period. This is modeled by multiplying the production/supply capacity of each node by a parameter $\beta \in [0, 1]$. When $\beta = 1$, no disruption is included while $\beta = 0$ represents a full disruption where all the node capacity is lost. Perturbing the capacity will have a linear effect on our model because the disruption is defined using a linear function (Section D). As a result, we focus on the extreme cases in our experiments. We define P_j as the total capacity of node j without disruption. In the full disruption state, the node loses all production capacity such that for node j we have $P_j^{full} = P_j$. Similarly, the no disruption state is defined

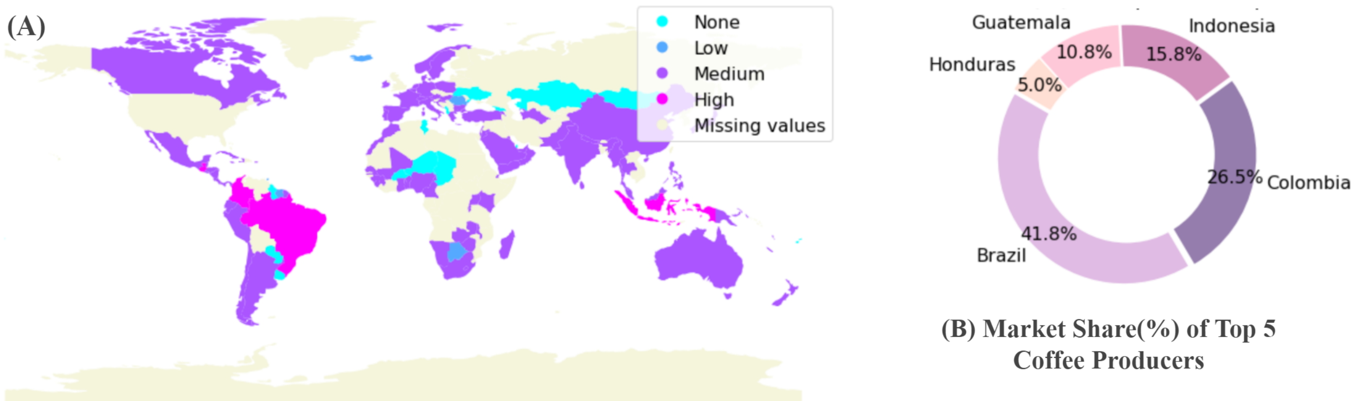

Fig. 1: Panel (A) illustrates the world map with countries coded by supplier category. They are classified into four categories: no supply, high, medium, and low volume suppliers. Countries with missing data are represented by the missing values category. In panel (B), a pie chart highlights the top five coffee supplying countries and their corresponding market share.

by $P_j^{none} = 0$ for every node j in the network. Therefore, a scenario consists of a vector of all the individual nodes with a selected capacity state. For our analysis, we assume that at most one node can experience a capacity disruption in each scenario. This leaves us with a number of scenarios upper bounded by the total number of nodes in the network + 1.

Not all nodes (countries) in our global supply chain have the capacity to produce and supply food products. It is important to select nodes with significant supply signals such that their disruption can influence the performance of the ASC. For this, we run our model using scenarios where a single country on the top 25th production percentile is fully disrupted. This analysis results in a set of 30 different scenarios, allowing us to quantify the impact on the costs compared to the baseline (deterministic, no disruptions) case. In this initial study, all scenarios are treated as equally probable.

B. Stochastic Allocation Model

We introduce the formulation of the global agricultural allocation model for one commodity under disruption uncertainty. Some key structural assumptions for our model include (1) Use a single product with deterministic demand at each node. (2) We do not allow self loops in the network. i.e we ignore demand of nodes satisfied locally and (3) Unmet demands are lost and assigned to dummy node,$\bar{k}$ We define a directed graph, $G = (\mathcal{N}, \mathcal{A})$ with nodes $i \in \mathcal{N}$ representing countries and the arcs $(i, j) \in \mathcal{A}$ denoting the flow of agricultural products from node i to node j.

Sets

- I: set of nodes (countries)
- S: set of scenarios (disruptions)

Decision Variables

- X_{ij}^s = Fraction of demand node j allocated to node i under scenario s

Parameters

- P_j^s: Production capacity of node j under scenario s
- D_i: Demand at node i
- c_{ij}: Transportation costs from node i to node j
- π: Penalty cost for lost demand
- $N = |I|$: Total number of nodes
- p_s: Probability of scenario s ($p_s = 1/|S|$).
- $f_{i,j}(X_{ij}^s)$: non-linear function (connectivity costs)

Then, we define the stochastic allocation problem $SAP(X)$ including node disruption (scenarios $s \in S$) as follows:

$$\min_x \sum_s p_s \left(\sum_{i,j} (f_{ij}(X_{ij}^s) + c_{ij} X_{ij}^s D_i) + \sum_i \pi D_i X_{i\bar{k}}^s \right) (**)$$

$$\text{s.t} \quad \sum_i X_{ij}^s D_i \le P_{j,s} \quad \forall j \in I, s \in S \tag{1}$$

$$\sum_j X_{ij}^s + X_{i\bar{k}}^s = 1 \quad \forall i \in I, s \in S \tag{2}$$

$$X_{ij}^s \in \{0, 1\} \qquad \forall i, j \in I, s \in S \tag{3}$$

In Eq. (**), the objective is to minimize i) connectivity costs associated with each node which is a function of allocation variables, X_{ij}^s (see Section D) and ii) penalty costs resulting from lost demand allocated to the dummy node $\bar{k}$. Eq. (1) ensures that we do not allocate beyond the production capacity of each node. In Eq. (2) we ensure that for each node, either demand is allocated to another node or lost (sent to the dummy node $\bar{k}$). Binary constraints are imposed in Eq. (3).

C. Connectivity Function

To estimate the connectivity costs we use a function $f_{ij}(X_{ij}^s)$, similar to the Connections Model from social and economic theory [16]. Thus, our connectivity costs function between node i and node j, under scenario s, becomes:

$$f_{ij}(X_{ij}^s) = \bar{c}_{ij} - \delta_{ij}^s w_{ij} - w_{ii} \tag{4}$$

where,

- δ_{ij}^{s}: Relative value that node i derives from being connected to node j under scenario s
- w_{ij}: quality (intrinsic value) product node i expects to receive from node j
- $\bar{c}_{ij}$: cost of maintaining edge (i,j)

The δ_{ij}^{s} parameter captures the variation in value that each connection has, associated with scenario s. To estimate its value, we use the concept of degree centrality, C_i, that measures the number of links incident to a node to assess the importance each node has within a network:

$$C_i = \frac{1}{N-1} \sum_{j=1, i\neq j}^{N} a(i,j) \tag{5}$$

with $a(i,j) = 1$ if i is connected to j, 0 o/w.

In our setting, the value of node i will likely decrease as it becomes saturated with connections. Thus, we estimate that node i will experience a lower value from being connected with j as its degree centrality increases. Since we are solving for allocation, and thus, do not know the values of $a(i,j)$, we use the allocation variable X_{ij}^{s}, obtaining:

$$\begin{aligned} C_i^s = C_i^s(X_{ij}^s) = \frac{1}{N} \sum_{j=1, i\neq j}^{N} X_{ij}^{s} \ \ \forall s \in S \\ \delta_{ij}^{s} = (1 - C_i^s) \ \ \forall s \in S \end{aligned} \tag{6}$$

We define w_{ij} as the quality of product node i expects to receive from node j. We assume that all nodes have the same constant intrinsic value: $A = 1$ to other nodes but 0 to themselves (i.e, $w_{ij} = A$ and $w_{ii} = 0$). We set $w_{ii} = 0 \ \forall i \in I$ because our data do not have information about demand fulfilled locally.

Replacing all the expressions in Eq. (5) and multiplying by $X_{i,j}^{s}$ to include only allocated edges, we get:

$$f_{i,j}(X_{ij}^s) \quad = \quad \bar{c}_{ij} X_{ij}^s - A(1 - C_i^s X_{ij}^s) \tag{7}$$

Thus our (non-linear) objective function becomes:

$$\min_x \sum_s p_s \left(\sum_{i,j} (A C_i^s X_{ij}^s + \alpha_{ij} X_{ij}^s) + \sum_i \pi D_i X_{i\bar{k}}^s \right) \tag{8}$$

where $\alpha_{ij} := \bar{c}_{ij} + c_{ij} D_i - A$ (interpreted as the adjusted edge maintenance and transport cost).

D. Data: Global Agricultural Network

Our data set consists of historical $(1996-2017)$ coffee trade flow values from the World Integrated Trade Solution database, created by the World Bank in collaboration with the United Nations Conference on Trade and Development (UNCTAD), International Trade Center, United Nations Statistical Division (UNSD), and the World Trade Organization (WTO) [17, 18]. We focus on the coffee trade data in 2015. A summary of the data can be found in Table I. In Figure 1 (A), we highlight four supplier classes (no supply, high, medium, and low volume suppliers) on a world map. Using statistics from the network (Table II), we divide the suppliers into high, medium, and low capacity based on their relative supply capacities. We use the following definition: high capacity is considered greater than the 75th percentile values, medium-capacity is close to the 50th percentile (median) values, and finally, low capacity is less than the 25th percentile values. This, excluding the zero supply countries which are grouped in a separate category (no supply). We create an additional category for countries with missing supply information. In panel (B), we present the top five coffee-supplying countries and their corresponding market share.

TABLE I: Global Coffee Supply Chain network Characteristics for 2015

Characteristic	Value
Number of Nodes	127
Number of Edges	918
Network Density	0.057
Clustering Coefficient	0.188
Time Resolution	1 year
Spatial Resolution	Country level

TABLE II: Summary statistics of coffee demand and supply data in 2015

Characteristic	Total Demand/[60kg bags]	Total Supply/[60kg bags]
Min	0	0
25th percentile	142	7
Median	2,676	275
75th percentile	75,703	5,836
Max	2,683,413	2.770,895
Mean	122,433	78,221

III. Results and Discussion

A. Deterministic solution: optimistic scenario

First, we run a baseline case in which no country experiences a capacity disruption, representing the most basic planning situation. Thus, we obtain a solution (lower bound) that will allow us to measure the impact and value of incorporating uncertainty in the planning process. In order to set the different components of our objective function on an equal scale, we normalize the demand and supply quantities, in the $[0,1]$ interval. As such, we obtain relative expected cost values for comparative purposes.

Solving the baseline case, we find an optimal objective equals 154.74 using $\pi = 10$ (deduced empirically from data; can be modified by decision-makers) and assuming there are no adjusted edge maintenance and transport costs, i.e. setting $\alpha_{ij} = 0$. Since we assume no transport or maintenance costs (subject of future studies), the model focuses on the trade-off between minimizing loss demand while ensuring that allocations are made with as few connections as possible. From the results, we observe how Brazil, Colombia, and Indonesia act as the main suppliers in the network, covering 35.3% of the total global demand. On average, each source supplies coffee to 23 countries, with negligible deviation from this number between suppliers. On the other hand, coffee-demanding countries tend to absorb an almost equal percentage of the total coffee

TABLE III: Summary statistics of solutions (Mean of Expected Costs (Objective), Mean Deviations of Objective from baseline deterministic case and standard deviation) for increasing number of scenarios considered in this study.

Number of Scenarios	Expected Costs	Mean Deviation from Baseline(%)	Standard Deviation
2	157.78	1.96	3.04
4	156.27	0.99	2.64
6	177.14	14.47	47.40
8	171.54	10.85	42.18
10	168.30	8.76	38.28
12	170.63	10.27	37.07
14	169.14	9.30	34.58
16	168.25	8,73	32.43
18	166.89	7.85	30.82
20	165.73	7.10	29.44
22	164.74	6.46	28.25
24	163.90	5.92	27.19
26	163.29	5.52	26.21
28	162.68	5.13	25.35
30	162.15	4.79	24.57

demand (0.8%) while being connected to 8.6 suppliers on average with a standard deviation of 16.7 countries. From the results, we note a complex supplier assignment structure where some countries are connected to as little as 1 supplier whereas others are connected to multiple suppliers. This pattern differs from the more uniform distribution we observe for the number of customers each coffee supplier can access.

We compare our model suggestions to real demand and supply allocations. The top three suppliers (Brazil, Colombia, and Indonesia) in our model correspond with the data. However, it underestimates the total contributions of the top coffee suppliers, with real contributions accounting for 63% of the total supply versus the 35.3% suggested by our model. We find greater diversity in allocations (both on the demand and supply side) within the real data with the top supplier (Brazil) having as many as 43 customers and Canada, the top importer, having being connected to 63 suppliers. The lack of diversity in supply allocations in our results suggest that the current connection function does not fully capture the intricacies of trade relationships between countries. Overall, we observe that our model is demand-driven. This can be a limitation as it prioritizes satisfying high-demand countries and would rather not allocate supply to countries with small demands.

B. *Disrupted network: the value of information*

When including uncertainty, we randomly select subsets of scenarios, incrementally increasing their number from 2 to 30. This procedure allows us to observe (Figure 2) the evolution and distribution of the objective costs as the number of scenarios increase. From the results (without including the two major outliers, Brazil and Colombia, to facilitate the visualization), we find that these high-impact countries coincide with the high-capacity suppliers (Figure 1), as expected. We note from this analysis that there exists a small set of very high-impact countries, such as Brazil and Colombia, that are responsible for providing a huge volume of coffee supply globally. As such, any disruption to the capacity of these nodes is translated into major cost increments. This unbalanced network structure makes the coffee supply chain network significantly vulnerable to disruptions, as any attacks on these critical nodes can severely reduce the overall coffee availability worldwide, significantly altering the market (the supply, demand, and price of the product, its substitutes, and complementary goods).

In Table III, we present the expected objective values, their mean deviations from the baseline (deterministic) case, and the standard deviation of the solutions as a function of the number of scenarios. We note that there is a spike in the expected objective (due to the disruptions of Brazil and Colombia) before the expected solutions begin to converge towards 163 (a 5% deviation above the baseline) as we increase the number of scenarios. We also observe similar patterns in the standard deviation values. From the data, we observe that the peak in the results is the consequence of the successive addition of the two extreme cases (Brazil and Colombia), translated in significantly higher values.

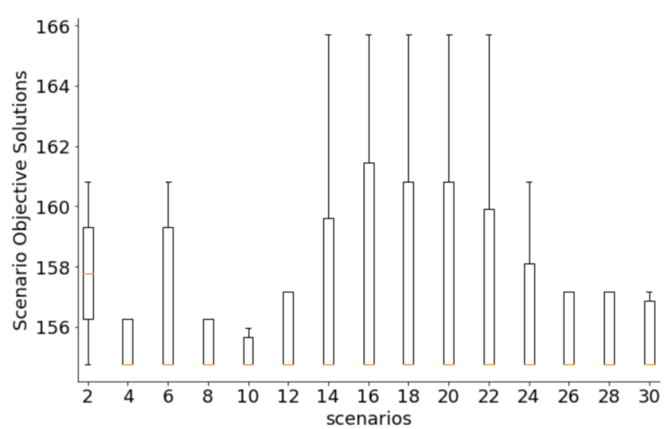

Fig. 2: Boxplot denoting Changes in objective costs distribution with increasing number of scenarios. The orange line represents the objective value for each instance.

At this point, we also note major differences between the deterministic and stochastic solutions. The limitations of the deterministic solution to adjust the allocation plan when dealing with uncertainty are translated into complex decision-making scenarios. For example, costly distribution alternatives would need to be explored to satisfy the demand and supply contracts of specific sections of the ASC. Moreover, countries could require to increase the consumption of substitute products to cover the existing demand. These situations are translated into a higher vulnerability and poor efficiency of the whole network when facing unexpected disruptions, significantly impacting multiple actors of the ASC. The inclusion of scenarios allows the planner to explore potential effects of disruption and make more robust and risk-sensitive allocation decisions.

IV. Conclusions and Future Work

In this work, we developed a general framework to analyze the performance of global agricultural supply chains. The proposed model is agnostic of the product and can be easily applied to multi-commodity networks. The inclusion of uncertainty modeled as disruptive events modifying the capacity of the nodes allow planners to explicitly incorporate potential events that could affect the performance of the network. This becomes crucial as certain agricultural networks, such as the one analyzed in this study, present a significant dependency on a small subset of countries/nodes, being extremely vulnerable to perturbations depending on their location. Therefore, planners and decision-makers would be able to incorporate this risk when analyzing potential solutions, providing support to, e.g., evaluate alternative transportation systems, identify backup suppliers to cover their demand, or plan for substitute products, among many other potential scenarios. Moreover, our framework attempts to expand the scale of previous studies where, traditionally, production disruptions (fractional or complete) are not included in the planning process for the allocation of agricultural goods.

Several extensions of this framework can be explored. First, a multi-stage version can be modeled by including inventory management of the commodities between periods. This will add an extra layer of complexity to the scenarios (and model), as multiple disruptions can be modeled between periods. Second, a risk-averse version can be formulated by explicitly including the risk of experiencing "bad" scenarios (i.e., with a strong impact on the performance of the network). For this, risk-aware stochastic formulations including terms such as the known conditional value-at-risk (CVAR, [19]) will be explored in future iterations of the framework. Finally, the framework can be naturally extended to incorporate multiple products simultaneously, analyzing the performance of the whole agricultural supply chain instead of focusing on one particular commodity.

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