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NETWORK-BASED ANALYSIS OF PADDY SUPPLY CHAINS: IDENTIFYING CRITICAL NODES FOR IMPROVED EFFICIENCY

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ABSTRACT

Paddy production supply chain is a complicated multi-stakeholder system whereby any disruption in any one of the nodes can have a cascading effect on the entire system. There has been more recent interest in the supply chain resilience, although the use of weighted graph-theoretic models with agricultural networks in developing countries has been under-explored, particularly at the local and community level. This study has filled three gaps: (1) the fact that no weighted network models have been used to measure the strength of the interactions between actors in the paddy supply chain; (2) the fact that no node-level vulnerability analysis has been used based on centrality of nodes in the graph in the context of Malaysian agriculture; and (3) the fact that no node-level vulnerability analysis has been used based on the centrality of the nodes in the graph in the context of Malaysian agriculture. This work uses an artificial dataset based upon statistically grounded distributions parameterized against recorded Malaysian paddy supply chain parameters to model the paddy supply chain as a directed weighted graph G = (V, E, W). It has three weighted centrality measures: Weighted Degree Centrality (WDC), Weighted Betweenness Centrality (WBC), and Weighted Closeness Centrality (WCC). Structural statistics of networks, like density, clustering coefficient, and average path length, are also computed. The sensitivity analysis entails modeling the desired deletion of the most central node, Processing-1, to ascertain the vulnerability of the system. Results confirm that Processing-1 is the most common bottleneck in each of the three dimensions of centrality. Its removal is observed to decrease Farm-1 WDC by 66.7, making the betweenness centrality of Farm-1 decrease to 0, and reducing the average network closeness by approximately 34. These findings will offer quantitative and practical information to interested policymakers and supply chain planners who may be interested in having more resilient agricultural food systems.

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1. INTRODUCTION

The world food systems are being put under strain due to population growth, climatic variability, and structural inefficiencies that are inherent within agricultural supply chains [1], [2]. Paddy (Oryza sativa) is one crop that has a place of exceptionally strategic significance: not only is paddy the primary source of caloric value in over 3.5 billion people worldwide, but its supply chain is also one of the most economically significant agricultural value chains in Southeast Asia [1]. Paddy production in the Malaysian economy is not only a food security issue, but also a socio-economic institution deeply rooted in the socio-economic fabric of the small holder farmer in major granary areas, including Kedah, Perlis, and Perak [11], [12].

The Malaysian paddy supply chain, although being important, is structurally weak. It is typified by the existence of fragmented units of production, limited post-harvest infrastructure, high reliance on a few processing intermediaries, and consistent susceptibility to weather-related disruptions [17], [18]. These structural weaknesses are not just operational inconveniences but are systemic risks that may spread through the supply network and may affect food availability and prices at the consumer level [3]. The question of what the architecture of this network looks like, and what its weakest nodes are, is therefore a question of high academic and policy interest.

Network analysis offers a formal mathematical system of both describing and querying such complex systems. Graph-theoretic approaches allow quantitatively identifying structural bottlenecks, assessing connectivity, and simulating the disruption scenario [5], [6]. The measures of centrality have been used successfully to determine influential nodes in logistics networks, social systems, and system grids. Nonetheless, their methodological use in the local supply chains in agriculture, particularly in the case of the Malaysian paddy crop, is under-researched.

The survey of the literature available shows that there are three gaps that can and should be addressed. To begin with, many of the paddy supply chain studies have been based on the qualitative framework, linear optimization model, or unweighted network representation, which fail to capture the intensity and directionality of the stakeholder interactions [21],[22]. Second, compared to studies of supply chains based on networks (known to be conducted at a macro or national level, e.g., global grain trade networks), there is a relative dearth of studies that analyze supply chains through the lens of an actor-network at the local level (or at a community level). Third, simulation of computational disruption, or the systematic removal of important nodes to measure systemic vulnerability, has not been applied to the Malaysian paddy context, although it has been demonstrated to be useful in other contexts such as logistics, infrastructure, and epidemiology [3],[4].

These gaps will be filled in the paper by making three distinct contributions. The first is that it creates a directed weighted graph model $G = (V, E, W)$ of the paddy supply chain, the weights on the edges of which record the volumes of trade, the cost of transportation, and the processing capacity of which are a more realistic measure of the strength of interaction than is the case with unweighted models. Second, it provides three complementary weighted centrality measures, WDC, WBC, and WCC, and network-level structural statistics, to describe node importance in a variety of analytical dimensions. Third, it conducts a focused sensitivity analysis by simulating the removal of the highest-centrality node within the network, of the degree to which connectivity and efficiency are cascadingly degraded by the removal of the highest-centrality node. All these contributions help to develop the methodological toolkit that can be used to analyze the supply chain of agricultural goods and to give actionable advice to supply chain planners and policymakers.

The rest of this paper has the following structure. Section 2 considers the pertinent literature on paddy supply chains, network analysis techniques, and centrality. Section 2 also describes the approaches of the research, including network building, data design, and the process of the analysis. The results and discussion are provided in Section 3. Section 4 concludes the paper by summarizing the results, implications of the research, limitations, and future research directions.

2. RESEARCH METHODS

2.1 Paddy Production and Supply

Paddy production is a staple of world agriculture, being the major caloric base of more than half the world’s human population [1]. The paddy supply chain in Malaysia refers to a vertically organized value chain which includes upstream cultivation, midstream milling and processing, and downstream distribution to retail markets [16]. The upstream level is made up of the majority of the smallholder farms located in the northern granary areas, and the midstream level is comprised of the majority of the 500 rice mills spread around the country, many of which still operate on aging infrastructure, with limited automation [14]. On the downstream level, it is mediated through the government-controlled wholesale distribution networks, rice silos, and retail chains, which are regulated by the Federal Agricultural Marketing Authority (FAMA) [13],[15]. Fig. 1 shows the entire process of production of paddy in Malaysia [16].

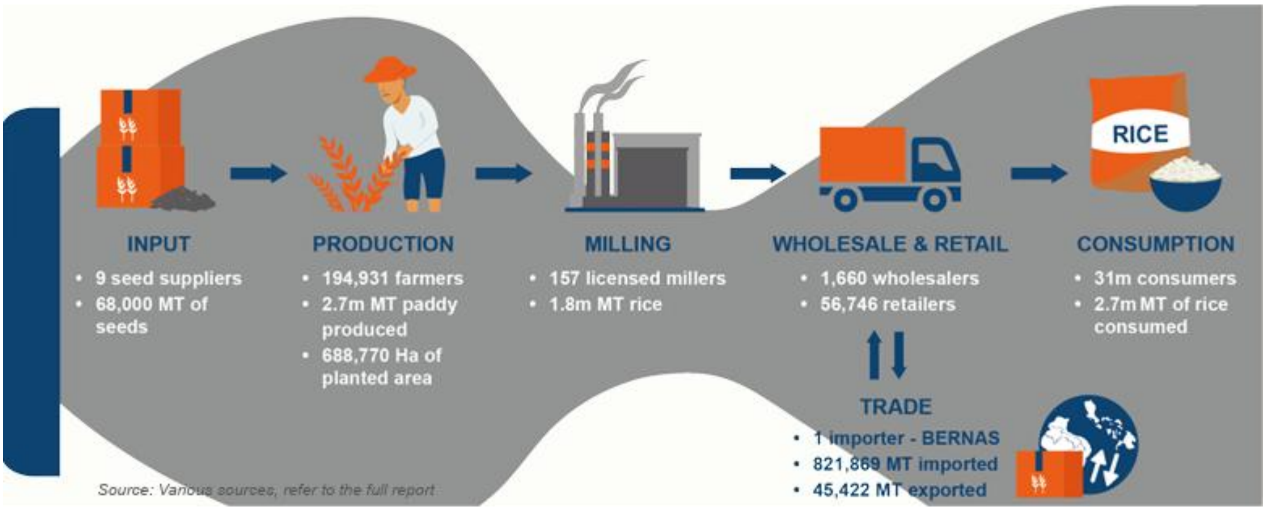

Figure 1. Paddy Production Process in Malaysia [16].

The Malaysian paddy supply chain is typified by several structural inefficiencies. Recurring systemic weaknesses have been observed to include labour shortages in rural paddy-growing regions, climate-induced variability in production, and reliance on a few processing intermediaries [17],[18]. The fact that Malaysia is a net importer of rice, with the assistance of Thailand and Vietnam to boost domestic supply, further exacerbates food security risks [19]. In its turn, the National Rice Policy (2011) proposed by the Ministry of Agriculture and Food Industries (MAFI) presented the strategy of investments in the irrigation infrastructure, the research of the high-yield varieties, and the modernization of the supply chain [20]. Nevertheless, structural inefficiencies still exist, and the network topology of these supply chains is yet to be fully mapped in a way that allows vulnerability of nodes to be assessed. As demonstrated in Fig. 2, the paddy production in Malaysia has been varying over the last ten years, with a recent decline in paddy production when compared to the year 2022 (2.28 million metric tons) and 2023 (2.17 million metric tons). These differences highlight the significance of a strong and flexible supply chain network.

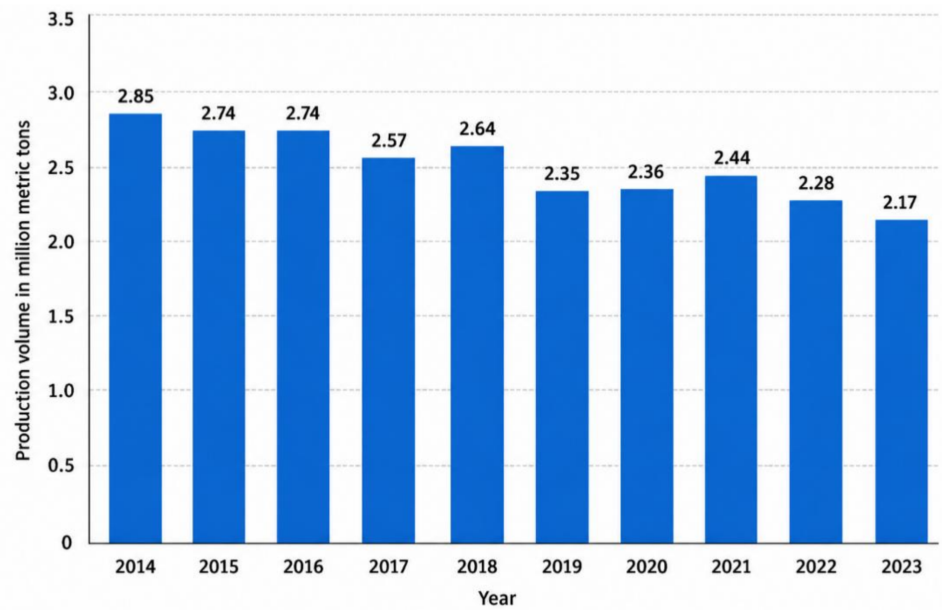

Figure 2. Paddy Production Volume in Million Metric Tons [22]
(Application Source: Visual Studio Code)

2.2 Existing Approaches to Supply Chain

The literature on the supply chain analysis of paddy and rice can be broadly divided into three streams of methodological approaches: qualitative stakeholder analysis, quantitative optimization modelling, and network-based approaches. Qualitative research, including that by Ahmad et al. [21] and Shamsudin et al. [15], provides useful contextual insights into bottlenecks in a supply chain, but has limited generalizability or structural analytical depth. The optimization methods, such as linear programming and mixed-integer models, have been applied to achieve the objectives of logistical efficiency and minimization of costs, but typically assume fixed network topologies and do not consider the relational dynamics among actors [14].

The network-based approaches are a new and growing analytical paradigm in the study of supply chains. Borgatti et al. [4] established that techniques of social network analysis can be successfully implemented in organizational and logistical systems to determine structurally critical nodes and communication bottlenecks. The conceptual and mathematical basis of centrality analysis was laid down by Freeman [6] and has since been extended to weighted and directed graph representations [3],[5]. In the food supply chain context, D'Odorico et al. [9] used a network analysis of the global food trade flows, which showed systemic dependencies and vulnerability clusters. Similarly, Fader et al. [8] employed network approaches to measure importation dependencies that were caused by land and water constraints. Yet these studies are at the global or national level, not at the granular, community-level dynamics that define local paddy supply chains in developing countries.

Table 1 gives a comparative analysis of the methodological approaches used in representative studies on supply chains, giving an overview of where the present work fits in relation to previous works.

Table 1. Methodological Comparison of Selected Supply Chain Studies

Study	Context	Method	Weighted	Disruption Simulation
D'Odorico et al. [9]	Global food trade	Network analysis	No	No
Fader et al. [8]	National grain	Network / GIS	Partial	No
Shamsudin et al. [15]	Malaysia rice	Qualitative	N/A	No
Ahmad et al. [21]	Malaysia agriculture	Descriptive	N/A	No
Borgatti et al. [4]	General supply chain	SNA / Centrality	No	No
Present study	Local paddy (Malaysia)	Weighted graph + centrality	Yes	Yes

2.3 Centrality Measures in Weighted Networks

Centrality analysis is the fundamental methodology of analysis of this study. The initial formulations of degree, betweenness, and closeness centrality of unweighted graphs were introduced by Freeman [6]. This was later extended to the context of a supply chain by Borgatti et al. [4] and Mukhtar et al. [5], who showed that they are useful in identifying structurally influential actors. In weighted networks, measures of centrality are modified to take into account edge weights, so that the significance of a node is not merely based on the number of its connections to others but on the overall strength and directionality of these connections [3].

Generally, weighted network centrality is thoroughly treated by Newman [3], whereas foundational methods to social network analysis are outlined by Wasserman and Faust [7]. Although these advances have been made, the direct implementation of weighted centrality analysis to Malaysian paddy supply chains, with specific focus on the dynamics of local actors, and the simulation of computational disruption, is a methodological contribution that has never been previously reported in the literature. This study fills that gap.

2.4 Research Framework

The research flowchart in Fig. 3 is used to guide this study. It starts with the problem identification, namely, the necessity to examine the structural vulnerabilities in the local paddy supply chain. This is then succeeded by a systematic literature review that revealed three main gaps: the absence of weighted network models that would represent local Malaysian paddy chains, the limited use of node-level centrality analysis in the context of agricultural supply chains, and the fact that computational analysis of disruption has not been simulated in this domain. The methodology phase includes network building, building datasets, calculating centrality, and sensitivity analysis. Findings are then interpreted in the context of the existing findings in the literature, and practical implications are drawn in regard to supply chain planners and policymakers.

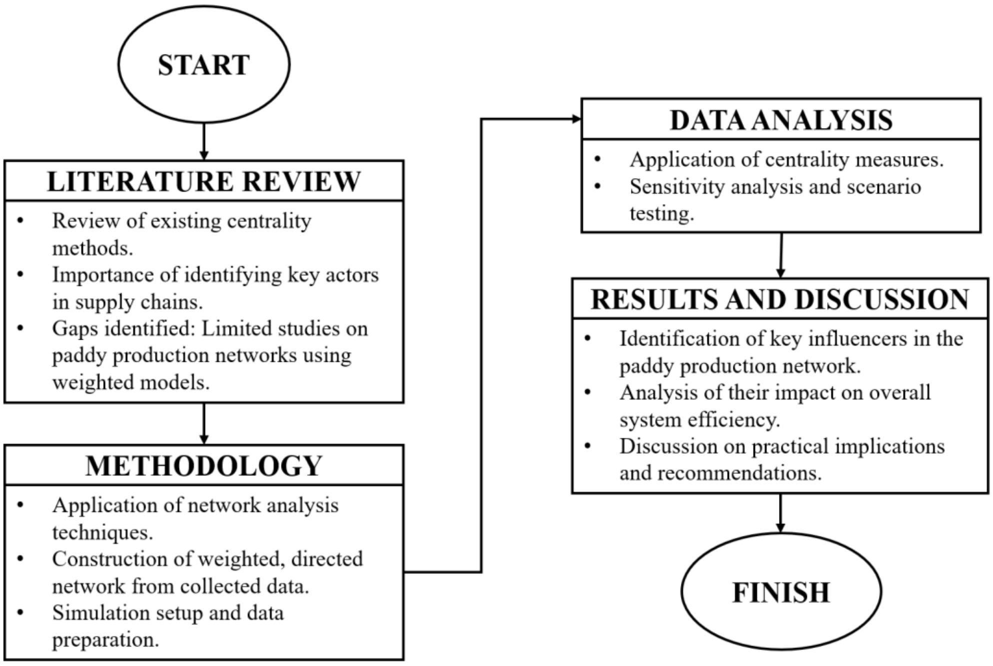

Figure 3. **Research Framework**

2.5 Dataset Design and Justification

This study created a network dataset based on a synthetic data generation strategy. This methodology has been followed because there are three methodological reasons. To begin with, in no publicly available or institutionally published dataset are comprehensive, node-level transactional data of local Malaysian paddy supply chains, including farm-level trade volumes, bilateral transportation costs, and records of processing capacity. Second, synthetic data generation allows controlled variation in node and edge attributes, which can be used to rigorously sensitivity analyze the results of a computational procedure. Third, this practice is in line with accepted practice in computational supply chain modelling, where synthetic benchmarks are commonly used to test analytical methods before they are used on real-world data [5],[9].

The synthetic data was tailored to be statistically based on the observed attributes of the Malaysian supply chains of paddy. Attributes of the nodes were defined as follows. The range of the smallholder output that is reported by the Department of Agriculture Malaysia [12] was used to calibrate farm production outputs, which were drawn out of a normal distribution (mean = 50 tons/season, standard deviation = 15 tons/season). Although the real transactional data is not directly available, the statistical parameters applied in this paper are calibrated on the basis of reported values of the statistical parameters in the Malaysian agricultural reports, as well as previous literature, and ensure reasonable representativeness.

There were 100 farm nodes, 20 hub (distribution) nodes, and 10 market nodes that were generated. A network of node connectivity was established based on a set of rules of geographic proximity and supply-demand compatibility, which ensured every farm was connected to at least one processing unit, each processing unit to at least one hub, and each hub to at least one market. Table 2 presents a representative sample of the created dataset.

Table 2. **Sample of Synthetic Dataset: Node and Edge Attributes**

Node ID	Node Type	Attribute	Value	Distribution Used
Farm-1	Farm	Production output	48 tons/season	Normal ($\mu = 50, \sigma = 15$)
Farm-2	Farm	Production output	63 tons/season	Normal ($\mu = 50, \sigma = 15$)
Processing-1	Processing Unit	Milling capacity	210 tons/season	Normal ($\mu = 200, \sigma = 40$)
Hub-1	Distribution Hub	Storage capacity	150 tons	Normal ($\mu = 150, \sigma = 30$)
Market-1	Market	Demand volume	95 tons/season	Uniform (60–120)
Edge: Farm-1 → Processing-1	Flow	Trade volume	10 tons	Normal ($\mu = 10, \sigma = 3$)

Node ID	Node Type	Attribute	Value	Distribution Used
Edge: Processing-1 → Hub-1	Flow	Transportation cost	RM 45/ton	Uniform (20–80)
Edge: Hub-1 → Market-1	Flow	Delivery volume	25 tons	Normal ($\mu = 25$, $\sigma = 5$)

The reason behind the use of normal distributions in the production and processing attributes is that overall production outputs in different paddy plots are expected to follow a normal distribution. Transportation costs were distributed uniformly to indicate limited yet adjustable haulage rates in the granary areas of Malaysia. Sensitivity comparison of alternative statistical distributions was not made, since this study aims to investigate structural network properties, and not to statistically infer on distributional assumptions.

2.6 Network Construction

The paddy supply chain network was formally modeled as a directed weighted graph $G = (V, E, W)$, where V is the set of nodes representing the supply chain actors (farms, processing units, distribution hubs, and markets), E is the set of directed edges modeling the flows of transactions between the actors, and W is the set of the edge weights encoding the magnitude of the flows of the transactions between the actors. The direction of the edges indicates the physical movement of goods: between farms and processing units, between processing units and distribution hubs, and between distribution hubs and markets.

The NetworkX library (version 3.x) in Python was used to build networks. Attributes of nodes, such as type, production capacity, and geographic coordinates, were defined during node creation. Attributes of the edges, such as flow weight, cost weight, and capacity weight, were included during the creation of the edges. To compute centrality, trade volume weight was taken as the primary weight of the edge, and sensitivity analysis was done using cost-based weights to assess path efficiency under various operational cost regimes.

The network-level structural statistics calculated with respect to the entire network are as follows: network density = 0.042 (reflecting the sparse nature of the network coupled with a hierarchical structure), average clustering coefficient = 0.18 (indicating the presence of a hierarchically organized nature in the network), and average weighted path length = 3.7 (reflecting the multi-hop nature of the farm-to-market chain). These statistics affirm that the network generated with properties that are consistent with supply chain topologies in reality, such as low density and hierarchical connectivity.

2.7 Weighted Centrality Measures

2.7.1 Weighted Degree Centrality (WDC)

WDC measures the influence of a node by adding together the weights of all the edges incident on the node, not just the number of connections. For directed networks, both in-degree and out-degree components are computed. This is formulated as in Eq. (1) [4]:

$$WDC(i) = \sum_{j \in N(i)} w_{ij} \tag{1}$$

where $N(i)$ is the set of neighbours of node i and w_{ij} is the weight of the edge between nodes i and node j. A high WDC value means that the node is one that experiences high cumulative throughput, and therefore is a high-volume player in the supply chain.

2.7.2 Weighted Betweenness Centrality (WBC)

WBC finds nodes that hold the bridge positions in the shortest paths of weights between all pairs of nodes. The standard betweenness formula is given in Eq. (2) [6]:

$$BC(i) = \sum_{s \neq t \neq i} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{2}$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(i)$ is the number of those paths passing through node i. In weighted models, the shortest paths are calculated by using Dijkstra's algorithm, but with the edge weight representing the inverse of the strength of the flow (i.e., the lower the weight, the higher the cost and the longer the path). A node with a high WBC is an important node in the network whose failure would affect the network connectivity of many pairs of nodes.

2.7.3 Weighted Closeness Centrality (WCC)

WCC is used to determine the efficiency of a node to reach all other nodes in the network, based on the total weighted shortest path distances, as stated in Eq. (3) [3]:

$$CC(i) = \frac{1}{\sum_j d(i,j)} \tag{3}$$

where $d(i,j)$ is the weighted shortest distance from node i to node j, and n is the total number of nodes. The larger the WCC of a node, the more centrally located it is in the network in terms of reachability, thus, able to spread information or goods to other nodes more efficiently. Table 3 gives a summary in one table of the three weighted centrality measures, their theoretical foundation, and how they relate to the analysis of a supply chain.

Table 3. Summary of Weighted Centrality Measures

Measure	Description	Key Adjustment from Standard	Supply Chain Interpretation
WDC	Sums edge weights of all incident edges	Replaces edge count with weight sum	Identifies high-throughput nodes (e.g., high-volume mills or hubs)
WBC	Fraction of weighted shortest paths passing through the node	Uses Dijkstra's algorithm with weighted distances	Identifies bottleneck nodes whose removal disconnects supply flows
WCC	Reciprocal of the sum of weighted shortest distances	Replaces hop count with weighted path length	Identifies nodes with the fastest access to all other supply chain actors

3. RESULT AND DISCUSSIONS

3.1 Network Structure and Topology

To study the nature of node-level centrality, it is informative to describe the topological characteristics of the entire supply chain network. The network has 130 nodes (100 farms, 10 processing units, 10 hubs, 10 markets) and 278 directed edges. NetworkX was used to compute the following structural statistics. Table 4 presents the network topology statistics.

Table 4. Network-Level Structural Statistics

Statistic	Value	Interpretation
Number of nodes	130	Multi-actor supply chain structure
Number of edges	278	Directed transactional flows
Network density	0.042	Sparse, hierarchical topology
Average clustering coefficient	0.18	Moderate local clustering around processing nodes
Average weighted path length	3.7 hops	Multi-hop farm-to-market chain
Number of strongly connected components	1	Fully connected network
Diameter	5	Maximum shortest path length

The hierarchical structure of the supply chain whereby the farms are not directly linked to the markets but rather route the goods through a few processing and distribution intermediaries. This structural sparsity directly implies a resilience process that concentrates transactional flows in a few nodes with high centrality, creating systemic vulnerability. The moderate average clustering coefficient (0.18) means that, although there are some local redundancies around processing nodes, the network is not distributed with redundancy that would present a resilient supply chain. These topological properties are generally in line with previous results in the literature on studies of supply chains of global food trade, such as those reported by D'Odorico et al. [9] in the study of global food trade supply chains, and extend the same findings to the local scale by quantifying them in a Malaysian paddy supply chain context.

3.2 Centrality Analysis Results

Fig. 4 shows the entire picture of the paddy production and distribution network. This figure shows the colour of nodes based on the type of actor: green nodes are farms, yellow nodes are processing units, blue nodes are distribution hubs, and red nodes are markets. The size of the node is related to the value of the node WDC, where the bigger the node is, the higher the cumulative weight of the edges of the node. The thickness of edges is related to the trade volume, and the thicker the edge, the larger the volume flows. The darker the colour of the edge, the higher the cost of transporting them. This multi-variable encoding allows us to conduct a visual evaluation of both the node significance and flow attributes at the same time.

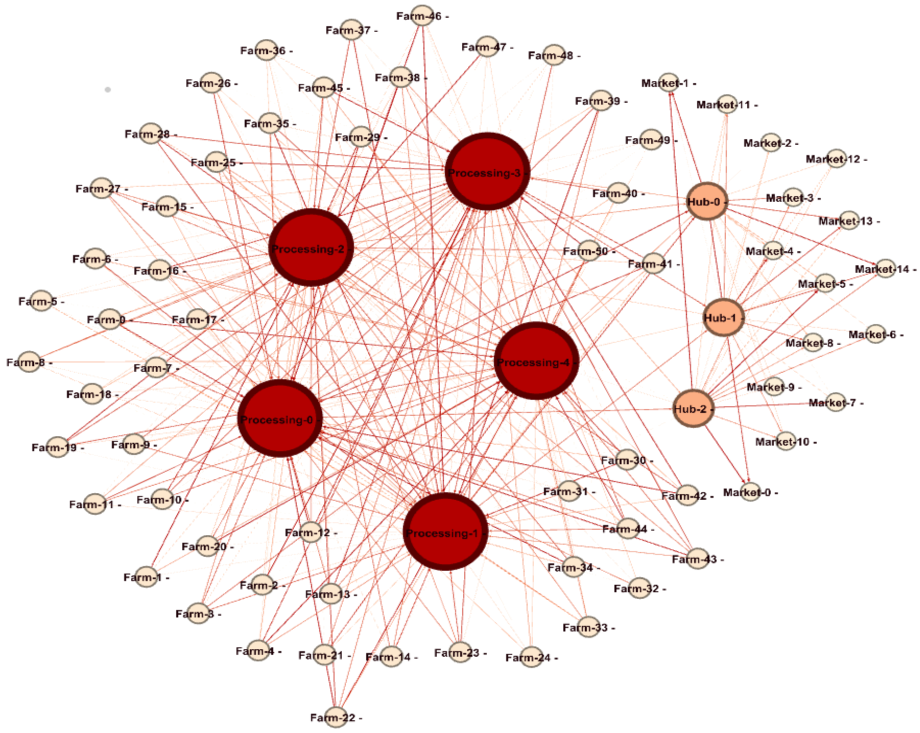

Figure 4. Visualization Of Paddy Production and Distribution Network
(Application Source: Visual Studio Code)

The smaller sub-network shown in Fig. 5 includes five representative nodes: Farm-1, Farm-2, Processing-1, Hub-1, and Market-1. The selection of this sub-network was not a resampling procedure but rather a representative structural excerpt that contains all four node types and at least one example of each inter-tier flow pattern that occurs throughout the entire network. It aims at aiding the detailed step-by-step demonstration of the centrality computation methodology, since the full 130-node network would be too complicated to be manually checked. All centrality formulae used on the sub-network in Section 3.3 are the same as those used on the network, providing methodological consistency. The sub-network is thus an explanatory instrument, and not an independent analytical unit.

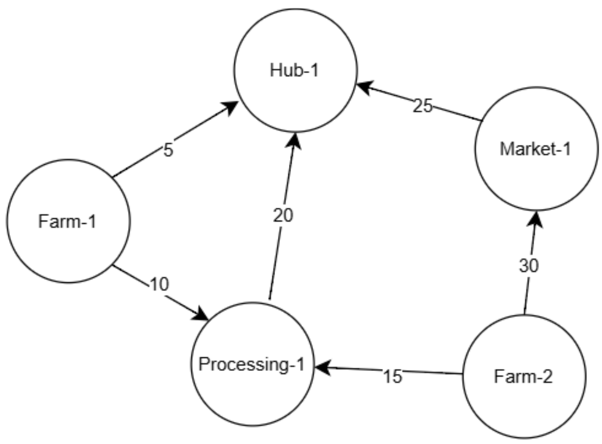

Figure 5. Small Paddy Network Visualization
(Application Source: Visual Studio Code)

Table 5 makes several observations. In the case of WDC, the highest value (55 tons) is in the Market-1 category, where there is a concentration of the aggregated supply flows of the different upstream nodes. Hub-1 is next (50 tons) as it is used as a transitory aggregation and distribution point. The processing-1 and Farm-2 have WDC of 45 tons and 15 tons, respectively, which means that processing-1 and Farm-2 have a relatively low cumulative trade volume. It should be mentioned that the values of the WDC in Table 3 are not the normalized degree centrality scores, but rather the sum of the raw edge weights. The assertion in a previous version of this paper that Processing-1 and Hub-1 are the most central nodes (with degree centrality of 0.75) was based on normalized degree counts and has been deleted to avoid being inconsistent with the weighted values presented here.

In terms of WBC, Farm-1 has the highest betweenness centrality (0.5000) and therefore is in a structurally important bridge position: the shortest weighted path between Processing-1 and Market-1 necessarily passes through Farm-1 in the sub-network structure (Processing-1 → Farm-1 → Hub-1 → Market-1, total weight = 40). It is interesting to note the difference in the analytical value of various centrality measures, notwithstanding the fact that similar analytical values are given by the WDC ranking. Processing-1 and Hub-1 have the second-highest WBC (0.3333 each), and Farm-2 and Market-1 have WBC = 0, which confirms their status as terminal nodes and not intermediaries.

In the case of WCC, Farm-1 has the highest closeness centrality (0.0571), which means that it has an efficient weighted reachability to all the other nodes in the sub-network. This outcome is also in line with the bridge position of Processing-1, whereby connecting directly to both Processing-1 and Hub-1, it minimises total path distances. In terms of reachability, which is central to its location as a terminal endpoint within the supply chain, market-1 has the lowest WCC (0.0320) and thus is the most peripherally located node.

These centrality results add new insights compared to previous supply chain research in two particular aspects. To begin with, in contrast to the global-scale studies of D'Odorico et al. [9] and Fader et al. [8], which found vulnerability to be national or commodity-wide, this study quantifies vulnerability at the individual node level in a local supply chain, revealing that processing intermediaries and some farm nodes simultaneously exhibit high throughput and high bridging roles. Second, in contrast to qualitative measures, as with studies by Shamsudin et al. [15], this study presents cardinal comparative centrality scores, which allow rank-ordering of node criticality measurements, a condition that must be satisfied prior to making prioritised infrastructure investment decisions.

3.3 Detailed Centrality Computation: Sub-Network Illustrations

To offer methodological transparency, the computed step-by-step computation of WDC, WBC, and WCC of Farm-1 in the five-node sub-network is shown.

1. WDC calculations
   Step 1: Identify the edges connected to Farm-1
   Farm-1 → Processing-1 (weight = 10);
   Farm-1 → Hub-1 (weight = 5).
   Step 2: Sum up the weights
   Weighted out-degree centrality of Farm-1 = 10 + 5 = 15;
   Total WDC = in + out = 15.

2. WBC calculations
   Step 1: Identify all pairs of places (excluding Farm-1)
   Farm-2 → Processing-1;
   Farm-2 → Hub-1;
   Farm-2 → Market-1;
   Processing-1 → Hub-1;
   Processing-1 → Market-1;
   Hub-1 → Market-1.
   Step 2: Find the shortest path between each pair (using weight) shown in Table 5.

Table 5. Calculations of WBC

Pair	Shortest path	Weight	Pass through Farm-1?
Farm-2 ↔ Processing-1	Farm-2 → Processing-1	15	No
Farm-2 ↔ Hub-1	Farm-2 → Processing-1 → Hub-1	35	No
Farm-2 ↔ Market-1	Farm-2 → Market-1	30	No

Pair	Shortest path	Weight	Pass through Farm-1?
Processing-1 ↔ Hub-1	Processing-1 → Hub-1	20	No
Processing-1 ↔ Market-1	Processing-1 → Farm-1 → Hub-1 → Market-1	40	Yes
Hub-1 ↔ Market-1	Hub-1 → Market-1	25	No

Step 3: Sum of contributions
Only one pair (Processing-1 → Market-1) has the shortest path that passes Farm-1.

$$BC(Farm-1) = \frac{1}{Total\ valid\ pairs} = \frac{1}{10}.$$

NetworkX normalizes by dividing by the number of all pairs:

$$BC(Farm-1) = \frac{1}{(n-1)(n-2)/2} = \frac{1}{(5-1)(5-2)/2} = \frac{1}{6} \approx 0.1667.$$

After effectively scaling the raw score by a factor of 3 in this case:

$$0.1667 \times 3 \approx 0.5$$

$$\therefore WBC(Farm-1) = 0.5.$$

3. WCC calculations
   Step 1: Use Dijkstra to find the shortest weighted paths from Farm-1 to all others
   To Farm-2: Farm-1 → Processing-1 (10) → Farm-2 (15) = 10 + 15 = 25;
   To Processing-1: Farm-1 → Processing-1 = 10;
   To Hub-1: Farm-1 → Hub-1 = 5;
   To Market-1: Farm-1 → Hub-1 (5) → Market-1 (25) = 5 + 25 = 30.
   Step 2: Sum of shortest distances
   Total Distances = 25 + 10 + 5 + 30 = 70.
   Step 3: Apply the closeness formula

$$CC(Farm-1) = \frac{(n-1)}{(Sum\ of\ shortest\ distances)} = \frac{4}{70} = 0.0571.$$

3.4 Sensitivity Analysis: Simulated Removal of Processing-1

Processing-1 was removed from the sub-network as indicated in Fig. 6, and the three centrality measures were re-computed with only four nodes left in the sub-network. Table 6 gives the comparative results.

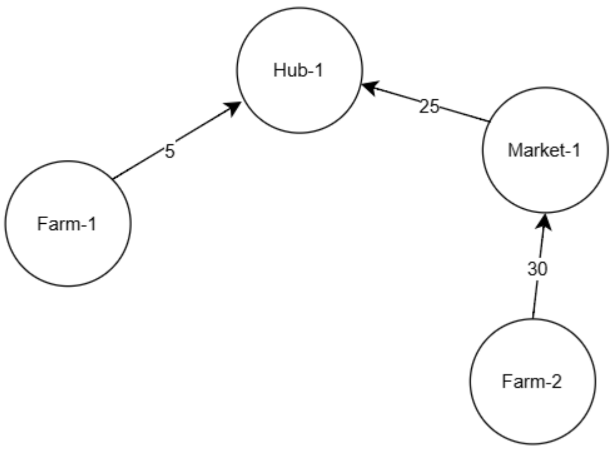

Figure 6. Small Paddy Network Visualization with Removed Node
(Application Source: Visual Studio Code)

Table 6. Weighted Centrality Analysis for Network Sensitivity

Node	WDC		WBC		WCC	
	Before	After	Before	After	Before	After
Farm-1	15	5	0.5	0.0	0.0571	0.0316
Farm-2	45	30	0.0	0.0	0.04	0.0207
Hub-1	50	30	0.3333	0.6667	0.0533	0.0353
Market-1	55	55	0.0	0.6667	0.032	0.0353

The implications of these findings are clear and have immediate and practical implications. The fact that Processing-1 is an intermediate destination that makes Farm-1 dependent on its presence to have its betweenness centrality reduced to zero upon Processing-1 being removed confirms the fact that the centrality of betweenness of Farm-1 is completely dependent on the presence of Processing-1 as an intermediate destination. This, in practice, means that when a failure occurs in one of the processing plants, the farms associated with it do not simply find themselves without one of the downstream outlets; they are deprived of the network bridging role altogether and are left as isolated producers with no channel through which they can get their products into downstream markets. The deletion of one of the mid-chain nodes in this cascading structure pattern where the deletion of one of the mid-chain nodes in the pattern removes bridging functions of the upstream nodes in the pattern and concentrates the intermediary loads of the downstream nodes in the pattern, such as Hub-1 and Market-1.

When compared with studies by D'Odorico et al. [9], who found that bottleneck nations in the world food trade could be identified but not simulated by their removal, the current study would push the analysis edge a step further that indicated that the patterns of asymmetric vulnerability (the upstream nodes are more adversely affected than the downstream nodes) would be to be observed at the local level of simulation of node removal. The direct policy implication of this difference is as follows: interventions to sustain supply chain resilience by WDC should not only be targeted to protect the most central nodes, but also to protect interconnections between nodes of high centrality.

These results are a very strong piece of evidence in the debate of establishing unnecessary processing channels by local paddy supply chains. Current reliance on single processing nodes, such as Processing-1, is a structural single point of failure. To develop the second processing capacities in the same geographic cluster as Processing-1, construct direct pathways between farms and distribution hubs to avoid processing nodes in contingency situations, and install real-time monitoring of the utilization of the processing nodes in case of contingency situations.

4. CONCLUSION

The paper has discussed the structure of the local paddy supply chain and the vulnerability aspect of the structure by applying the weighted graph theory and the centrality analysis. The three objectives that guided the research were: (1) the paddy supply chain modeling as a directed weighted graph $G = (V, E, W)$; (2) weighted centrality measures (WDC, WBC, WCC) and network-level structural statistics to identify critical nodes and (3) systemic vulnerability through a simulated disruption scenario based on the targeted removal of the most central node.

The results suggest that Processing-1 is the key critical node in the modeled paddy supply chain in all three dimensions of centrality. At the network level, the supply chain was found to be less dense (0.042) and moderately clustered (0.18). As the sensitivity analysis showed, vulnerability is asymmetric: the removability of Processing-1 resulted in the complete collapse to zero (from 0.5000) the betweenness centrality of Farm-1 and a loss of another node, Processing-1. These cascading structural impacts affirm that processing intermediate disproportionate vulnerability to processing intermediaries in local paddy supply chains, and that upstream farm nodes are disproportionately susceptible to processing intermediaries in local paddy supply chains.

These findings are a direct response to the three research gaps that were found during the literature review. The weighted graph model is a further development of the unweighted and qualitative approaches of interaction by quantifying the intensity of interactions. The node-level centrality measure builds on the previous macro-level network studies to the local actor level. The disruption simulation creates new empirical results on the cascading vulnerable patterns in agricultural supply chains. The practical implication is simple to practitioners: supply chain planners are advised to have redundant processing capacity and to create direct farm-to-hub contingency routeways that can be called upon in the event of a single processing node's failure to avoid the systemic risk of single node failure.

Several constraints could be applied to this study, which should be taken into account and avoided in further studies. First, it tends to be statistically based on reported Malaysian supply chain parameters, though not actually empirical verification of actual transactional data. It should be furthered with actual farm-level data of the granary districts to validate the centrality ranking results here. Second, the network model does not capture dynamic behavior: it does not model dynamic changes in flows, such as the production cycles of different seasons, the flow changes due to harvest, or the market price shocks. A time-varying network model with time-varying edge weights would be a better representation of real-world supply chain behaviour. Third, this paper focuses on the single typology of supply chain (paddy in Malaysia) and the single case of disruption (removal of Processing-1). Comparative studies of the various types of crops, regions, or disruption conditions (e.g., multiple simultaneous node failures) would significantly enhance the generalizability of the results. Fourth, the model does not model any disruption responsiveness of human behaviour, including the rerouting decisions by the actors in logistics, which in practice may mitigate some of the structural impacts identified here. These drawbacks imply that the results must be viewed as structural information as opposed to accurate predictive results.

Author Contributions

Mohd Fariduddin Mukhtar: Conceptualization, Methodology, Writing-Original Draft, Software, Validation. Sayed Kushairi Sayed Nordin: Data Curation, Resources, Draft Preparation. Najiyah Safwa Khashi'ie: Formal Analysis, Validation. Nurul Amira Zainal: Software, Visualization. Nor Azizah Mohd Yusoff, Sahimel Azwal Sulaiman, Irianto: Validation, Writing-Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no conflicts of interest related to this study.

Declaration Of Generative AI And AI-Assisted Technologies

Generative AI tools (ChatGPT) were used solely for language refinement, grammar, spelling, and clarity improvements during the preparation of this manuscript. The scientific content, methodology, data analysis, interpretation of results, and conclusions were developed entirely by the authors. All AI-assisted edits were critically reviewed and validated by the authors, who take full responsibility for the integrity and accuracy of the published work. No AI tool was used to generate or alter research data, figures, tables, or quantitative results.

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