UNDERSTANDING THE ROLE OF SEASONAL FOOD TRADE NETWORKS IN INVASIVE SPECIES SPREAD

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Summary

Trade and transport of goods is widely accepted as a primary pathway for the dispersal of invasive species. A temporal network-based approach is used to model market-to-market seasonal flow of agricultural produce and examine its role in pest spread. Through dynamical analysis of the network, we apply it to study the role of trade in the spread of a major pest of tomato, *Tuta absoluta*. Network analysis reveals that the roles of nodes as sources or hubs of spread changes with season, and hence makes the network more vulnerable to attacks. We apply a novel ranking-based inference approach to show that tomato trade is a driving factor in the rapid spread of this pest.

Background

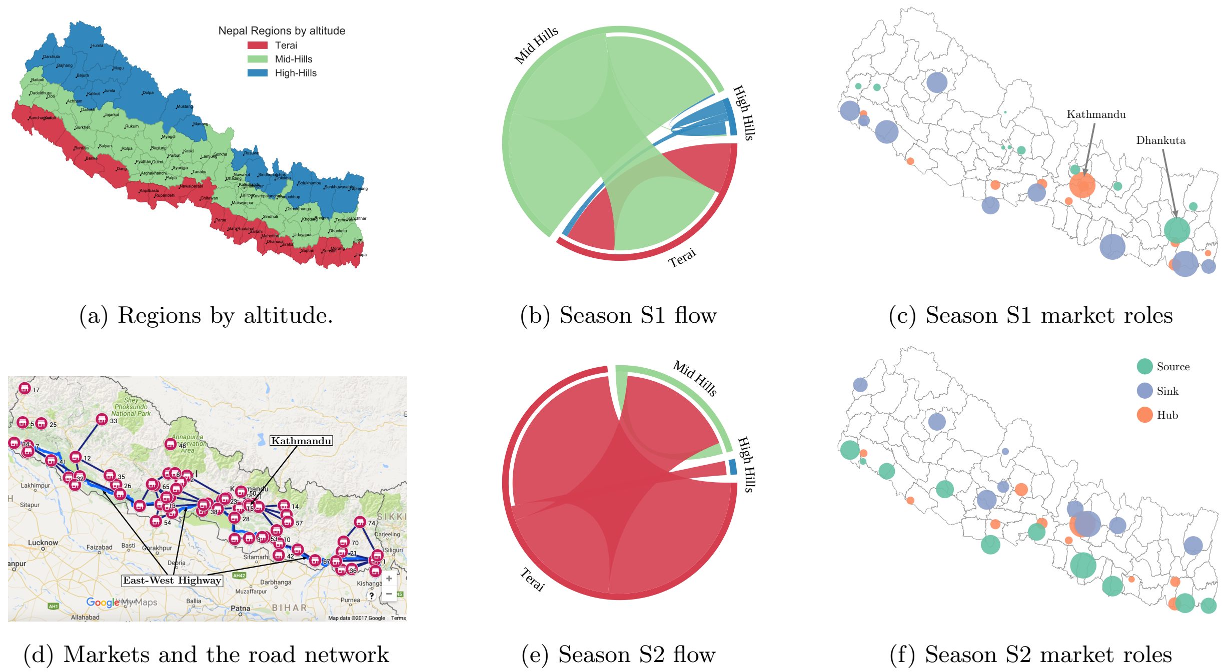
Trade of agricultural commodities is a quintessential component of our food systems. However, global trade increases the risk of rapid spread of invasive species and bio-terrorism, similar to spread of infectious diseases in human and animal populations. Not much is understood as regards to the role of human mediated pathways (such as trade and travel) in preventing introduction and mitigating immediate impact. See [2,4] for further discussion on this topic.

We develop an integrated data-driven methodology for synthesizing realistic spatio-temporal networks of seasonal agro-products between major markets [6] from diverse, multi-type, and noisy datasets. We illustrate the methodology by developing a spatio-temporal domestic tomato trade network in Nepal and investigate its role in the spread of *Tuta absoluta*, a devastating pest of the tomato crop [1]. Through dynamical analysis of the networks and a novel rank-based inference approach, we show that tomato trade has facilitated the rapid spread of the pest in the region. Further, we analyze the spatio-temporal properties of the flow networks, identifying important actors in the market network that facilitate spread and establishment of the pest.

Network construction. We model the flow of agricultural produce among major wholesale markets using a doubly constrained gravity model. The total outflow from a market depends on the amount of produce in its surrounding regions, and the total inflow is a function of the population it caters to and the corresponding per capita income. The details and justification for the assumptions are provided in Venkatramanan et al. [6]. The flow also depends on the time taken to travel between the markets. Based on the physiography, districts of Nepal are partitioned into three regions, namely Terai, Mid Hills and High Hills (see Figure 1a). Due to altitude and temperature variations, the tomato production season varies among these regions. Production in the Mid Hills and High Hills is largely restricted to the summer months of June to November (referred to as season S1), while Terai region produces during the winter months of December to May (referred to as season S2). The nodes of the flow network are the major markets, 69 in all. District level production and population data is distributed to each node [6]. We modeled the total inflow into a market as a product of the population catered to by the market and a function of the average per capita income associated with the market.

Results

Role of trade in pest spread. We used a discrete-time SI (Susceptible-Infected) epidemic model on directed weighted networks to model pest dispersal. A node i in state I infects each of its out-neighbors j in the network with probability proportional to the flow at each time step t. The model is based on two assumptions: (i) an infected node remains infected and continues to infect its neighbors and (ii) the chance of infection is directly



(a) Regions by altitude.
(b) Season S1 flow
(c) Season S1 market roles
(d) Markets and the road network
(e) Season S2 flow
(f) Season S2 market roles

Figure 1: The physiographic division of Nepal and how it affects trade flows during different seasons is shown. Our analysis shows that a hub or a source in one season can be a sink in another season, making it not only vulnerable to attacks in one season, but also influencing other nodes in the following season.

proportional to the volume traded. We adopt the *dynamic message passing algorithm* [3] to estimate the probability of infection for each node at time t and given initial condition. The experiment was setup under the premise that *T. absoluta* was first introduced to the Kathmandu valley, based on expert opinion. Given the pest reports, we evaluated our model based on the following backward inference problem: for an observation of node states at time t, what is the most likely origin of invasion? (also known as the source detection problem [5]). We examined the likelihood of markets or regions being the source nodes, and in particular, we compare this with the likelihood of the region around Kathmandu being the source. Our results show that Kathmandu and nearby markets are the top likely sources of invasion [6].

Sources, sinks and hubs Given the flow network, we define the *projected flow network* as follows: For each edge (a, b) of the road network, $w(a, b)$ is the sum of all flows F_{ij} of FN where the identified shortest path between i and j contains edge (a, b) and the flow direction is from a to b. The final flow on (a, b) is $|w(a, b) - w(b, a)|$ with direction $a \to b$ if $w(a, b) \geq w(b, a)$, or $b \to a$ otherwise. To identify sources (high outflow), sinks (high inflow) and hubs (high inflow and outflow), we define the parameter $h(v) = 4\frac{I'_v O'_v}{(I'_v+O'_v)^2}$, where I'_v and O'_v are the net inflow and outflow at v in the projected flow network. A node is a perfect source or sink if $h(v) = 0$. The hub score of a node v is computed as the product of the town/municipality population and $h(v)$.

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