Disaster Risks and Impacts on Supply Chains: Building a Model Using a Bayesian Network Analysis

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Project Summary

The objective of this study is two-fold:

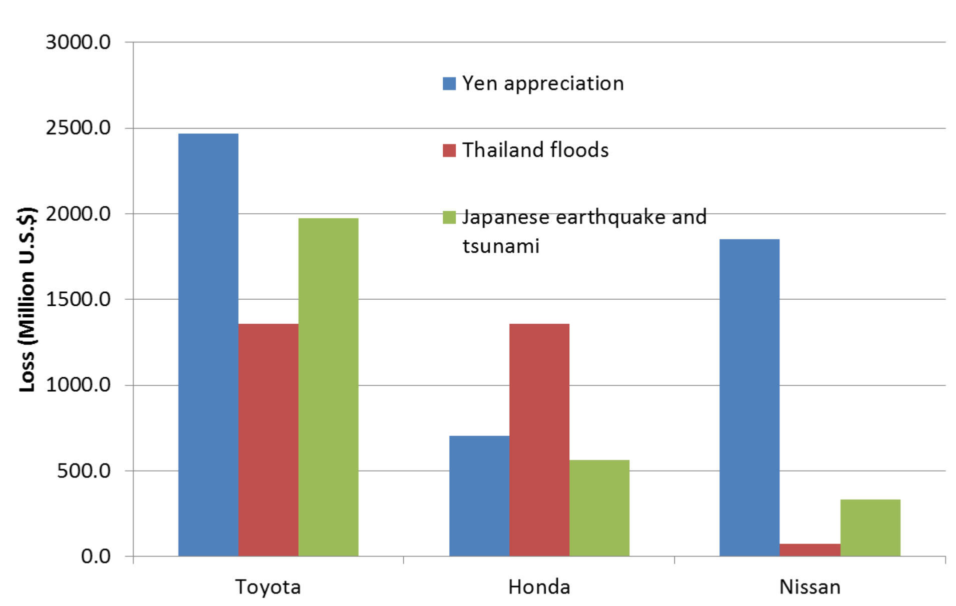
(a) To investigate the impacts of floods on supply chains using the case of Thailand's 2011 flooding focusing on automobile and electronics industries.
(b) To propose a simple model using a Bayesian network to address this issue.

A Recipe for Disaster: Factors behind the Floods

- "La Niña" event that caused rainfall to increase by 143% in the Northern regions of Thailand and consequently doubled river runoff
- Topological condition: Gentle slope of the downstream parts of the river
- Inefficient land-use management: Bangkok is located on former floodplains and land subsidence occurs in Bangkok
- Poor governance and coordination between national and local governments

Effects of Thailand Floods on Global Supply Chains

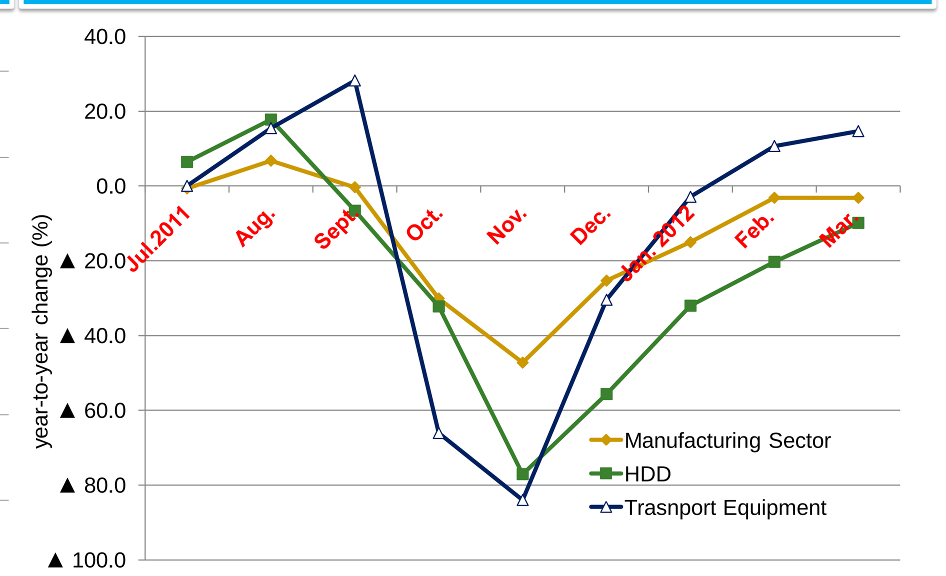
Automobile



Decrease Operating Profits of Japanese Major Automakers (Apr-Dec 2011)

- Nissan recovered more quickly than other auto companies because it had dissolved the KEIRETSU system, diversified sources of supply, and globalized the procurement system (Kushima 2012).

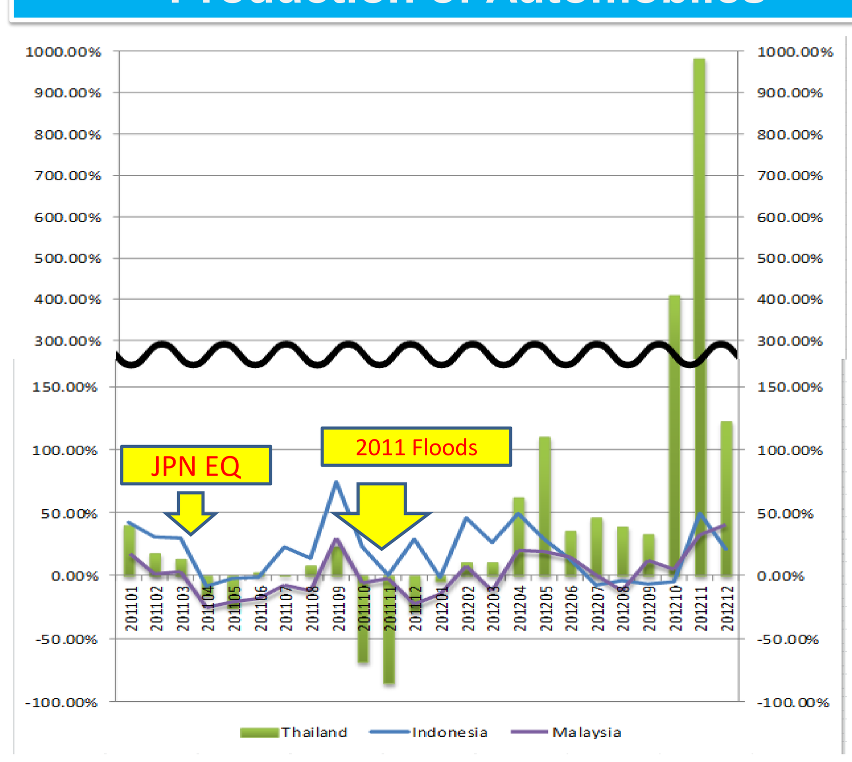
Electronics



Production Index of Manufacturing HDD and Transport Equipment

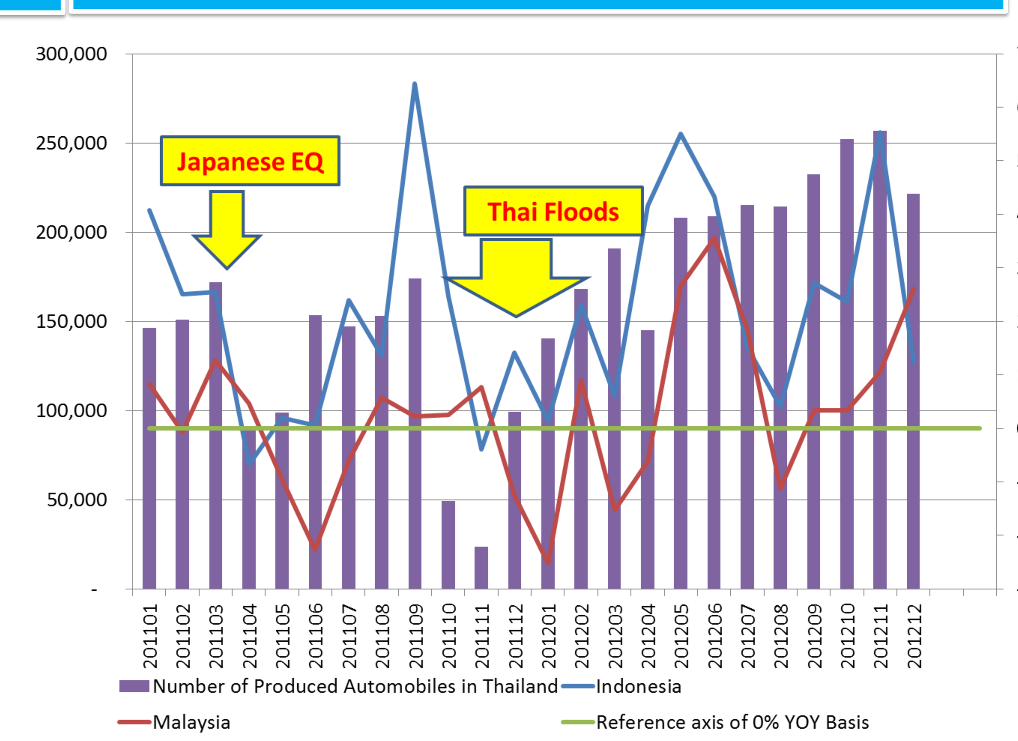
- In the beginning of 2012, Western Digital's earnings decreased 35%, up to 145 million dollars, while Seagate increased its profit from 150 million dollars to 563 million dollars, because Western Digital's factories were in the flood zones, while Seagate was mainly affected through their supply chain (Vilches 2012).

Production of Automobiles



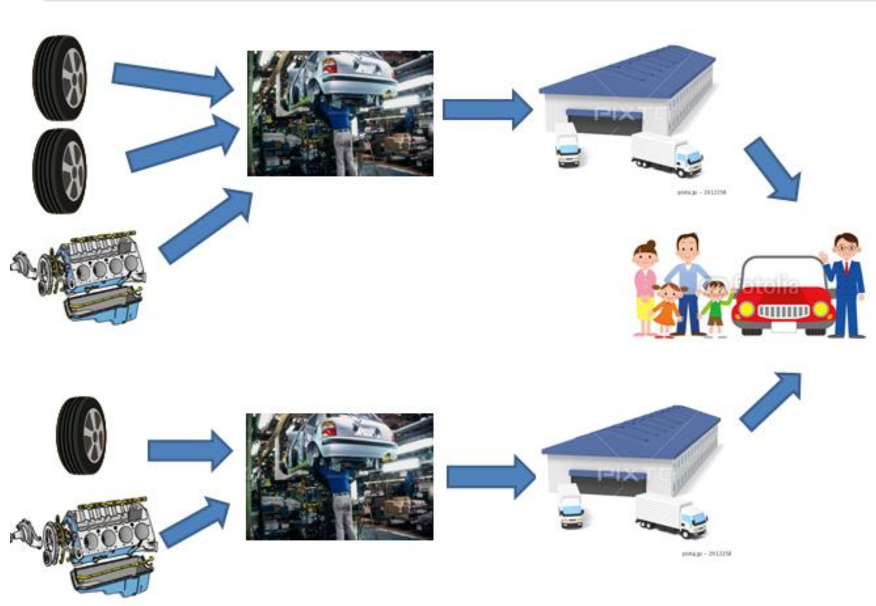
Production of automobiles in Thailand, Indonesia, and Malaysia on YOY basis.

Sales of Automobiles



Number of produced automobiles in Thailand and YOY Basis of number of sold automobiles in Malaysia and Indonesia

Conclusions from the Case Study



Q1: How can ***critical nodes and/ or links*** such as assembly factories or transportation hubs whose flooding would lead to significant and persistent supply chain losses be reliably identified in the supply chain network?

Q2: How can the effectiveness of ***bridge ties*** to a different supply network be established as an aid to recovery from a flood induced supply chain problem? What are the associated global material supply chain constraints and resulting impacts?

Q3: How does ***the complexity of a network***, including ***the direction of links*** affect the robustness and resiliency of a supply chain network to floods?

Q4: How do ***transportation and lifeline systems*** affect the performance of entire supply chains during floods?

H1: If a supply chain is comprised of ***strong ties*** to one company exclusively, then immediate damages from a disaster will likely be greater. Yet, even if business partners in the same supply chain network are not directly impacted by disaster, the impacted node may receive help from them and may therefore be able to recover more quickly, with the result that damages may be mitigated.

1) Model Buildings (Without Evidence)

Table 3

Normal		Disrupted	
Store Inventory	Dont Store	Store Inventory	Dont Store
500	10000	4500	-5000

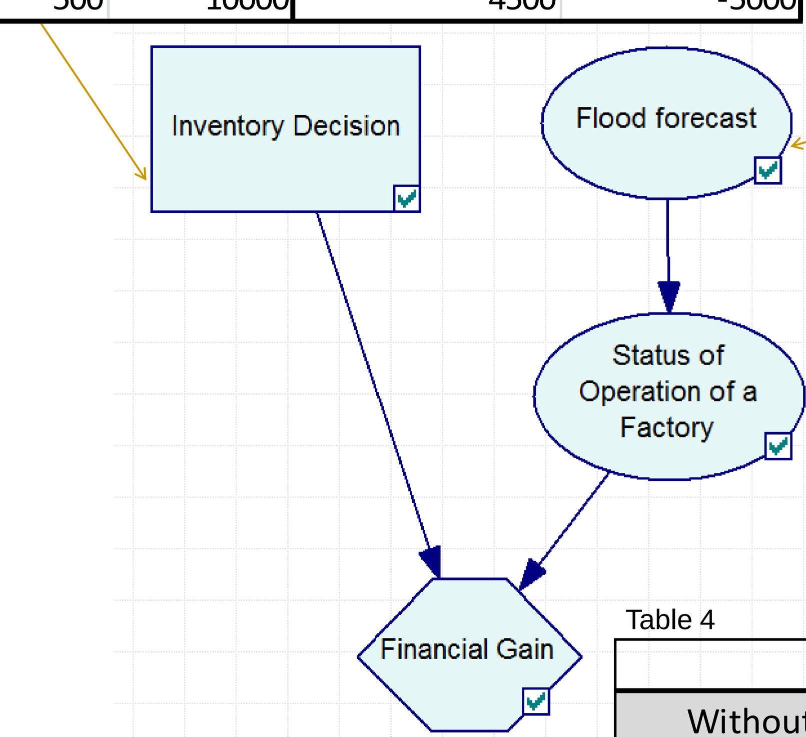


Table 1

Prior	P(FLD)
Unlikely	0.4
Neutral	0.4
Likely	0.2

Table 2

	Unlikely	Neutral	Likely
Op=normal	0.8	0.5	0.2
Op=disrupted	0.2	0.5	0.8

Table 4

	Expected Utility	
Without Forecast	Ex (Store)	2260
	Ex (Don't Store)	3400

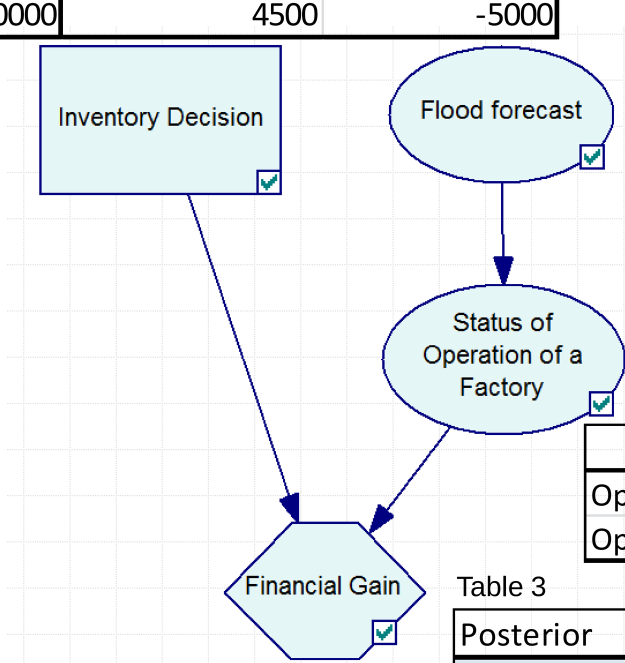
Result: Decision will be don't store inventory

- This simple model shows that chance nodes are two: the one is how a status of operation in a factory and the other is flood forecast. The decision node is inventory decision. The financial gain from the inventory depends on whether the inventory is made or not and on what is a status of operation of a factory.

2) Model with Evidences of Floods

Table 4

Normal		Disrupted	
Store Inventory	Dont Store	Store Inventory	Dont Store
500	10000	4500	-5000



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	Unlikely	Neutral	Likely
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Op=disrupted	0.2	0.5	0.8

Table 5

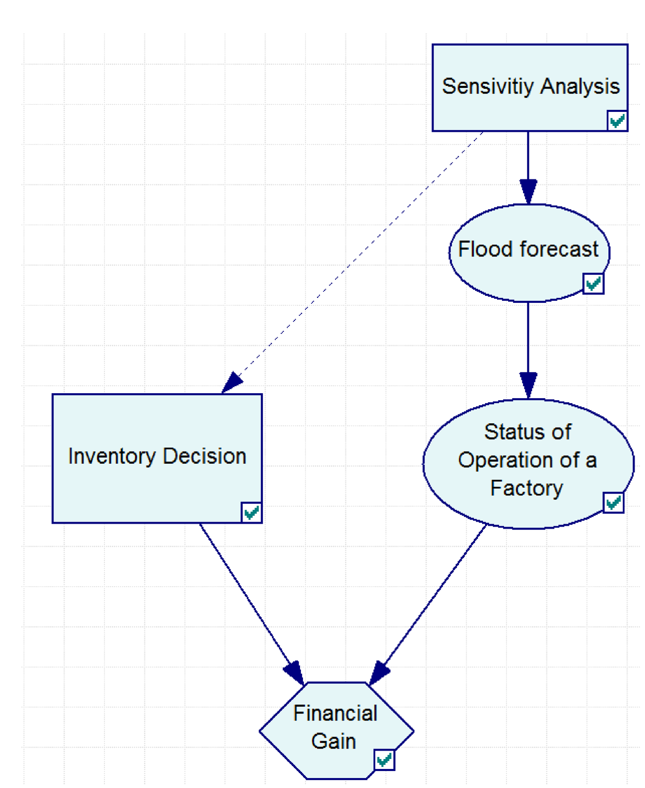
	Expected Utility	
Without Forecast	Ex (Store)	2260
	Ex (Don't Store)	3400
if Evidence is Unlikely	Ex (Store)	1300
	Ex (Don't Store)	7000
If Evidence is Neutral	Ex (Store)	2500
	Ex (Don't Store)	2500
If Evidence is Likely	Ex (Store)	3700
	Ex (Not)	-2000

Table 3

Posterior		P(OpIFLD)
if evidence is unlikely	Normal	0.80
	Disrupted	0.20
if evidence is set as neutral	Normal	0.50
	Disrupted	0.50
if evidence is set as likely	Normal	0.20
	Disrupted	0.80

Result: Decision will be depending on evidences

3) Model with Sensitivity Analysis of Flood Probability



Prior P(FLD)	Low	Medium	High
Unlikely	0.4	0.3	0.2
Neutral	0.4	0.4	0.4
Likely	0.2	0.3	0.4

Expected Utility	Low	Medium	High
Ex (Store)	2260	2500	2740
Ex (Don't Store)	3400	2500	1600

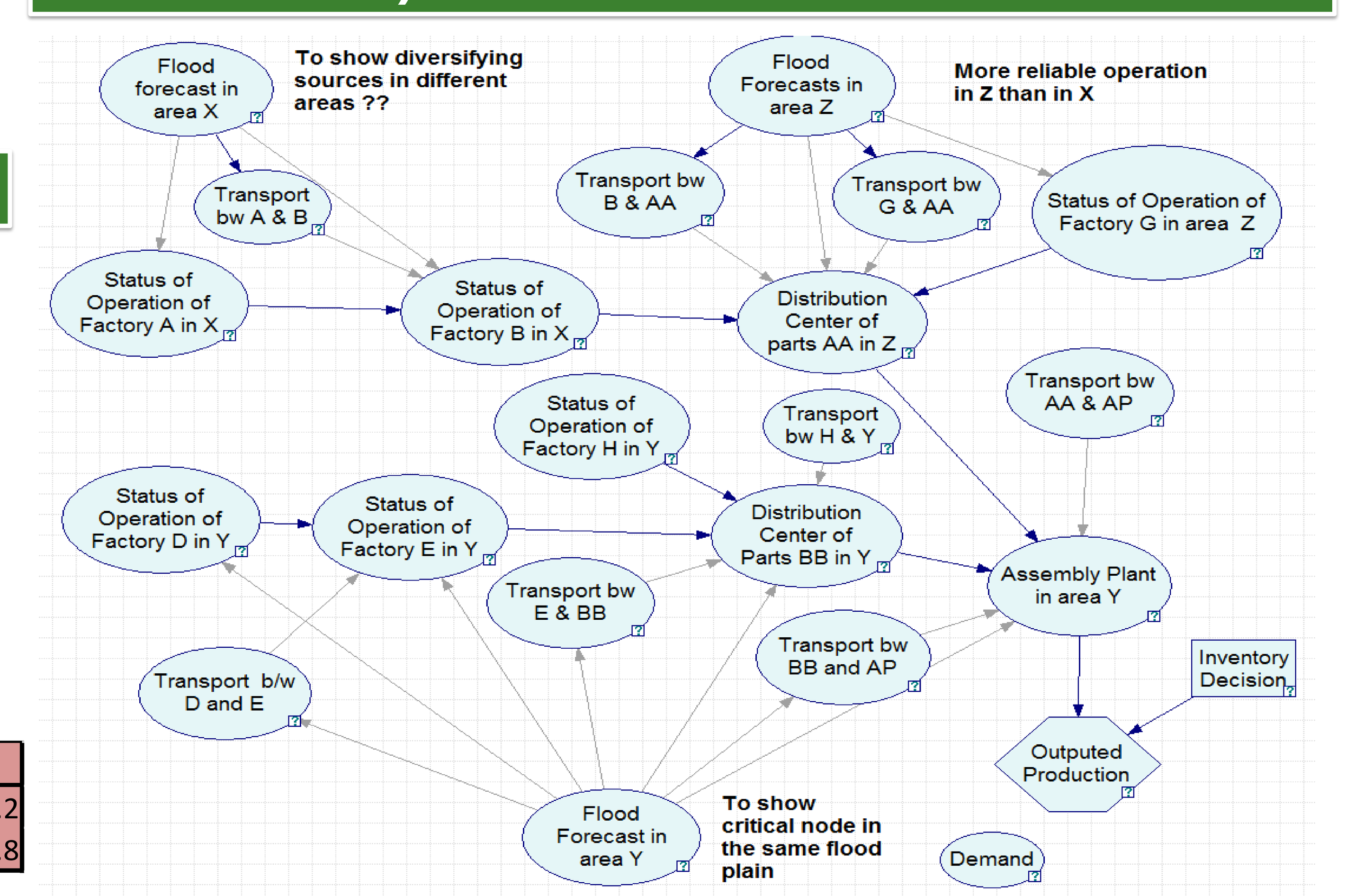
Result: Decision will be don't store inventory

4) Model with Sensitivity Analysis of Investment Return of Inventory

Ratio of Invetory	Destroyed Store Invtry
4	2000
5	2500
6	3000
7	3500
8	4000
9	4500
10	5000
11	5500
12	6000
13	6500
14	7000
15	7500

Ratio of Invetory (D9)	Low	Medium	High
4	Dont Store	Dont Store	Dont Store
5	Dont Store	Dont Store	Store
6	Dont Store	Dont Store	Store
7	Dont Store	Dont Store	Store
8	Dont Store	Dont Store	Store
9	Dont Store	Neutral	Store
10	Dont Store	Store	Store
11	Dont Store	Store	Store
12	Dont Store	Store	Store
13	Dont Store	Store	Store
14	Dnt Store	Store	Store
15	Store	Store	Store

5) Extension of the Model



Decision Node							
Store Inventry				NoStore			
Normal	Partial Dstryd	Half Dstryd	Complete Dstryd	Normal	Partial Dstryd	Half Dstryd	Complete Dstryd
500	500	100	100	100	50	50	-1000000

Posterior	
X=Likely, Y=Likely, Z=Likely	
Normal	0.9070
Partially_Destroyed	0.0789
Half_Destroyed	0.0126
Completely_Destroyed	0.0015
X=Maybe, Y=Maybe, Z=Maybe	
Normal	0.9166
Partially_Destroyed	0.0724
Half_Destroyed	0.0099
Completely_Destroyed	0.0012
X=Unlikely, Y=Unlikely, Z=Unlikely	
Normal	0.9507
Partially_Destroyed	0.0456
Half_Destroyed	0.0032
Completely_Destroyed	0.0004

Expected Value	
X=Likely, Y=Likely, Z=Likely	
Ex(Store)	494
Ex(Not)	-1414
X=Maybe, Y=Maybe, Z=Maybe	
Ex(Store)	496
Ex(Not)	-1085
X=Unlikely, Y=Unlikely, Z=Unlikely	
Ex(Store)	499
Ex(Not)	-290

Conclusion

- The Bayesian network is an effective tool to analyze supply chain risks management and propose resilient network properties.
- Future studies should address:
  - How to incorporate costs and demand?
  - How to deal with routing/transport?
  - How to capture cooperation among suppliers?
  - How to incorporate lifelines in the network?
  - How to do continuous cases?
  - Should calculate the value of information of floods prediction?
  - Can validate model results with real-world data?

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