Quantifying the Direct and Indirect Role of Insect Pollinators in the US Economy

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Ecosystem goods and services are consistently undervalued as critically important resources to all humans in sustaining human and industrial activity. One such crucial ecosystem service is pollination mediated by both wild and managed insect species. Close to 90 percent of wild flowering plants and more than one third of global crops by production depend on animal-mediated pollination, in some capacity, for yield or quality. Perhaps even more critically, these crops include some of the most nutritionally-rich crops including many fruits, vegetables, seeds, nuts, and oils[1]. Although renewable, many ecosystem goods and services are being extended beyond their rate of replenishment as ecosystems are degraded and demand increases[2]. Despite this and significant interest in pollinator wellness in the wake of the devastating introduction of Colony Collapse Disorder (CCD) to the U.S. in 2006, the extent to which economic sectors, especially non-agricultural sectors therein, depend on insect-mediated pollination service remains uncertain.

This work investigates the role of insect pollinators in both agricultural and non-agricultural sectors, using methodologies and metrics from various disciplines including economics, ecology, geography, industrial ecology, statistics, and life cycle assessment. This research quantifies and extends existing research to better capture the dependence of U.S. crops on insect-mediated pollination by both honey bees and wild pollinators, estimating both economic value and associated uncertainty. In addition, it identifies economic sectors and regions of the U.S.

especially vulnerable to pollinator decline. An IO framework is utilized to quantify direct and indirect economic dependence of U.S. industry sectors on insect-mediated pollination service and to assess cascading economic impacts of potential pollination losses. Lastly, this research creates a new environmental vector compatible with existing EIO-LCA tools to quantify the contribution of pollination services, focusing on service provided by honey bees, to facilitate more complete life cycle analyses. This new impact category progresses the incorporation of ecosystem goods and services into process-based life cycle assessments of products, allowing for unintended environmental externalities of industrial production to be better identified. This valuable perspective provides framework for the use of mixed IO models for analyzing ecosystem services, overall contributing to efforts to conserve ecosystem health and biodiversity.

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1.0 Introduction

Pollinators serve a crucial role in ecosystems, human nutrition, and the economy. While some pollination is performed by wind, water, or auto-pollination, pollinators are essential for most pollination-dependent plants to move pollen from male to female structures resulting in fertilization and production of seed and or fruit. Over one third of the world's food supply and about 75 percent of angiosperms (flowering plants) depend upon animal-mediated pollination service. While there are many birds, bats, and other larger mammals responsible for pollination, most pollination service is performed by both wild and managed populations of insects including ants, wasps, thrips, flies, honey bees, bumble bees, solitary bees, butterflies, and moths[3, 4]. Pollination-dependent crops include many of the most nutritious such as nuts, seeds, oils, fruits, and vegetables (Table 1) [3, 5]. Pollination service provided by pollinating organisms has value to human nutrition, and through aiding the production of commodities with material benefits, the service has economic value to the agricultural industry responsible for the growth, harvest, and distribution of these nutritive crops.

Table 1. Crops dependent upon insect-mediated pollination service [5-7]

Almonds	Citrus (other)	Lettuce	Persimmons	Tangerines
Apples	Coffee	Limes	Plums	Tomatoes
Apricots	Cranberries	Macadamias	Plums & Prunes	Turnips
Avocados	Cucumbers	Mangoes	Pomegranates	Watermelon
Beans	Currants	Melons	Prunes	
Beets	Eggplant	Nectarines	Pumpkins	*Alfalfa*
Berries, Other	Figs	Okra	Rapeseed	*Broccoli*
Blueberries	Flaxseed	Olives	Raspberries	*Carrots*
Boysenberries	Grape	Oranges	Safflower	*Cauliflower*
Brussels Sprouts	Grapefruit	Papayas	Sesame	*Celery*
Buckwheat	Guar	Passion Fruit	Soybeans	*Clover*
Cabbage	Guavas	Peaches	Squash	*Cotton*
Canola	Kiwifruit	Peanuts	Strawberries	*Onions*
Cherries	Kumquats	Pears	Sunflower	*Sugarbeets*
Chestnuts	Lemons	Peas	Sweet Potatoes	
Chicory	Lentils	Peppers	Tangelos	

Lower-right italicized list of crops is indirectly-dependent upon pollination service, all others are directly-dependent upon pollination service.

In addition to the value of pollination services to the agricultural sector, there are many complex economic linkages pollination-dependent crops affecting non-agricultural sectors, products, and processes [8]. These are sectors which do not depend upon pollinators for input directly, but indirectly, they have inputs from industries related to production that is dependent upon pollination service.

Pollinators also support the habitat and nutritional resources for many other organisms [9]. As with many ecosystem services, pollination provides many nonmaterial benefits for which value is either not easily calculated or is not possible to enumerate, but these intangible benefits can have much more significance to humans than the material benefits [10]. There is aesthetic value to a meadow of flowers or a diverse landscape of angiosperms that pollinators create and sustain, however, pollination-dependent plants are important cultural and social assets that go beyond aesthetic benefits. Pollination service provides these assets that contribute to human spiritual and heritage values, their sense of place, and cultural identity [11].

Pollinator diversity also means a diverse diet for other wildlife [9, 12]. Insectivores gain a portion of their diet from the pollinating insects being a part of their diet. Many freshwater fish depend upon pollinators as a stable part of their diet. Indirectly, pollination underpins other ecosystem services with their own benefits (e.g. fishing as recreation/sport, culture, tradition, subsistence) [10]. Herbivores rely upon the many plants that are able to reproduce due to pollination service. Seed-eating animals also depend upon pollinators as the seedset of many plants is dependent upon insect-mediated pollination service [5, 6, 12].

1.1 Quantifying Pollination Services

It is difficult to assess the total value of pollination services because the dependence of systems, both ecological and industrial, on the services are complex and many aspects are without simple or tangible metrics[9, 11]. How does one quantify the aesthetic value of seeing a field of flowers, or breathing in its captivating scent? Despite the difficulty in doing so, valuation of pollinators through valuation of the services they provide is a key method to motivating and stimulating conservation efforts that benefit pollinators[12]. It is useful to put the value of any ecosystem service into monetary terms, as economics gives us a scale against which to measure immeasurable services [11]. However, monetary terms are difficult to assign to nonmaterial benefits of pollination service [9, 11]. One aspect of value which can be more readily measured in economic terms, and therefore quantified, is the economic value of pollination service to agricultural and non-agricultural industrial sectors.

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1.1.1 Challenges to Quantification

Each of economic method necessitates a valuation of the dependence of pollination-dependent plants or specifically crops. Crops can be dependent upon pollination service for yield and/or quality of seed and/or fruit, but the level to which each is dependent varies relative to plant-specific botanical characteristics [5, 6, 9]. A crop can be dependent upon pollinators for either fruit or seed set, thus dependence is also based on which part of the plant is the commodity of the crop because crops can be directly or indirectly dependent upon pollination service. If a crop is dependent upon pollination service for seed set, but the commodity of that plant is not the seed (e.g. onion), that crop is said to be indirectly dependent upon pollination service [5, 6]. Crops are directly dependent upon pollination service is if the commodity of that crop is developed with aid from pollination service (e.g. apple, almond). Some crops have an essential relationship with pollinators where fruit or seed set cannot occur without pollination. Others are somewhat self- or wind-pollinated and so can still produce some of the commodity of the plant without pollinator assistance. Sometimes referred to as dependency or a dependence-ratio, the dependence of a given crop is a proportion of the commodity that is dependent upon pollination service [5, 6, 9].

Dependence estimates are complex and can be determined by various methods of field study in which researchers compare the plant under conditions of pollinator presence in varying pollinator density and under conditions of pollinator absence [5, 9]. A determination can be made by using this comparison to analyze the improvement or deterioration of commodity yield or quality between the two conditions. However, there is a great complexity reflected in an estimate of dependence determined by these studies [5]. Characteristics of the crop such as floral morphology across a variety of commercial cultivars, the capacity of those cultivars to self-pollinate or the necessity to cross-pollinate for production, and the structure and composition of the landscape can all affect the efficiency of pollination service and the dependence of that plant on pollination service [13]. In addition, the composition of the pollinator community where these crops are grown, their relationship with the specific crop, pollinator abundance and density, and the characteristics of those pollinators such as body size and pollen load, as well as environmental conditions such as temperature and precipitation affect the measurement of factors that contribute to calculating dependence of a specific crop [5, 13].

Information on pollination dependence has been collected and summarized by several widely-accepted sources for dependence estimates (Table 2). This work has had great value in the field of valuation, however, due to overall lack of field study data considering the complexities of the relationship between pollinators and pollination-dependent crops, estimates have been derived from crop production knowledge, some field data of production, and expert opinion [5]. The estimates are either point estimates that do not recognize a bound of variance or uncertainty [6, 7, 14], or wide, categorical range estimates [5] that do not reflect the nuances of the variety of crops that the estimates represent. There is also some discrepancy between sources, and reconciliation is necessary to aptly determine the value of pollination service to the agricultural and subsequently, non-agricultural sectors [13]. Reconciliation can only be achieved with the acquisition of proper field study data that considers cultivar, landscape, pollinator, and climate variation [13]. This lack of consensus or detail in estimates of dependence can pose as a challenge to subsequent valuation of pollination service.

Table 2. Summary of literature estimating crop pollination dependence coefficients

Pollinator Inclusion	Estimate Type	Source, Year
Honey bees	Point	[7], 1992
		[14], 2000
		[15], 1989
All Insects		[6], 2012
	Categorical Range	[5], 2007

Another challenge can be determining the scope and limits of valuation [13]. Where do you draw the line with the boundaries of valuation? As discussed in section 9.2.3, it can be difficult to quantify many aspects of the value of pollination services. Non-use, option use, or indirect use values often do not have simple means to estimation and direct use value can be determined using terms that are not readily measured or that lack consensus. Much of the valuation can be time and resource expensive, and there may simply not be enough data to draw meaningful conclusions making a complete analysis challenging. It is up to the analyst to draw the boundaries of where to end quantification, which aspects of value to include, and which approach to use—however, such boundary drawing must be done with caution. The boundaries of the valuation will ultimately determine the communication and impression of the value of pollination services to other members of the field, agencies, and ultimately the general public or those with power to influence the welfare of pollinators [13].

1.1.2 Direct Use Value

Direct use value refers to consumptive and productive use of pollination service. Although other industries (e.g. floral industry, recreational industries) also benefit directly from pollination service, the direct use value of pollination services is by far dominated by the agricultural value [11].

The direct value of pollination service is evident through the well-established beekeeping industry through which farmers can buy or rent colonies of bee species or pay to have them maintained as a standard agricultural production process [13]. There are three methods that have been used to quantify the economic value of pollination services to agriculture: consumer surplus, production value, and replacement cost. Each of these are built upon an initial determination of dependence coefficients. Although there are merits to each of these methods, the production value method lends itself well to subsequently determining the economic value of pollination services to other non-agricultural industrial sectors[8, 11]. Any of the described methods could be used to determine the value of a subset of pollinators (honey bees, all managed species of insect pollinators, wild pollinators, mammals) or all pollinators given enough available data. Likewise, the methods are scalable at varying levels of flexibility and can be adjusted to provide estimates for a range of interests (local, multistate, national, international). Locality-specific valuation analyses can be performed to motivate pollinator protection policy (e.g. Pennsylvania Pollinator Protection Plan[16]).

The consumer surplus method determines the economic value of pollination service attributable to managed honey bees in terms of the change in consumers' and producers' surpluses of pollination dependent crops in the presence of pollination services [7, 17, 18]. In 1992, Southwick and Southwick introduced this method to determine the value of honey bees in the US to the agricultural sector by assessing the surplus of pollination-dependent crops gained from pollination service by honey bees [7]. (In this method, the long- term supply curve is assumed elastic such that no constraints of land availability or increased production cost is incurred on the behalf of farmers to switch to production of a different crop.) A variation of this method utilizes constant price elasticity in the calculation of demand for all crops and instead estimates value based on the loss of agricultural production for each crop. This loss is transformed into a consumer surplus loss which results in an estimate of the social cost of pollinator decline [17].

The production value method determines the economic value of total crop production that is attributable to pollinators [11]. This method is more relevant for agricultural sectors and has been utilized by many studies on a range of economic scales. This method is especially useful for multi-sector (including non-agricultural sectors) or large-scale economic analysis that is built upon input-output framework discussed in section 9.2.3[8, 11].

The replacement cost method determines the economic value of pollination service in terms of the cost to replace the service by alternate means of pollination such as hand- or mechanized-pollination [19]. This cost of replacement is incurred by beekeepers or producers.

In addition to agricultural production sectors, there are many other industrial sectors both relating to agriculture (pesticides, fertilizers) and not relating to agriculture (pharmaceuticals, recreation) that benefit from the production use of pollination service through use of pollination dependent crops. There are many industrial sectors that rely upon output from these secondary sectors and so on[8]. These higher-order economic relationships can be quantified through several methods (Table 3).

Input-output analysis is an economic modeling technique that is utilized by industrial ecologists and sustainable engineers to provide a systems-level framework to describe interactions between industries. The model simplifies the economy based on production in each industrial sector organized as transactional data between sectors [20]. This model allows for higher-order value of pollination service to be valued. In addition to direct use value, it is important to consider other value attributed to pollination service through indirect usage and non-use.

Table 3. Summary of estimates of pollination service value by various methods

Valuation Method			Author(s)	Year of study	Differentiation of wild and managed Pollinators	Scale	Estimates	Note
Production Value	Economic Value		Butler	1943	No			
			Fluri and Frick	2005				
			Levin	1984				
			Martin	1973				
			Metcalf et al.	1962				
			Winston and Scott-Dupree	1984				
	Total economic value of insect pollination	GEM	Bauer and Wing					
		Dependence Ratio	Robinson et al.	1989	Honey bees		8,300,000,000[1]	• Captures variation in pollination benefits across crops, but may generalize between cultivars • Applicable at all scales • Only estimates producer benefits • Assumes maximum efficiency of pollination or maximum density of pollinators
			Morse and Calderone	2000	Honey bees		14,600,000,000[2]	
			Losey and Vaughan	2006	Wild	National, Fruit and Vegetable	3,070,000,000[3]	
			Winfree et al.	2011	Managed and Wild	Multi-state		
			Calderone	2012	All	National	19,200,000,000[4]	
			Gallai et al.	2009	All	Global	200,000,000,000[5] [153,000,000,000[6]]	
		Consumer Surplus			All	Global	265,000,000,000-425,000,000,000[7]	• With regard to pollinator decline, estimates social cost to consumers • Considers market price fluctuation
			Southwick and Southwick	1992	Honey bees		1,600,000,000-5,200,000,000[8]	
			Kasina et al.	2009				
			Lautenbach et al.	2012				
			Chacoff et al	2010				
			O'Grady	1987				
			Ashworth et al.	2009				
Replacement Cost	Replacement of all pollinators by labor or wild pollinators by managed bees		Alsopp et al.	2008				• Applicable at all scales • Does not over-estimate pollination benefits • No reliance on crop prices • Assumes producer willingness and ability to pay • Relies upon input and labor prices • Most appropriate in circumstances where replacements have or will be made • Replacement options may not fully replace all benefits or be as effective because this model does not represent all benefits
			Mouton	2011				
			Muth and Thurman	1995				
Contingent Valuation method	Willingness to pay for wild pollinator protection		Mwebaze et al.	2010	Yes		1,770,000,000[9]	• Captures non-use in monetary terms • Dependent on order of valuation • No reliance on market prices • Reflects public opinion • Requires a full understanding of pollination service benefits • Can overestimate as payment is not actually required • Expensive
Landscape service flows	Relate landscape patterns to bee diversity and abundance and crop yields		Chaplin-Kramer et al.	2011	Yes			
			Morandin and Winston	2006				
			Olschewski et al.	2006				
			Ricketts et al.	2004				

1.1.3 Indirect Use and Non-Use Value

Indirect use describes the function of pollination service to support other species and the ecosystem and society as a whole or other uses including non-consumption uses, option value or non-use value. This value surpasses the direct use value as it reflects a whole picture of ecology and society [11]. Option value is ascribed to pollination service for the option of benefiting from pollination service in the future or to retain benefits that may not be currently understood. Non-use value refers to the intrinsic value ascribed to pollination service and pollinators for simply existing (existence), for benefiting others even though it may not benefit the party assigning value (altruism), or for being available for future generations (bequest) [11].

Indirect use value has been evaluated by willingness-to-pay methods for ecosystem services including pollinator protection policy [21] and through work that seeks to incorporate ecosystem services into life cycle assessment studies[22]. Willingness to pay can be assessed directly (e.g. by survey), or consequentially through assessing costs to finding substitutes for the benefits provided by pollination service either physically (a parallel that can be measured in the market) or behaviorally (as costs to obtain other service or for not having the benefits of the service) [9, 11, 21]. Physically, this might be the cost of hand- or mechanized-pollination, or it may be the cost of something like artificial flowers as an aesthetic substitute for those provided for by pollination service [11, 19]. Behaviorally, this could be the cost of gaining nutrients typically provided by pollination-dependent foods (vitamin supplements), or the cost of increasing land, water, fertilizer, and pesticide usage to achieve the same level of production provided when pollinators are present. There is also inherent value to pollination service as well as value from the cultural, social, and aesthetic activities provided, enhanced, and maintained by pollination services. Estimations of these can vary depending on the stakeholders involved. Lastly, in addition to pollination value in the aforementioned facets, there are also benefits that are either not well understood or may be completely unknown. The ecosystem is a complex web of interdependence. Other ecosystem services depend upon pollination service including disease control, pest management, disturbance regulation, erosion control, and nutrient cycling [9].

1.2 Pollination in a Life Cycle Assessment Framework

Process and input-output life cycle assessment (LCA) can be used to determine the environmental burdens associated with a product, process, or activity[23]. By assessing the entire life cycle of the object of interest, one can evaluate the environmental impact of released emissions or of materials and energy used during various stages (material extraction, manufacturing, usage, disposal) of the object's life within boundaries of the system relevant to the scope of the analysis. It is vital to include ecosystem goods and services in LCA in order to provoke sustainable development, however currently ecosystem services are not well represented in life cycle methods. Some LCA tools have been developed for the purpose of assessing the role of ecosystem services in process and input-output life cycles (EIO-LCA, Eco LCA)[24-26]. Data on managed species is continually more widely recorded and available, and there are tools being developed for estimating parameters that are useful to determining the role of wild pollinators in LCA (InVEST[27]).

1.2.1 Process LCA

Generally, process life cycle assessment (LCA) does not account for pollination service[28]. Managed pollinators (mostly honey bees with some other species of managed bees) currently have enough data to be included in some process LCAs, but services provided by wild pollinators are presently difficult to include due to a lack of available data on the contribution of wild pollinators to production relative to managed pollinators or all pollinators (with no delineation of wild versus managed) [9, 28].

1.2.2 Economic Input-Output LCA

Economic Input-Output Life Cycle Assessment developed at Carnegie Mellon University builds upon existing economic input-output modeling by combining the economic relationship matrix of EIO with environmental and energy flow[24, 29]. This is done by adding an environmental effects vector to the economic model developed from the work of economist Wassily Leontief. In the 1930s, Leontief formulated an economic input-output table for the United States economy showing the transactional relationships between economic sector[29, 30], EIO-LCA takes final demand estimates (Y) and direct/indirect economic requirements (X) from the EIO model and combines them with an environmental impacts sector[27]. This environmental sector (E) is defined by the following:

$$E = RX = R[I - A]^{-1}Y \qquad \textbf{\textit{[1]}}$$

In equation 1, R is a matrix with diagonal elements representing the environmental impact per dollar of output in each sector. The R matrix has units of environmental burdens per dollar of output (e.g., kg CO_2/\$). This matrix is multiplied by vector X, the output of each sector in dollars.

Vector X is defined by $[I-A]^{-1}$ (equation 2), the total requirements matrix, multiplied by Y, the vector of desired output or final demand[27, 28]. It is called as the total requirements matrix (sometimes the Leontief inverse[30]) because to calculate the term, $[I-A]^{-1}$, all direct and indirect purchases are totaled[29]. In that definition, I is the identity matrix, A is the direct requirements matrix, and -1 represents the multiplicative matrix inverse. The total environmental burden, vector E, includes both direct and indirect environmental effects with units of burdens (e.g., kg CO_2) by sector[24, 29].

$$X = [I - A]^{-1}Y \quad \textbf{\textit{[2]}}$$

The EIO-LCA model can include an array of environmental burdens such as air pollutant emissions, global warming potential, ozone depleting substances, or estimates of resource inputs such as fuels, fertilizers, or electricity[24, 29]. As indicated in equation 1, these burdens are calculated using economic output data from each sector (X) and the R matrix. The values for the R matrix from which these burdens are derived comes from public datasets that report these emissions on a sector-level such as those provided through the United States Environmental Protection Agency (EPA). Sometimes translation, conversion, or reclassification of the reports is necessary to derive the matrices. The EIO-LCA method developed by CMU utilizes the EIO matrix and associated environmental data in U.S. Benchmark Models using the North American Industry Classification System (NAICS) for defining sectors[24, 29].

Benchmark models are created every five years in the U.S. and include more than 400 industry sectors[24, 29]. The data sources and publications used for these models are vast, and much comes from surveys of operating facilities in each industry in addition to reports from the United States Environmental Protection Agency. For example, the 2002 U.S. Benchmark Model uses the U.S. EPA Toxics Release Inventory for updated toxic emission data and the U.S. EPA Inventory of U.S. Greenhouse Gas Emissions and Sinks for estimating greenhouse gas emissions by industrial sectors. Other examples of data sources include the Manufacturing Energy Consumption Survey (MECS), U.S. EPA National Emissions Inventory (NEI), and U.S. EPA National Biannual Resource Conservation and Recovery Act Hazardous Waste Report[24, 29].

The data used to compile many of these surveys and reports has varied quality. It is often self-reported and is subject to measurement error[24, 29]. In addition, reporting requirements vary widely by industrial sector and thus there are gaps in the information available. There are similar international surveys and models, but none are as extensive in the amount of sectors included. Another limitation to this method is that each sector is represented by an aggregated average, and despite having over 400 sectors disaggregated, this can still hinder detailed assessment. For example, there is no distinction in the plastics sector for the type or grade of plastic that may be specific to a product or process. In addition, there is no distinction between mills and plants with varied efficiency or pollution output that may be specific to or used primarily in a life cycle. Process LCAs can be more specific in this distinction for a particular material or process[24, 29].

Along with inherent uncertainty coming from the original data source, the aggregation of these sources compounds uncertainty, and there is often missing or incomplete data or estimations where data is lacking[24]. There are also many assumptions made for allocation of environmental burden when sectors from the economic data and environmental data are not aggregated in the same way. In addition, the data is only from publicly available sources and not industry-specific such that information that may exist in industry reports is not incorporated into the model simply because it is not available publicly. The model is also based on producer price as opposed to purchaser price which can differ vastly[24]. In addition, the model is based on constant coefficients which work for short-term assessments but not in the long term when consumers and industries may adapt to disruptions in sectors. Also, the model's linear nature may not aptly represent production processes or flows of economy as they are often non-linear[24,30].

Finally, many burdens are not represented for lack of data or because they are not incorporated into the framework of the model. Pollination service, like many ecosystem services, is neglected in LCA, including CMU's EIO-LCA method. Ecosystem services are often considered free and with infinite supply; however, the renewability of these resources has limitations[31, 32]. This limit has been made apparent for many of these resources including pollination as pollinators have faced significant decline due to many factors including industrial use of pesticides[31, 33, 34]. The role of this service in industrial sectors is unexplored compared to finite or nonrenewable sources.

An environmental vector for pollination service does not currently exist in Carnegie Mellon University's online tool for EIO-LCA[24]. In fact, ecosystem goods and services are overlooked in this model. As a resource, "Pollination," exists in EcoLCA, an IO-LCA tool developed by The Ohio State University, however, the vector is not developed and exists as a placeholder in this tool at present[25].

1.2.3 Future Directions

Although managed species of pollinators, especially *Apis mellifera* and *Apis cerana* (European and eastern honey bees), are relatively well-studied and data pertaining to managed species is widely recorded and available, there is still much data missing for wild pollinators. In addition, crop-specific field data are available for some crops and cultivars, however, there is generally a lack of systematically collected data across representative crops, cultivars, and landscapes. Creation and implementation of an environmental vector for pollination services for

LCA tools (e.g. EIO-LCA, EcoLCA) for managed pollinators and subsequently wild pollinators will allow for an account of the role of pollination services in product and process life cycles.

1.3 Effect of Loss of Pollinators

Decline or loss of pollinators has widespread impacts to agricultural and nonagricultural industries, cultural and social institutions, and various ecosystems and biodiversity. We have already seen significant declines in both managed and wild populations of pollinators[25, 34] and continued loss would be devastating to human nutrition, culture, and industrial activity as well as ecosystems. Obviously, the types of pollinators lost, the amount at which they are lost, and the resulting composition of the pollinator community would influence the type and magnitude of the impacts associated with the loss. However, one can pursue a thought exercise to assess potential impacts by loss of pollinators. Without proper valuation and understanding of the material and nonmaterial benefits that pollinators provide, it is not possible to fully understand the effects of the loss of pollinators.

1.3.1 Agricultural Impact

In agriculture, there is a direct impact to the production of food crops with pollinator loss. In a realistic scenario, the agricultural industry would mitigate losses through various strategies [13]. Speaking only in the interest of preserving the value of capital (weak sustainability), elastic prices of many pollination- dependent crops would respond to the decrease in production and increase accordingly, likely narrowing the gap between current production value and after any pollination service loss. Elasticity in supply and demand allow for substitution on the part of both producers and consumers. Production losses could also be mitigated by increasing acreage of pollination-dependent crop. This would require greater resources for the additional crop acreage and associated costs and impacts. For some crops, there would be total production loss without pollination and the industry would have to respond with technological substitution through manual pollination performed by hand by field workers, or through mechanical pollination[11]. There may also be a greater increase in demand for managed pollinator species. The managed pollinator industry has already faced significant losses over the last fifty years and labors substantially the meet current demand given current seasonal losses[35]. It is very important to understand that preserving pollination service is not a complete solution. As mentioned, pollination service can be provided, albeit at an efficiency deficit, by augmenting current managed pollinator trends or substitution by means of manual or mechanical pollination[11, 18]. However, the preservation of pollinator diversity is essential for long-term ecosystem fitness[9]. The importance of pollinators extends far beyond human endeavors.

1.3.2 Non-agricultural Impact

The impact of pollinator loss would extend beyond agricultural production and have effects upon the production of other related, non-agricultural industries[8]. Related economic sectors relating to fibers, materials extraction, pharmaceuticals, and construction rely on production output from agricultural sectors and indirectly rely on the benefits pollinators provide. These indirect, complex linkages are not well-quantified or understood, but would cause unquantified effects cascading through the economy. Moreover, loss of pollinators would be a detriment to ecosystem function and biodiversity [9]. In fact, many pollinator species with no agricultural production value are necessary to ecosystem function [12].

1.3.3 Ecosystem Impact

Through the delivery of pollen to plants, pollinators ensure set and enhance quality of wild fruits and seeds. Many of these wild plant pollinators have no influence on agricultural production value despite their crucial role in nature. This provides and maintains diverse habitat for other organisms and supplies nutrition through trophic webs (including consumption of pollination-dependent plants, pollinators, and secondary or tertiary consumption) [12].

A loss of pollinators also has the potential to disrupt existing cultural behaviors and practices [9, 12]. Recreational activities, tourism, apple- and strawberry-picking, activities relating to identity and celebration of heritage or self would all be interrupted with potentially no suitable substitute. Other important services like disease and erosion control, ecosystem resilience, biological diversity, would suffer for lack of pollinators [9, 11]. These services are incredibly valuable and connected to the health and welfare of humans as well as greater ecosystems.

1.4 Summary

The preservation and restoration of pollinators are critical to the welfare of humans and ecosystems. Already significant declines in abundance and biodiversity of pollinators has underscored a need for valuation of the benefits they provide. There are tools available for useful valuation of pollinators and pollination services from an economic perspective. However, the pollinators serve ecosystems indirectly through many pathways that ensure ecological and environmental resilience that cannot be accounted for in current economic methods. In addition, many cultural, non-material benefits derived from pollinators may not ever be entirely captured by economics. As with any valuation, it is critical to consider material and nonmaterial benefits and choose the scope of a valuation of pollinators and pollination service with care and always with clarification of limitations as the influence of a valuation can be far-reaching and highly influential.

Current life cycle methods do not adequately account for ecosystem goods and services, and pollination service is especially not represented in process or product LCAs, although placeholders and intuitive avenues for implementation exist. Loss or decline of pollinators will be significant and extensive, having impacts directly in agriculture, indirectly in non-agricultural industries and human culture, and finally in essential ecosystem function. Future directions include creation and integration of this environmental impact category into life cycle analyses and systematic collection of data on both wild and managed pollinators to better understand their role in production as well as the cultural and social benefits attributed to pollinators. More acute valuation of pollination services will motivate and guide conservation, revitalization efforts, policy decision-making.

2.0 Economic Dependence and Vulnerability of United States Agricultural Sector on Insect-Mediated Pollination Service

The following chapter is based on a peer-reviewed article under second review with Environmental Science & Technology with the pending citation:

Alex Jordan, Harland M. Patch, Christina M. Grozinger, and Vikas Khanna. *Economic Dependence and Vulnerability of United States Agricultural Sector on Insect-Mediated Pollination Service.*

2.1 Chapter Summary

Deficits in insect-mediated pollination service undermine ecosystem biodiversity and function, human nutrition and economic welfare. Global pollinator supply continues to decline while production of pollination-dependent crops increases. Using publicly available price and production data and existing pollination field studies, we quantify economic dependence of United States crops on insect-mediated pollination service at the county-level, and update existing coefficients of insect dependence of sample crops when possible. Economic value dependent on pollination service totals 34.0 billion USD in 2012. Twenty percent of US counties produce eighty percent of total economic value attributable to insect pollinators. We compile county-level data and consider the spatial relationship between economic value dependent on insect-mediated pollination, region-specific forage suitability, and crop-specific agricultural areas within US landscapes. We identify vulnerable, highly dependent areas where habitat for wild pollinators has

been reduced. These results can help inform future efforts to conserve and bolster managed and wild pollinator populations to ensure sustainable production of key agricultural crops.

2.2 Introduction

Ecosystem goods and services (derived from the world's natural capital) are critically important in sustaining human and industrial activity, yet remain consistently undervalued and underappreciated. One of these crucial ecosystem services is pollination mediated by animals, including both wild and managed species. Often considered to be inexhaustible, natural systems can be limited and degraded, and services can indeed be exhausted beyond their rate of replenishment[2, 36, 37]. More than 75 percent of global food crops depend on animal-mediated pollination, in some capacity, for yield and/or quality[5, 38]. This accounts for a little more than one third of global crops by production volume, but perhaps even more critically, these crops are some of the most nutritionally rich foods, including many fruits, vegetables, seeds, nuts, and oils[38, 39].

The majority of pollination service by animals is performed by insects including widely-managed *Apis mellifera* and *Apis cerana* (honey bees), bumble bees, and solitary bees as well as unmanaged pollinators such as wild bees, flies, butterflies, moths, beetles, wasps, thrips, ants, and midges[38]. Crop yield (of both fruit and seed) and quality (such as color, nutrition, and shape) depend on pollinator abundance as well as pollinator species diversity. While the demand for pollinator-dependent crops has increased by 300% in fifty years[40], populations of insect pollinators have exhibited extensive decline in many regions due to interacting stress factors including loss in habitat, poor nutrition (due to lack of abundance and diversity of flowering plant species), climate change, pests, parasites, pesticide use[41], as well as management and transport practices[38]. In addition, declines in insect populations have been recorded across the globe[42], including in protected natural areas[33], with nearly half of all evaluated insect species declining rapidly and a third facing threat of extinction[34]. Furthermore, the yield of pollination-dependent crops has been unstable compared to pollination-independent crops[38, 43]. In addition to farming sectors, numerous other industry sectors depend upon pollination by insects indirectly (e.g. medicine, biofuels, processed food, fibers), potentially making them vulnerable to decline of insect pollinators[8, 39]. Furthermore, insect pollinators support other vital ecosystem functions such as structuring ecological communities to support biodiversity and disease control as well as provide cultural and recreational benefits[9, 38, 44].

Economically, the value of insect pollinators is apparent in the agricultural sector where there is a well-established connection to the beekeeping industry through buying or renting colonies of bee species and where the management or upkeep of those colonies is a common agricultural production practice. In previous research, crop dependence on insect pollinators and the economic value of insect pollination has been calculated using limited field data[13]. In the case of Klein *et al.*, global crop dependence on insect pollinators was determined broadly, assigning categorical values of essential, high, modest, little, no, or unknown dependence insect dependence (based on a proportion of crop (fruit or seed) yield or fruit set and expert opinion)[5]. These proportion values are referred to as dependence coefficients. In the cases of Free *et al.*[45] and Delaplane and Mayer[46], the mechanics and biology of crop pollination were described without quantification of dependence. Dependence coefficients were determined as point estimates by Robinson, Southwick and Southwick, and Calderone *et al.*[6, 7, 47]. Overall, the data used in these studies were not necessarily generated from detailed assessment of pollination biology of a specific crop system (meaning, how pollinator visits or activity correlates with fruit or seed set), nor did they consider variation in crop cultivar, crop growth conditions, pollinator density, or surrounding landscape and weather conditions. Thus, these evaluations lack uncertainty estimates and are largely qualitative. Moreover, most previous estimates often focused on managed honey bees[6, 7, 14], neglecting significant contributions of wild insects whose conservation stabilizes pollination efficacy and reduces demand from the honey bee industry. Others have applied similar production value methodology to estimate the economic production value that depends on to wild pollinators[9, 48]. Alternative value methodologies based on the cost of replacement of pollination service by manual or hand pollination[19] or based on the change of consumer and producer surpluses of pollination-dependent crops have also been utilized[7, 17].

There is also considerable spatial variation in crop production systems and availability of pollination services from wild populations. Lonsdorf *et al.* developed a model informed by landcover data estimating wild bee relative abundance across the United States, and demonstrated considerable variation[49]. Koh *et al.* utilized this bee abundance model to spatially evaluate demand for wild bees in the US[50]. Not an economic analysis, the "demand" component of the Koh *et al.* study is based on acreage of pollination-dependent crops grown in the US available in the United States Department of Agriculture (USDA) Cropland Data Layer (CDL), which gives high-quality spatial resolution. However, previous studies of the economic valuation of pollinators have not been conducted at this spatial resolution. Studies instead have aggregated value at an international or national scale (which can dilute region-specific information) or at a finer scale with limited scope within local ecosystems, farms, or states (which can be impractical for assessment in other locations)[18, 48].

Here, we build on previous work on economic valuation of pollination systems by including more detailed analyses of economic dependence on pollinators, supported by data reported in the scientific literature. Through extensive literature review, we update existing dependence coefficients when possible with quantitative estimates of crop dependence and associated uncertainty of the estimate, determined using robust statistical methods. We take a rigorous approach to determining the national economic value of pollination in terms of production value, using publicly available USDA Census of Agriculture acreage data and National Agricultural Statistics Service (NASS) survey yield and price data. We provide high spatial resolution (county-level) of the economic value to agriculture dependent on pollinators and report uncertainty for this value derived from thorough simulations. Moreover, we integrate this information with the CDL and evaluate pollinator dependence and value with previous published model of wild pollinator abundance from Lonsdorf *et al.*[49] to identify counties in the United States especially vulnerable to pollinator decline. Overall, our studies considerably increase understanding of the economic dependence on pollination service by insects in terms of magnitude, spatial resolution, and commodity class.

2.3 Methods

Accompanying this detailed outline of methodology is a flowchart of significant methodological steps for visual aid, available in the Appendix (**Figure A2**).

2.3.1 Calculating Dependence Coefficients

Approximately 352 available crop commodity pollination studies were reviewed for the 25 most valuable pollination-dependent crops according to the Food and Agriculture Organization of the United Nations (FAO) 2012 United States Gross Production Value (GPV) estimates (***Table 9***). Data from 2012 was used as this is the most recently available Census of Agriculture year, and FAO data was used over USDA production estimates for their ease of reporting and compiling in this stage of the research. Crops can be directly dependent on pollination service mediated by insects for yield and/or quality of the commodity of the crop such as the flesh of the apple for apples or the nut for almonds. Indirectly-dependent crops are dependent on pollination for seed, but not for the commodity of the crop. For example, alfalfa and onions are dependent on pollination for seed set, not for the growth of hay for alfalfa or bulb for onions. Indirectly-dependent crops are represented as italicized in ***Table 9***. The economic value of pollination for indirectly-dependent crops is inherently more difficult to assess due to no direct measure of the commodity that is influenced by pollination. For example, fruit yield is measurable but not affected by pollination. Seed set is also measurable, but not the basis for the economic value of the commodity. Thus, determining how much of subsequent fruit yield is dependent on seed dependence on pollination service is complex and indirect. We have chosen to remove alfalfa from analysis as an indirectly dependent crop with high economic value for alfalfa hay, which is not in one generation dependent upon insect-mediated pollination service. It is such a high value crop (18.6 billion USD, 2012[51]) that it overtakes the resulting analysis. The 17 crops represented in the data account for 82% of the total GPV of the 25 most valuable pollination-dependent crops.

To find field study data, we first searched the extensive EndNote database of pollination biology publications (more than 13,000 publications) compiled and continuously updated by Dr. David W. Inouye of the University of Maryland with each common and scientific crop name. Studies were retrieved from the database based on the title of the article when indicative of a field study of the crop and insect pollinators. We also searched the library system of the University of Pittsburgh using its online PittCAT interface using key terms of the crop name (common and scientific), "pollination," or "pollinator." For inclusion, articles must have had a comparison of fruit set or crop yield under open pollination conditions with fruit set or crop yield under pollination exclusion conditions. It is not clear in each study that pollinators were abundant enough to suggest saturation (i.e. no pollinator limitation), however, open pollination conditions were that with a mix of both ambient pollinators (wild) and honey bees (managed) present (as is typical of an agricultural setting).

Of the more than 325 studies reviewed, 16 studies spanning 7 crops met these criteria and were used for analysis. *N* estimates of dependence coefficients (**Table 1**) per each crop were used to resample for uncertainty analysis. Each of *N* estimates are derived from a pair of yield/fruit set (open pollination, pollination exclusion) for a given crop from which a dependence coefficient could be calculated using the equation[13]:

$$D = 1 - \frac{f_{pe}}{f_{op}} \tag{3}$$

D: dependence coefficient

f_{pe}: fruit set of commodity under pollinator exclusion conditions

f_{op}: fruit set of commodity under open pollination conditions

Dependence was not estimated for crops for which there was insufficient field study data (<3 estimates) available in the literature. The dependence of at least one representative crop from each classification group (***Table 8***) was determined. The main cultivars of rapeseed and soybean grown in the US are autogamous and therefore do not need insect-mediated pollination service, however, there is some controversy on this topic as both crops have shown some yield benefits in specific settings and as both remain important forage for insect pollinators[46, 52-55]. With large field crops like these, the edge of the field benefits from the ecosystem service while the center of the field receives little if any benefit. This can cause smaller field studies on open pollination to give an inflated estimate of fruit set effects and subsequently our dependence calculation. Others have adjusted for this common over-estimation[50]. Not wanting to make a capricious adjustment of dependence, our study makes no adjustment and instead cautions the reader when reviewing analysis.

Crops with $N \geq 3$ estimates of dependence coefficients (6 crops) underwent bootstrapping analysis to derive a mean dependence coefficient and two-sided 95% confidence interval (CI) after 10,000 resamples with replacement. For crops with $N < 3$ estimates of dependence coefficients and crops with limited field study literature (56 crops), the range of dependence described in Klein *et al.* for that crop was treated as a uniform distribution for Monte Carlo estimation of the mean dependence and the two-sided 95% CI was calculated sampling 1000 times with replacement. For crops with no dependence coefficient described by Klein *et al.* but described by either Calderone (2012, 6 crops) or Southwick and Southwick (1992, 5 crops), a point estimate of dependence coefficient from those sources respectively was used, using most recent estimation[6] first (***Table 10***).

2.3.2 Economic Valuation of Crops

This work uses a production value method to calculate the economic value of the crop production dependent upon insect-mediated pollination. Using Python scripting, acreage data were obtained from the 2012 USDA Agricultural Census and yield and price data were obtained from the 2012 NASS survey. The agricultural census data gives a more rigorous, county-level estimate than the yearly NASS survey, which therefore leads to a representation of that crop's value at a higher spatial acuity. Acreage harvested (vegetables) or bearing (fruit), yield, and price data for pollination-dependent crops for the 2012 year were compiled for each county (acreage and yield) or state (price) when available. When unavailable, values were estimated using state-level, other states, or national-level data for 2012 in that order. If 2012 price or yield data were not available, data from a previous year up to 2007 were used with several exceptions utilizing 2001 data. The product of the harvested or bearing acreage, yield, and price data were used as the total economic value for each pollination-dependent crop for a given county in the US.

2.3.3 Valuation of Economic Dependence on Insect Pollination

The pollination value was calculated using a bootstrapping method modified from that described in the previous section. The product of the total economic value (previous section) and the dependence coefficient of the crop sampled randomly with replacement from either the field data pool (6 crops), a uniform distribution between the range estimated by Klein *et al.* (56 crops), or the point estimates given by either Calderone (6 crops) or Southwick and Southwick (5 crops) to calculate the pollination value for the crop in this county. The sum of the pollination value for each crop grown in the county is the total pollination value for that county. This total pollination value was calculated 1000 times for each county, state, and the national value, and the mean and confidence interval of each pollination value were derived from the empirical distribution of the sample mean. Coefficient of variation (CV%) is reported for the pollination value at the county-level (Figure 18). Crop economic data for directly-dependent crops was aggregated for each county according to FAO crop classification into four categories: Fruits and Nuts, Vegetables and Melons, Oilseed, and Other (***Table 8***) by the same bootstrapping methodology (1000 times with replacement). The economic value dependent on pollination service by insects was plotted spatially using ArcMap and GIS with an Albers Conical projection (**Figures 1** & **2**).

2.3.4 Determining Regions of Economic Vulnerability

The spatial model of relative wild bee abundance used in this study combines expert knowledge with spatial land cover data, nesting and floral resource assumptions and was used to make assessments of regional vulnerability[49]. The relative bee abundance given by this model was compared with economic dependence to identify US regions with low relative bee abundance that also have high direct economic dependence on pollination services. These areas have high vulnerability to pollinator declines and losses.

2.4 Results and Discussion

2.4.1 Identification of published studies quantifying pollination dependence coefficients

One of our goals was to develop estimates of the pollination dependence of US crops, using data generated from the scientific literature and a statistically explicit method of calculation. Though the methodology used to achieve these estimates is broadly useful, there is a general lack of data for many crop cultivars that limit our understanding of pollination dynamics and complicate significant improvement of existing dependence coefficients. Using a systematic approach to screening the scientific literature, we identified field studies which provided quantitative comparison of fruit or seed set of pollination-dependent crops grown in the absence of pollinators and in circumstances of open pollination (as is typical of an agricultural setting). Of 75 insect pollination dependent crops, only 7 had available field studies with information for quantitative estimation of crop dependence coefficients (Table 4). This highlights the lack of systematic field studies to understand crop dependence on insect pollination and underscores the need for additional studies—a trend common in entomological science[56] in order to fully understand crop dependence, although those field studies can be temporally and financially expensive. The incorporation of computational research methodology, and more cost-effective data-driven approaches with quantification of uncertainty may enhance the practicality of this level of understanding. In addition, focusing systematic field study efforts on a select, highly-valuable (in terms of pollination value) subset of crops would mitigate some temporal and financial cost while being highly informative for the uncertainty associated with total pollination value[57]. The crop dependence coefficients determined using field study data showed no distinct pattern compared to previous estimates; in some cases, coefficients were higher and in others coefficients were lower than previously estimated (Table 4).

Of the studies used for dependence coefficient estimates, 62 percent were US studies. Sunflower and soybean lacked any US studies that compared open pollination and pollinator exclusion effects on production yield. Though climate, landscape, and cultivar choice may vary across different continents and influence pollination dependency, in the interests of using as large a data set as possible, we included data from all these studies in our analyses. However, compiling these studies demonstrates that information on crop pollination dependency across diverse landscapes is very limited. In studies where pollinator dependence coefficients were assessed for different cultivars or in different fields, we treated each of these assessment as separate estimates (see No. Estimates in Table 4) rather than averaging to create a single value for one study. This allowed us to capture potential variation in environmental conditions.

2.4.2 Calculation of pollination dependence coefficients for representative crops

Table 4 Pollination Dependence Coefficient Estimates of Select Crops by Source[5-7, 58-73]

Indirect/ Direct	Commodity	No. Studies	No. Cultivars	No. Estimates	Bootstrap (this study)	SW	Cald	Klein *et al.*
D	Apple	3 (1)	1+ (1+)	56 (46)	0.91 [0.87-0.94]	0.8	1.00	0.65 [0.41-0.89]
D	Avocado	2 (1)	4 (3)	4 (3)	0.43 [0.18-0.73]	0.2	1.00	0.65 [0.41-0.89]
D	Blueberry	6 (6)	~11 (~11)	18 (18)	0.73 [0.59-0.85]	0.7	1.00	0.65 [0.41-0.89]
I	Onion	1 (1)	2 (2)	20 (20)	0.91 [0.87-0.94]	0.3	1.00	-
D	Soybean	1 (0)	1 (0)	3 (0)	0.37 [0.37-0.37]	0.01	0.10	0.25 [0.11-0.39]
D	Strawberry	2 (1)	3+ (3)	15 (6)	0.37 [0.19-0.57]	0.3	0.20	0.25 [0.11-0.39]
D	Sunflower*	1 (0)	1+ (0)	10 (0)	0.96 [0.89-0.99]	0.8	1.00	0.25 [0.11, 0.39]

I: Indirectly-dependent crop (commodity of crop not dependent on insect-mediated pollination)

D: Directly-dependent crop (commodity of crop not dependent on insect-mediated pollination)

No. Studies: Number of studies represented in the estimate (US studies)

No. Cultivars: Number of cultivars represented in studies used, + indicates unknown number of additional cultivars such as when “Various” reported (Cultivars from US studies)

No. Estimates: Number of Dependence Coefficient (*D*) estimates used in bootstrapping analysis; Estimates of *D* come from paired fruit set values within the study composed of fruit set excluding pollinators and fruit set under open pollination circumstances

Bootstrap: Derived by bootstrapping method using existing field study data mean [95% CI] (current study)

SW: Southwick and Southwick, 1992

Cald: Calderone, 2012

Klein *et al.*: Klein *et al.*, 2007; categorical estimate Monte-Carlo mean [95% CI]

*Sunflower bootstrapped values were calculated using this methodology, but the Monte Carlo values were used in this study as described in the Methods section

It is important to note that studies on a wider variety of cultivars from a diverse range of US landscapes are necessary to fully understand the effects of pollination service on yield, fruit set, quality, and nutritional aspects of crops[74]. Furthermore, quantification of crop dependence through this methodology is a simplification of nature and farming systems, and dependence coefficients are derived from a formula (Equation 1) that requires field studies comparing pollinator exclusion to open pollination. This contrast represents an extreme and uncommon case in nature; in reality, pollination service is provisioned on a gradient of pollinator activity. As an example, sunflower varieties have varying self-compatibility and therefore dependence, with hybrid seeds and confection varieties requiring pollination by insects completely (complete self-incompatibility), but oilseed cultivars having a wide range (17-90%) self-compatibility[5, 60]. While understanding crop dependence along a gradient of pollinator activity would provide a highly resolute image of pollination service dynamics and predictions for increasing pollination service, studies of this caliber for all pollination-dependent crops are impractical. Further, our use of a contrast between circumstances of open pollination and pollinator exclusion captures the full range of pollinator activity and provides a logical foundation for subsequent analysis regarding economic value of insect-mediated pollination service[75].

2.4.3 Pollination Value

To estimate the economic value of insect-mediated pollination services, we multiplied the production value of each crop by its dependence coefficient. Hereafter, this value will be referred to as *pollination value* in this article. The pollination value of crops which are directly-dependent or indirectly-dependent on crop pollination mediated by insects will be referred to as the *direct-pollination value* and *indirect-pollination value*, respectively.

Combining USDA agricultural census (acreage) and NASS (price and yield) data resulted in a detailed representation of crop production value that utilizes the best of both datasets. Subsequently, a detailed and finely-resolute spatial analysis of the economic value of crops which are both directly- and indirectly- dependent on pollination service by insects totals between 31.8 billion and 36.2 billion USD (average 34.0 billion USD) for 75 pollination-dependent crops in 2012 (**Figure 1**). Close to 87% (30.0 billion USD) of this production value represents direct-pollination value. These values are considerably higher than previous estimates, and likely more accurately reflective of current economic value, since we used more recent production data (2012) and included more crops. For example, using a similar production value method, Chopra *et al.* estimated a dependence of 14.2 billion to 23.8 billion USD (mean of 19.0 billion USD) for fifty pollination-dependent crops on pollination mediated by all insects in 2007[8]. Calderone estimated dependence on all insects to be 29 billion[6] USD for 58 pollination-dependent crops in 2010. For crop dependence on honey bees alone, Calderone estimates 19.2 billion USD in 2010[6], while Morse and Calderone estimate 14.6 billion USD for forty five crops in 2000[14]. For crop dependence on wild pollinators alone, Losey and Vaughan estimated 3.07 billion USD for fifty three pollination-dependent crops in 2004 using an adaptation of this method[9]. In the same way the referenced recent studies have developed the methods and valuations proposed in other, important prior work[47, 76], the results presented here update estimates for production conditions in the latest available crop year and expand previous work with the inclusion of a greater number of pollination-dependent crops grown in the US. The value of dependence is expected to continue to increase over time as our demand for pollination-dependent crops increases and is unevenly distributed throughout the country. Only 20 percent of US counties account for 80 percent of the total pollination value of directly-dependent crops which is consistent with the Pareto principle (SI, **Figures S5 & S6**). Lastly, this estimate of pollination value of crops does not consider the 656.6 million USD that farmers paid for managed bee pollination services in 2012[77].

The pollination value estimates described in this work are a conservative estimate of the magnitude of economic value dependent upon insect-mediated pollination service in a given area. They do not represent the economic value of what may be lost with decline of this service. That magnitude would be difficult to capture as many factors beyond the scope of this study could mitigate economic losses due to pollination decline including price adaptation[17] (increasing price of dependent crops to adapt to value loss resulting from lower yield), crop substitution (growth of an alternative crop with less or no dependence on insect-mediated pollination service), or an increase of other inputs into production (fertilizers, water, land)[78]. Nonetheless, the estimates in this work serve as a conservative estimate of economic value provided by insect pollinators.

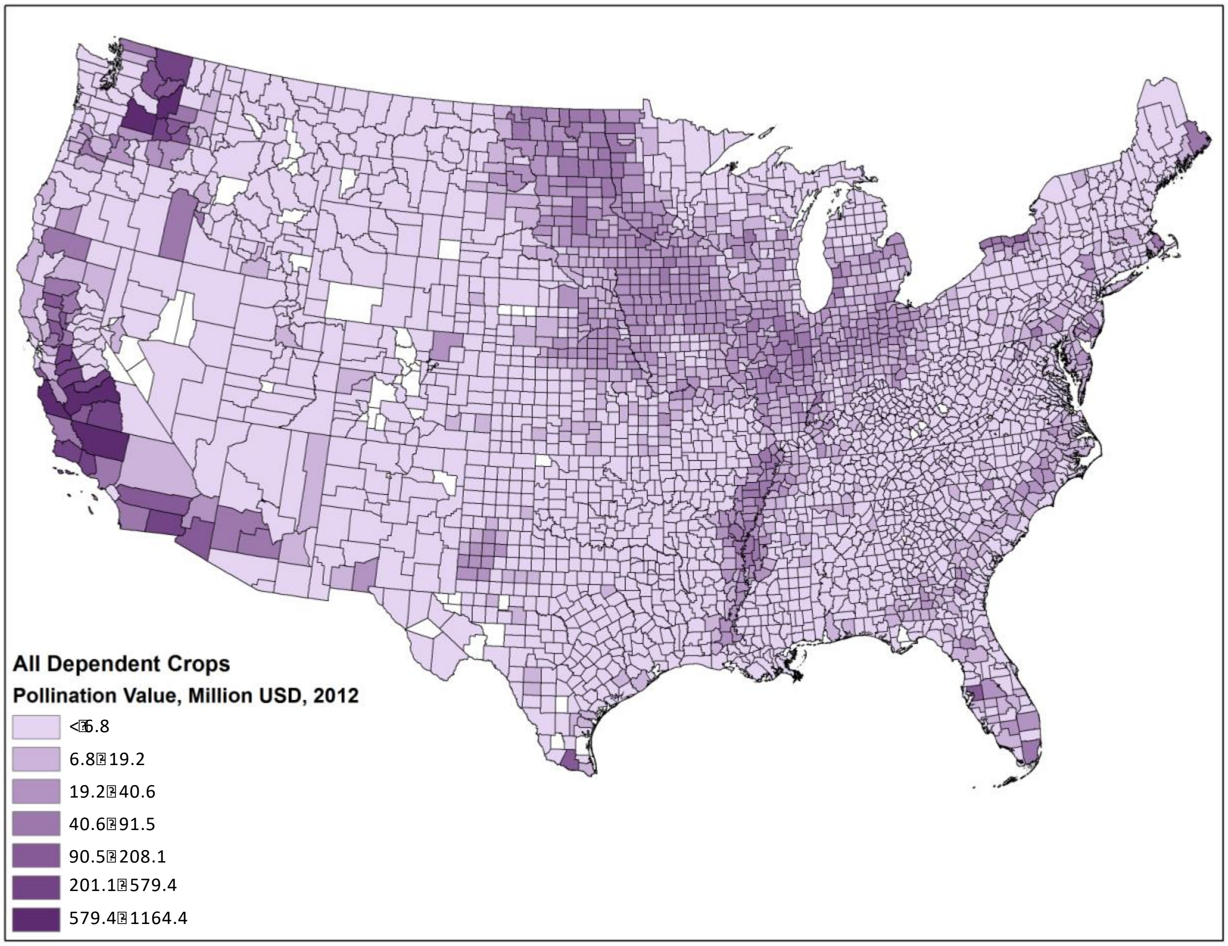


Figure 1. Average total pollination value mediated by insects both directly and indirectly, billions USD (2012) per county. White counties indicate a pollination value calculated from values that are lower than USDA reporting thresholds.

Regional differences in landscape suitability for crop growth are reflected in spatial heterogeneity in economic dependence of broad crop categories on insect-mediated pollination service (**Figure 2**). Along the east and west coasts, production of fruits, nuts, melons, and vegetables dominate the economic dependence, whereas in the Central and Midwestern US, the economic dependence stems from growth of oilseed crops. Pollinator deficiencies in these areas will have different implications on the national production of crops based on the composition of crop farming in these regions.

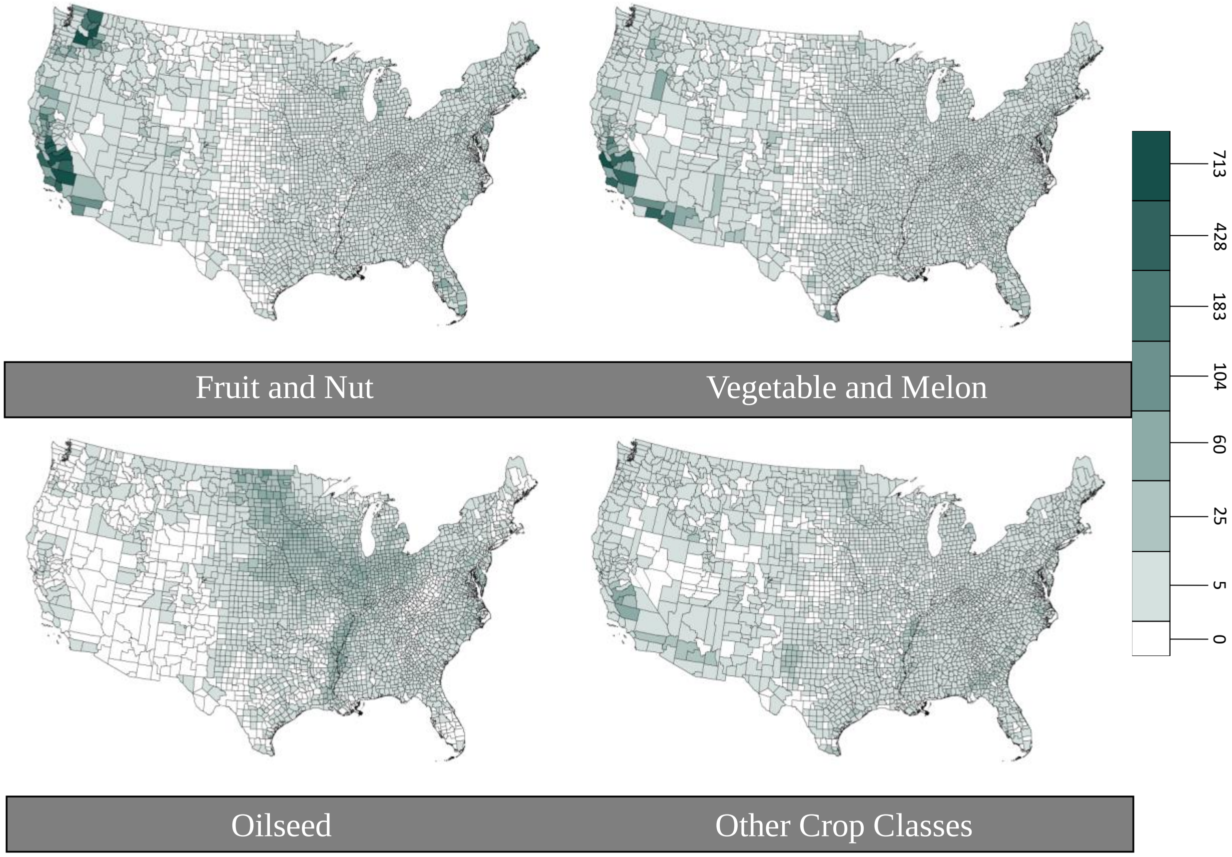


Figure 2. Regional economic value of crops dependent on insect-mediated pollination service by commodity class, millions USD (2012)

The total economic value of crops that is directly dependent on insect-mediated pollination service, or direct-pollination service is greatest in the oilseed class, which is predominantly attributable to soybean and canola production. In addition, the uncertainty associated with the pollination value is relatively low in these regions (Figure 18). It is important to cautiously interpret such a large production value, as it is primarily a result of the scale of production as opposed to the dependence of the crop on insect-mediated pollination service. These crops are also those with substantial economic value before crop dependence is considered. Specifically, the production value of soybean is $43 billion (2012). Thus, even a small fraction of that large production value being dependent on insect-mediated pollination service will cause the crop to dominate the commodity class. In addition, low uncertainty is expected as available soybean field study data used in bootstrapping is limited and homogeneous (**Table 1**). The field study data used to calculate soybean dependence is qualitatively inconsistent with the literature[46, 52-55] and is further discussed in the methods section. It is apparent here the necessity for thorough and systematic field studies to inform dependence. While these field studies are expensive, as previously discussed, systematic field studies of the crops with the greatest pollination value can be highly informative for the uncertainty of pollination dependence and subsequently value, overall[57].

It is also important to note that while there is monetary significance to crop dependence on insect-mediated pollination service, the value of pollination service can extend well beyond agricultural economics through versatile industrial and non-industrial uses of crops[8]. For example, cotton is used for fibers for many applications including clothing, cleaning, and personal care products. Also, many crops dependent on insect pollination are some of the most nutritionally rich crops (fruits, vegetables, nuts, oils, seeds), thus highlighting their importance for human health[79, 80].

2.4.4 Economic Vulnerability

When compared with the index of relative bee abundance given by the wild bee abundance model[49], there are regions in the US with high direct-pollination value that simultaneously are predicted to have relatively low wild pollinator abundance (**Figure 3**). Areas with high oilseed production (Central and Midwestern US) as well as central California and small areas along the Atlantic coast are predicted to have low wild pollinator abundance (≤10th percentile) while having a high (≥75th percentile) direct economic dependence on pollination service mediated by these insects. The direct-pollination value of those counties in the 75th percentile is greater than or equal to 10.7 million USD, 2012 and total 25.3 billion USD, 2012. The direct-pollination value of those counties in the 95th percentile is greater than or equal to 32.3 million USD, 2012 and total 13.9 billion USD, 2012. Of these counties, notable vulnerabilities with very high direct-pollination dependence (≥95th percentile) and very low wild bee abundance (≤10th percentile) include several counties in North Dakota (Cass, Stutsman), Illinois (McLean), Indiana (Benton), and Minnesota (Traverse). These results must be viewed cautiously because, as previously mentioned, the domination of oilseed crops, especially soybean, in the Midwest can inflate the economic dependence in those counties.

While there are certainly areas of concern, there are also regions producing high direct-pollination value (≥90th percentile) while simultaneously having suitable forage and landscape supportive of wild pollinators (≥90th percentile wild bee abundance) (**Figure 4**). These include several counties in California (Ventura, Santa Barbara, Riverside, and San Diego), Arizona (Yuma, Maricopa), and Oregon (Wasco). The direct-pollination value of those counties in the 90th percentile is greater than or equal to 23.6 million USD, 2012 and total 18.0 billion USD, 2012.

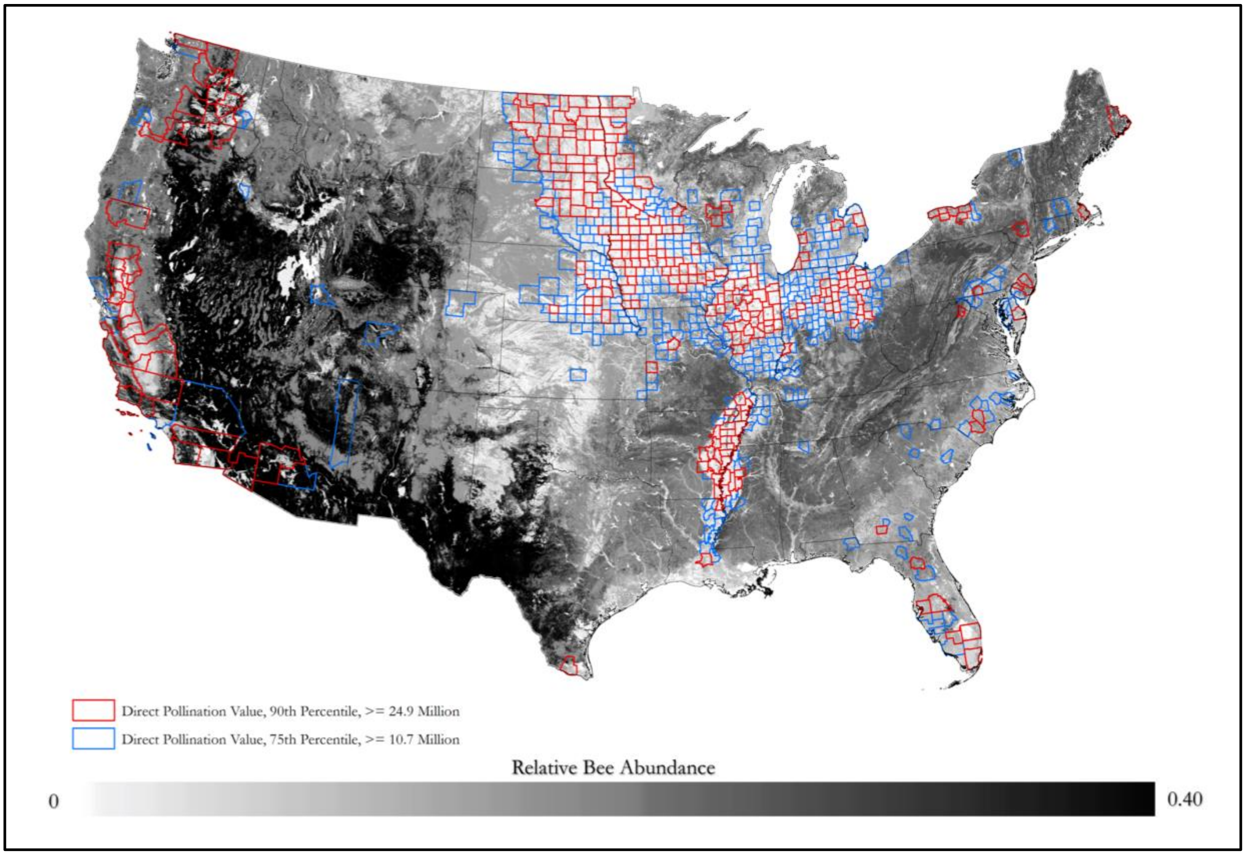


Figure 3. Counties of high direct economic dependence on insect-mediated pollination service highlighted over relative wild bee abundance.

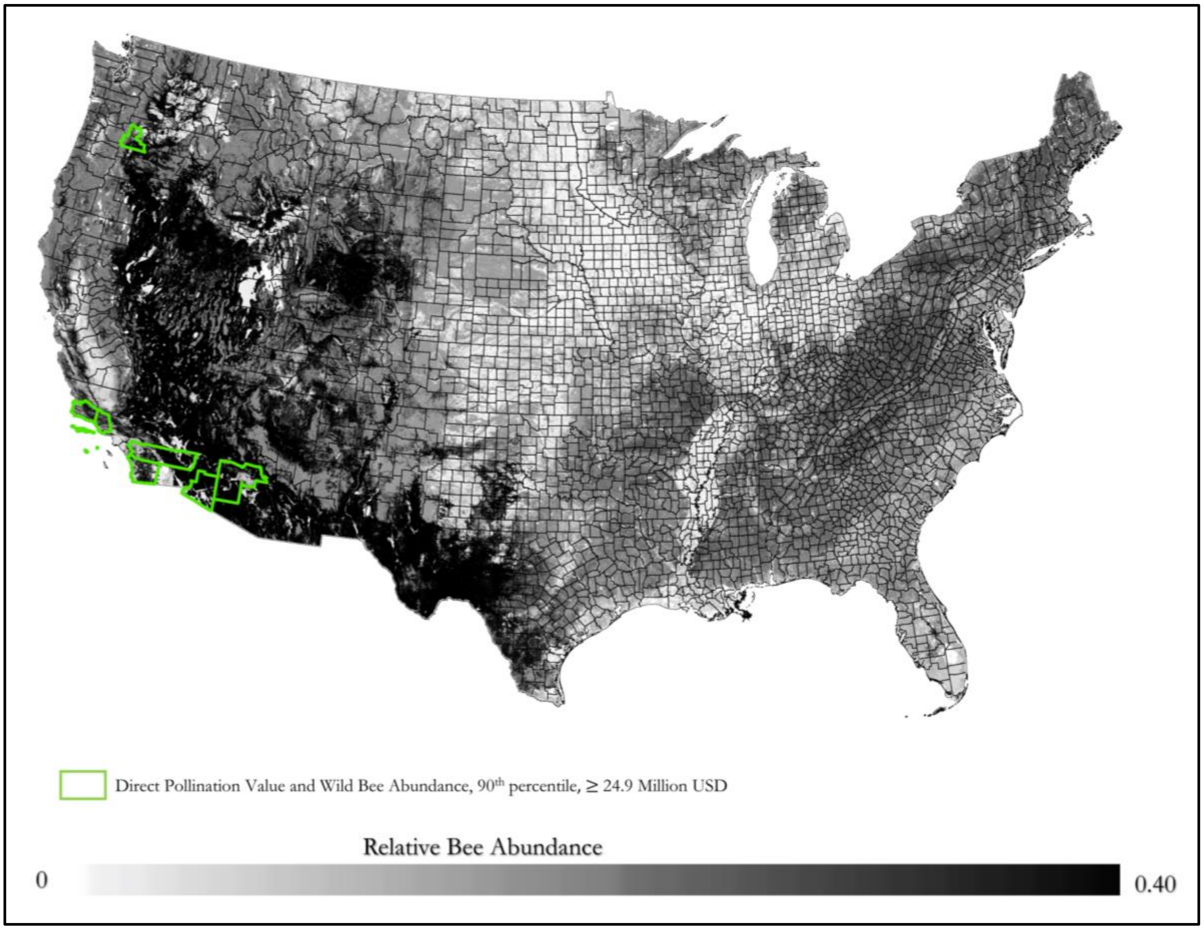


Figure 4. Counties of high direct economic dependence on insect-mediated pollination service (≥90th percentile) and high wild bee abundance (>90th percentile) highlighted over relative wild bee abundance.

A model developed by Lonsdorf *et al.* estimates wild bee abundance and is being used as a proxy in this study for all wild insect pollinators[49]. These results do not show the quantity of managed pollinators in the US as it is beyond the scope of this study, however, the beekeeping industry (including migratory beekeeping) has struggled to mitigate losses in managed honey bee colonies[35, 81]. While overall the number of honey bee colonies in the US have been relatively stable in recent years, this is due to substantial work by beekeepers to recover from substantial annual winter losses. Each winter, 30-40% of honey bee colonies, die in the United States, and a surprisingly large number of colony deaths are also recorded in the summer[35, 82-85] . While some areas may have a sufficient supportive network of wild pollinators with which to pollinate their high density of pollination-dependent crops (**Figure 4)**, aforementioned vulnerable counties (**Figure 3**) may have a higher reliance on managed species (predominantly honey bee colonies) that must be rented or purchased and maintained[5, 7]. This can potentiate difficulties and assumes that pollination by wild pollinators is perfectly substitutable with that by managed species, which is not well understood[86-88]. It has been shown that although managed colonies of honey bees can help to mitigate wild insect pollinator losses and are themselves important pollinators to crops, honey bees are also less effective, generalist pollinators, and are not a full replacement for many specialized species or the combination of several wild pollinators[89]. Evidence suggests that this occurs at varying degrees according to the crop being pollinated, and a mix of both wild and managed species of pollinators is optimal for pollination efficacy[86, 90]. Thus, the beekeeping industry may mitigate some lack of the supply of wild pollinators, however, it does so by generating other potential issues.

Economic valuation such as those presented in this work highlight the need to consider the role of ecosystem goods and services for agricultural and other products, however the value must be considered with caution. For example, a production value approach indicates that changes in the production value of the crop indicate changes in the production (yield) of this crop, however, this is not necessarily true. Market fluctuations influence price, making it difficult to label the production value as purely yield-related. It follows that changes to yield may not be captured entirely by comparing time periods using a production value approach. In addition, this value represents the economic value dependent upon insect pollinators and does not reflect a value of potential loss by the agricultural sector. Realistically, were there to be a decline in pollinators, and thus a decline in crop production or yield, the agricultural sector, and downstream sectors may adjust prices to compensate for economic losses in the short-term[91]. Further, no approach to economic valuation can capture the true value of pollinators which is arguably infinite[32]. Results presented here are a representation of static dependence of the agricultural sector in economic terms on insect pollinators.

It could also be argued that from a consumption standpoint, if demand remains consistent while supply wanes, there may be compensation in other ways such as increased land, water, and fertilizer use[78]. Future investigations evaluating such trade-offs can improve valuation. In addition, one must consider how the value of a diverse body of pollinator resources creates long-term stability that is critically important for the longevity and sustainability of humans and the environment[88]. There are also other aspects to the value of pollination service, in the form of non-agricultural plant and ecosystem biodiversity and reproduction, quality of fruits (which is positively correlated with economic and nutritional value), and stability of food crop yields, that are generally not captured[43, 44]. Lastly, insect-mediated pollination service can also be a difficult subject to investigate as studies frequently combine service mediated by wild insects with service mediated by managed insects[13], leaving important distinctions unexplored. While exploring these distinctions and incorporating other aspects of the value of pollination service can improve the economic valuation presented here, these improvements would require longitudinal studies which are not presently available, but could be the directive of future work.

Here, we have demonstrated that there is high direct-economic dependence on insect-mediated pollination service in areas of the US which are lacking in wild pollinator abundance. This work updates existing estimates of dependence and provides a framework for improving estimates as more data become available. Results show substantially higher economic dependence on insect pollinators than prior estimates. Farmers in areas lacking wild pollinator abundance can target mitigation efforts to improve nesting and forage resources in these areas. While this work presents spatial analysis greater than previous publications with the latest available economic data, even greater spatial resolution of economic data in future work can enhance specific understanding of vulnerability by matching the resolution of current estimates of wild bee abundance at 30m[92]. Importantly, the high direct-economic dependence of these regions is only intensified when one considers any indirect, downstream dependence of industry sectors beyond agriculture. The dependence of non-agricultural sectors is based on linkages to the directly- and indirectly-dependent crops within the agricultural sectors. The downstream dependence of non-agricultural sectors merit quantification in future work, and the current resolution of economic dependence allows for future quantification of downstream economic dependence at national and local scales. This work necessarily frames the discussion of the importance of pollinators to the welfare of farming sectors, and it provides foundational work for examining dependence of economic sectors outside of agriculture.

3.0 Apples to almonds: a case study of quantifying economic dependence of U.S. industry sectors on insect-mediated pollination using an input-output framework

The following chapter is based on an article to be published in a peer-reviewed journal with the citation:

Alex Jordan, Harland M. Patch, Christina M. Grozinger, and Vikas Khanna. *Apples to almonds: a case study of quantifying economic dependence of U.S. industry sectors on insect-mediated pollination using an input-output framework.*

3.1 Chapter Summary

Pollination mediated by insects is one of many ecosystem goods and services critical to the welfare of humans and their industrial activity. These services impact a significant portion of the economy while currently facing substantial decline in both biodiversity and abundance globally. While direct economic dependence of pollination-dependent crops on insect-mediated pollination service has been estimated in recent literature, linkages to farming sectors create cascading indirect economic dependence throughout the economy that is largely neglected in quantifying impact and significance of insect pollinators. Using an input-output framework, this study establishes a framework for estimating indirect dependence of non-agricultural sectors on insect pollinators using two case studies of model crops. The upper bound of the indirect dependence on pollination of apples by insects totaled 2.2 billion USD in 2012, increasing total economic dependence from 3.3 billion to 5.5 billion USD. For almonds, the upper bound of the indirect dependence totaled

2.9 billion USD, increasing total economic dependence from 4.4 billion to 7.3 billion USD. Impacted sectors revealed through structural path analysis, extend the recognized dependence of economic sectors beyond farming and agricultural sector with unexpected influence spread widely throughout the economy. These results underscore the significance of indirect dependence and provide support for including indirect dependence in value estimates of any ecosystem service.

3.2 Introduction

Globally, there are thousands of diverse insect pollinator species such as midges, wasps, solitary bees, moths, butterflies, and the well-known honey bee which has been groomed to pollinate a great many plants while simultaneously producing large volumes of high-quality honey [5, 93]. Of these insects, many pollinate essential food and habitat resources necessary for the survival of many species including humankind. Pollination and other ecosystem goods and services are benefits derived from nature that sustain all human life and activity. The value of ecosystem goods and services often goes unnoticed and exceeds what is traditionally attributed to nature. Approximately 75 percent of global food crops require animal-mediated pollination, and insects serve as the primary pollinators for these crops as well as other flowering plants, totaling 85 percent of the world's angiosperms that depend on insects for pollination service [94]. At present, there is a critical need for intervention as abundance and diversity of insect pollinators decline worldwide [95]. In Germany [33], including in areas of natural protection, flying insect biomass has declined up to 82 percent in only 27 years, and in Puerto Rico [96] arthropod biomass has declined up to 98 percent in 36 years. Europe and North America in general have faced some of the largest declines while simultaneously seeing decreases in beekeepers and viable colonies [97]. Many stressors are responsible for these declines including pesticide use, climate change, lack of suitable floral and nesting resources, pests, and parasites. Economic valuation of ecosystem services including pollination mediated by insects reveals prospective repercussions and impacts of the loss of such services. In doing so, economic valuation can motivate conservation efforts as well as social and economic development.

Methods of valuation often begin with quantifying the proportion of crop production that depends upon insect-mediated pollination service. This proportion, or *dependence coefficient*, can be multiplied by the value of crop production to estimate *pollination dependence*, or the economic value of a crop dependent upon insect-mediated pollination service. Numerous existing studies have used this approach for quantifying the pollination dependence with estimates ranging from 14.2 billion and 23.8 billion for the United States [8, 14, 98]. Differences in values across studies can be attributed to the number of crops accounted for in the study, differing years of study, the way production value was acquired for the study, and the inclusion of wild or managed pollinators (or both). More recently, Jordan *et al.*, 2020 estimated pollination dependence for all pollination-dependent crops grown in the US in 2012 using existing field study data and reconciling previous estimates from literature [5, 6]. Pollination dependence can be referred to as direct-dependence as the throughput of crop sectors directly depends on the pollination of crops by insect pollinators. The dependence of crop farming sectors on insect pollinators may be obvious as yield and/or quality of nutritious crops depend on the pollination service insects provide. However, dependence on insect pollinators extends beyond agricultural production and has effects upon the production of other related, non-agricultural industries [8]. Related economic sectors such as fibers, materials extraction, pharmaceuticals, and construction rely on production output from agricultural sectors and thus indirectly rely on the benefits pollinators provide. Additionally, economic sectors like fertilizer, pesticide, and support services provide critical inputs for agriculture production and hence create indirect dependencies in sectors upstream of crop production. These indirect linkages are not well-quantified or understood, but result in unquantified effects cascading throughout the economy. The complex interplay between sectors can be modeled in a number of ways including input-output (IO) analysis, the approach utilized in the current work.

Input-output analysis is an empirical approach to assess complex interdependencies between industry sectors in a region or economy. These interdependencies can be represented in matrix form with rows and columns representing industry sectors and matrix elements representing the economc flow between sectors. While an IO model is linear and static, the model allows for an especially detailed analysis for a specified period (2012 for present analysis, based on most recently available empirical data). However, an IO model does not account for substitutions, price fluctuation, or other market adaptations as a result of disruptions to pollination-dependent crop supply. IO models are informative for identifying vulnerabilities in industry sectors which are dependent upon insect-mediated pollination service specifically short-term or immediate vulnerabilities. However, it is important to note that the present model cannot predict economic losses due to pollination declines or losses. It can, however, serve as a tool for assessing sector dependence and provide information for immediate risks facing industry sectors.

Despite accessibility of other valuation methods that may have some of the same benefits IO models offer, those methods are not ideal for our application. For example, partial equilibrium models can retain sector detail but limit economic scope to a specific subset of the economy only (i.e. agricultural sectors, specific markets). Therefore, partial equilibrium models have a limited scope focused on a single-market and do not account for inter-market impacts. While this can be useful for certain applications, we are interested in the indirect dependence of other markets on insect-mediated pollination service. We can understand these by including upstream (input) and downstream (output) linkages to other sectors. For example, disruptions in the production of fruit and nut farming sector will have implications for producers of other commodities that use fruits and nuts such as snack manufacturing. Some have used a computable general equilibrium model which accounts for market and consumer preferences but still lacks significant detail on sector interdependencies having an order of magnitude fewer sectors [86]. A general equilibrium model captures these inter-industry dependencies. Valuations based on changes to producer or consumer surplus embrace a partial equilibrium economic structure. Another method of valuation is the replacement cost method which bases the value of pollination services mediated by insects on the cost to replace them with alternative methods of pollination such as hand- or mechanical-pollination. Valuation of direct-dependence based on production value is compatible with IO modeling as IO modeling utilizes accounts of the economy based on production and is the methodology used in the present work. The present study considers dependence on all insect pollinators while previous analyses consider only dependence on honey bees [14, 47, 76]. All insects are valuable pollinators, and at present, we believe there is not enough data to aptly distinguish between dependence on wild pollinator species and dependence on managed honey bees. The IO model informs the magnitude of economic dependence and affected industries. Further analysis of the relationship between affected sectors and industrial communities can illuminate the structure of dependence in the economy.

This work explores the contribution of insect pollinators to the US economy using an input-output model to evaluate the value of US economic sectors both directly and indirectly dependent on insect pollination service to two model crops, apples and almonds.

3.2.1 Dependence

Previous work has discussed the dependence of all pollination-dependent crops on insect-mediated pollination service. Here, we focus on one farming sector—fruits and tree nuts—and a model crop representing each of the two major classes of commodities aggregated within this sector: apples and almonds.

3.2.1.1 Apples

In 2012 in the U.S., 8.9 billion pounds of apples were produced over 336,947 bearing acres[99]. The majority of apples are grown in Washington state by a large margin. While other major producers include New York and Pennsylvania, apples are grown all around the United States. Apples also have a high dependence on insect pollinators, with a dependence coefficient between 0.875 and 0.945[100]. A dependence coefficient is simply the proportion of the fruitset of a given crop dependent upon insect-mediated pollination service. For this reason, apples were chosen as a representative fruit crop for the fruit and tree nut farming sector.

3.2.1.2 Almonds

In the same year, over 1800 pounds of almonds were produced over 820,000 bearing acres[99]. California grows more almonds than anywhere else in the by a substantial margin, growing 100 percent of U.S. commercial almonds and 80 percent of the global share of almonds[101]. This is much more localized production than that of apples. With a production value of 4-5 billion USD a year (4.9 billion USD in 2012), almonds are the second-most valuable grown crop in California[102]. Commercial almonds have an incredibly high dependence on insect pollinators, with a dependence coefficient between 0.4 and 0.9[5, 6, 100], and the pollination of this crop requires over 1.5 million hives of managed honey bees each spring[101]—the largest pollination event in the world[103]. As the most valuable pollination-dependent nut in the US, it is an appropriate representative nut crop for the fruit and tree nut farming sector.

3.3 Methods

This work utilizes an input-output framework to assess indirect dependence of economic sectors. A flowchart outlining this framework and its data sources for visual aid accompanies this detailed outline of methodology (***Figure 5***).

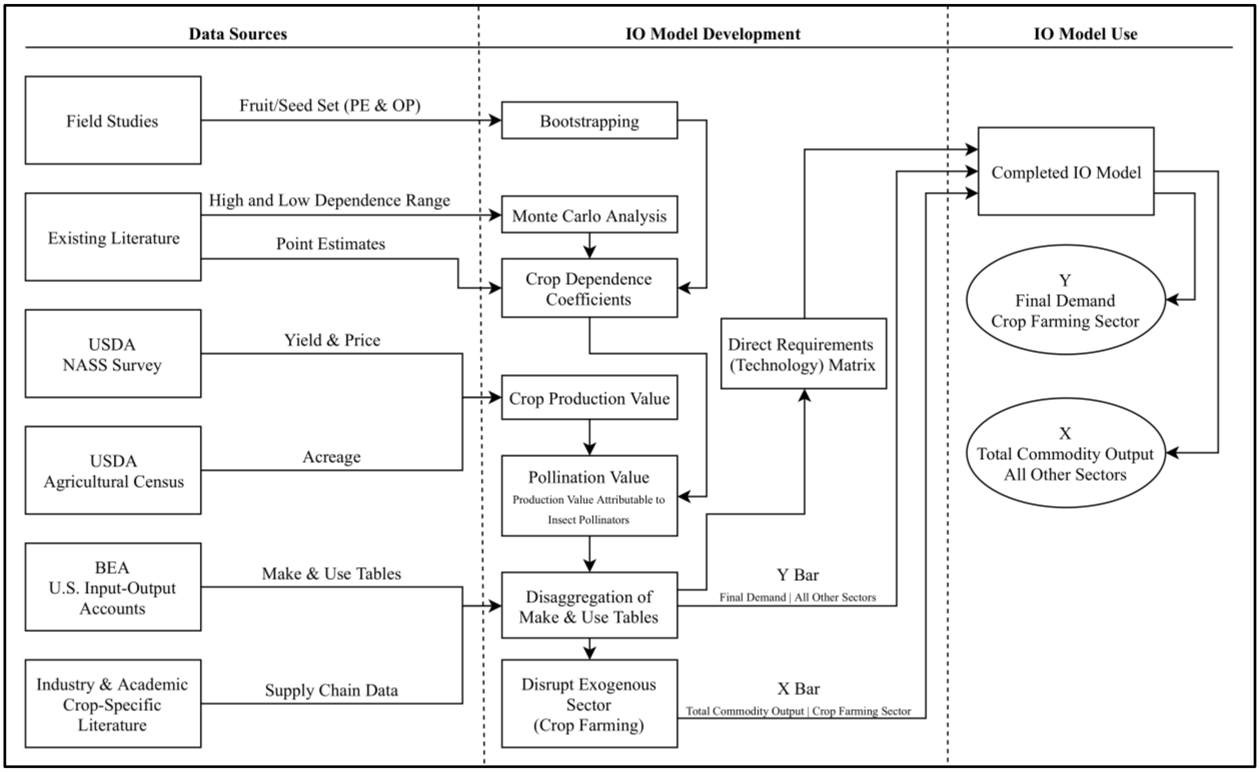


Figure 5. Flowchart outlining methodology and data sources for the creation of the IO model and its outputs.

3.3.1 Input-Output Framework

3.3.1.1 Model Overview

In the original input-output model developed by Wassily Leontief in the 1930s, the economy is divided into industrial sectors with various transactions (inputs and outputs) between them recorded as a transaction table[30]. The sums of transactions for a one-year period create a “snapshot” of the economy within the IO model. This model shows the relationship between sectors and can be used to assess interdependencies and hence cascading impacts caused by changes in connected industry sectors. In the original model, each sector’s output ($\boldsymbol{X}$) is given by the equation:

$$\boldsymbol{X} = [\boldsymbol{I} - \boldsymbol{A}]^{-1}\boldsymbol{Y} \qquad [\mathbf{4}]$$

and the final-demand of an industry ($\boldsymbol{Y}$) is defined by the following:

$$\boldsymbol{Y} = [\boldsymbol{I} - \boldsymbol{A}]\boldsymbol{X} \qquad [\mathbf{5}]$$

The total requirements matrix, $\mathbf{[I\text{-}A]^{-1}}$, or the Leontief inverse, is called as such because all direct and indirect purchases are totaled to calculate the term. In that definition, $\boldsymbol{I}$ is the identity matrix, and $\boldsymbol{A}$ is the direct requirements matrix. Each column of matrix *A* represents the production recipe (or supply chain) of the sector represented by that column. This model is referred to as demand-driven and is suitable for assessing the impact of changes in the final demand of industry sector(s) on the entire economy. However, the model is limited in its ability to assess the impact of sudden disruptions in loss or deterioration of ecosystem services or sudden shocks such as oil shortages. For example, a traditional demand-driven model can model changes that affect final demand of an industry, however, it does not model changes that may cause a reduction in the total output of a disrupted sector [30]. Modifications to the basic IO framework (Eq. 1) have been proposed and successfully utilized previously to study the effect of such sudden changes [8, 104]. A supply-driven or supply-constrained model, also known as the mixed IO model importantly allows for the exogenous definition of total economic throughput of the disrupted sector, and estimating the resulting impacts on the throughput of non-supply-constrained sectors as above, given some disruption in the outputs of supply-constrained sectors [105]. With the mixed IO model, one can exogenously specify the final demand ($\boldsymbol{Y}$) for some sectors and the total output ($\boldsymbol{X}$) of remaining sectors. This is an important distinction between the mixed IO model and demand-driven models (i.e. Leontief's traditional model) or supply-driven models which only exogenously specify either final demand or value-added, respectively. Previously, mixed IO models have been used to evaluate shocks to key resources such as oil and gas or fisheries, or to understand the cascading indirect impacts of component failures in integrated energy systems [105-108]. Chopra *et al.* modeled a disruption to the aggregated Fruit and Nut Farming sector resulting from a shortage of animal-mediated pollination service [8].

The modeling of the aforementioned disruption in our work affects the output of the Fruit and Nut Farming sector in the form of a reduction relative to the dependence of our two model crops, apples and almonds on insect-mediated pollination service. This dependence is measured using a crop dependence coefficient which is simply the proportion of the fruitset of a given crop dependent upon insect-mediated pollination service.

3.3.1.2 Crop Dependence Coefficient

Previous work [100] has discussed the dependence of all pollination-dependent crops on insect-mediated pollination service. Here, we focus on one farming sector—fruits and tree nuts—and a model crop representing each of the two major classes of commodities aggregated within this sector: apples and almonds.

3.3.1.3 Apples

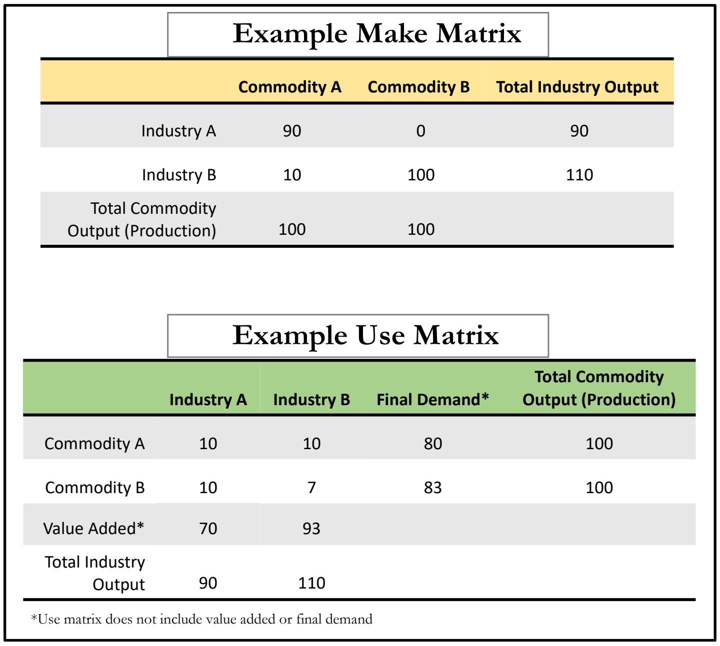
In 2012 in the U.S., 8.9 billion pounds of apples were produced over 336,947 bearing acres [51]. The majority of apples are grown in Washington state by a large margin. While other major producers include New York and Pennsylvania, apples are grown all around the United States. Apples also have a high dependence on insect pollinators, with a dependence coefficient between 0.875 and 0.945[100]. For this reason, apples were chosen as a representative fruit crop for the fruit and tree nut farming sector.

3.3.1.4 Almonds

In the same year, over 1800 pounds of almonds were produced over 820,000 bearing acres [51]. California grows more almonds than anywhere else in the by a substantial margin, growing 100 percent of U.S. commercial almonds and 80 percent of the global share of almonds[101]. This is much more localized production than that of apples. With a production value of 4-5 billion USD a year (4.9 billion USD in 2012), almonds are the second-most valuable grown crop in California[102]. Commercial almonds have an incredibly high dependence on insect pollinators, with a dependence coefficient between 0.4 and 0.9[5, 6, 100], and the pollination of this crop requires over 1.5 million hives of managed honey bees each spring[101]—the largest pollination event in the world[103]. As the most valuable pollination-dependent nut in the US, it is an appropriate representative nut crop for the fruit and tree nut farming sector.

3.3.1.5 Disaggregation

We use 2012 benchmark US input-output industry accounts reported by the Bureau of Economic Analysis (BEA) which are interindustry flows represented as monetary transactions between industries (i.e. economic sectors) in the United States. The BEA reported *make* and *use* tables are a subset of BEA IO tables (IOTs) and are these transactional records. They are used to create a 405 x 405 interindustry transaction matrix. The methodology to create this transactional matrix has been described previously [8, 30] and is detailed in ***Figure 5***. A generalized example of a *make* and *use* matrix are illustrated in ***Figure 6***.



Example Make Matrix

	Commodity A	Commodity B	Total Industry Output
Industry A	90	0	90
Industry B	10	100	110
Total Commodity Output (Production)	100	100	

Example Use Matrix

	Industry A	Industry B	Final Demand*	Total Commodity Output (Production)
Commodity A	10	10	80	100
Commodity B	10	7	83	100
Value Added*	70	93		
Total Industry Output	90	110		

*Use matrix does not include value added or final demand

Figure 6. Generalized depiction of matrices derived from the BEA *make* and *use* tables.

One challenge to using the mixed IO approach is the highly aggregated nature of industry-level data. Each single industrial sector in the national economic accounts represents an aggregate of a number of industries with conceptually similar products [109]. Despite having over 400 sectors disaggregated, this can still hinder detailed assessment. For example, the Fruit and Tree Nut Farming sector represents all crops classified as a fruit or nut. Despite product similarity, these crop farming industries likely have different input requirements, agricultural practices, industrial linkages, and environmental impacts. This can be problematic as it means adjustments to a given sector based on pollination dependence does not reflect the actual magnitude of economic effects through interindustry linkages. This shortcoming of IO models can by addressed with disaggregation where possible, and depends on available data for a given sector [109-111]. Disaggregation occurs through manual adjustments to the BEA-recorded IOTs. For example, one may disaggregate how much of the total value of Fertilizer Manufacturing used by the Fruit and

Tree Nut Farming sector is represented by the Apple Farming sector using apple-specific supply chain information retrieved from industry literature.

In this case study, the Fruit and Tree Nut Tree Farming sector was disaggregated when possible into individual crop farming for each of two pollination-dependent crops, apples and almonds. In each circumstance, the Fruit and Tree Nut Farming sector was disaggregated into either Apple Farming or Almond Farming, respectively, and the adjusted Fruit and Tree Nut Farming sector which includes all remaining fruit and tree nut crops. The allocation of inputs and outputs from the Fruit and Nut Farming sector to each the apple and almond farming sectors was determined using existing available supply-chain data for apple and almond farming [112-114].

For the apple case study, the endogenous sector ***k*** represents the Apple Farming Sector (111300A1) whose total throughput (X) gets impacted by reduction or loss of pollination service. For the almond case study, the endogenous sector ***k*** represents the Almond Farming Sector (111300A2). Exogenous sector, ***(n-k)***, remain as the other 404 industrial sectors of the economy. As described above, the IOTs can be disaggregated before calculating the Leontief Matrix to reflect specific pollination-dependent crop farming as in the conceptual representation of the disaggregation for the apple case study presented in ***<u>Figure 7</u>***.

Figure 7. Conceptual representation of disaggregated Leontief Matrix with regard to Apple Farming. Asterisk (*) indicates sector has been altered from the original BEA sector.

3.3.1.6 Quantifying indirect dependence of the economy on pollination service

To quantify indirect dependence of the economy on insect pollination service, we first estimate the direct dependence of the associated crop sector on insect pollination. This is done using a combination of pollination dependence coefficients and crop production value and has been described previously[100]. The economic value of each of the disaggregated crop sector (apples and almond) in the IO model is then reduced by the amount dependent on insect pollination. This serves as the starting point for assessing the economic dependence of the rest of the economy on insect-mediated pollination service, capturing cascading dependence resulting from linkages to the crop sectors. For the apple case study, dependence was assessed according to the range of dependence of apples on insect-mediated pollination service, 0.875 and 0.945. The total output, $\boldsymbol{X}$, was reduced to reflect this range to 13 and 5.5 percent respectively. For the almond case study, the range of dependence of almonds on insect-mediated pollination service is between 0.4 and 0.9. The total output, $\boldsymbol{X}$, was reduced to reflect this range to 60 and 10 percent respectively.

3.3.1.7 Structural Path Analysis (SPA)

The supply chain linkages of other industry sectors to apple or almond farming sectors causes the cascading dependence of pollination dependence throughout the economy. These linkages are characterized in terms of *influence*, or connectedness. The strength of the influence or arcs between sectors informs the structure of the relationships between sectors. Sectors with highest influence are most strongly connected to the sector of interest (demanding sector, $\boldsymbol{j}$)[115].

First order influence indicates the sector $\boldsymbol{i}$ is directly connected to the demanding sector, $\boldsymbol{j}$, and the direct impact, or first order influence can be expressed as a_{ij} [116, 117], A second order influence represents flows from sector $\boldsymbol{i}$ to sector $\boldsymbol{k}$ before sector $\boldsymbol{j}$, and is represented as $\sum_{k=1}^{n} a_{ik} a_{kj}$. Third order influence represents flow from sector $\boldsymbol{i}$ to $\boldsymbol{l}$ to $\boldsymbol{k}$ before ending at sector $\boldsymbol{j}$, and is represented as $\sum_{l=1}^{n} \sum_{k=1}^{n} a_{ik} a_{kj}$. Influence continues representation in this way. The maximum order of influence is set as the third level with a threshold of reported path equal to 0.00001 million dollars which is defined as relatively insignificant for the interindustry relationship.

Using structural path analysis (SPA)[115], the supply chain of a specific crop can be isolated. Supply chain paths to affected industries can be extracted and ranked per magnitude or distance from the disrupted agricultural sector [116, 118, 119]. This can give compelling insight into the order of dependence of affected sectors. SPA at its base utilizes a Boolean matrix of adjacency in this case where cells within the $\boldsymbol{A}$ matrix wherein $\boldsymbol{a_{ij} \neq 0}$ are replaced with a 1 and otherwise zero[30]. This matrix is referred to as $\boldsymbol{W}$ and has a directed graph associated with it. On the directed graph, each industry is represented as a vertex and an arc connects each nonzero entry in column $\boldsymbol{j}$ (demanding sector) to the supplying sector, $\boldsymbol{i}$. *Connectedness*, or *influence*, is then examined at various orders [30].

3.4 Results

3.4.1 Economy-wide Indirect Dependence on Insect Pollinators

In our previous work, we determined the pollination dependence of apples to be between 3.1 billion and 3.3 billion USD in the year 2012. This value is defined as the agricultural production value of apples attributable to insect pollinators and is obtained using the crop's dependence coefficient, bearing acreage, yield, and price for all of the counties in the U.S. In the present work, the pollination dependence is referred to as the *direct pollination dependence*, as it refers to the value derived directly from insect pollinators as they pollinate the crop in the apple farming sector. This direct pollination dependence is defined endogenously in the IO model for the purpose of quantifying indirect economic dependence of the economy on insect pollinators.

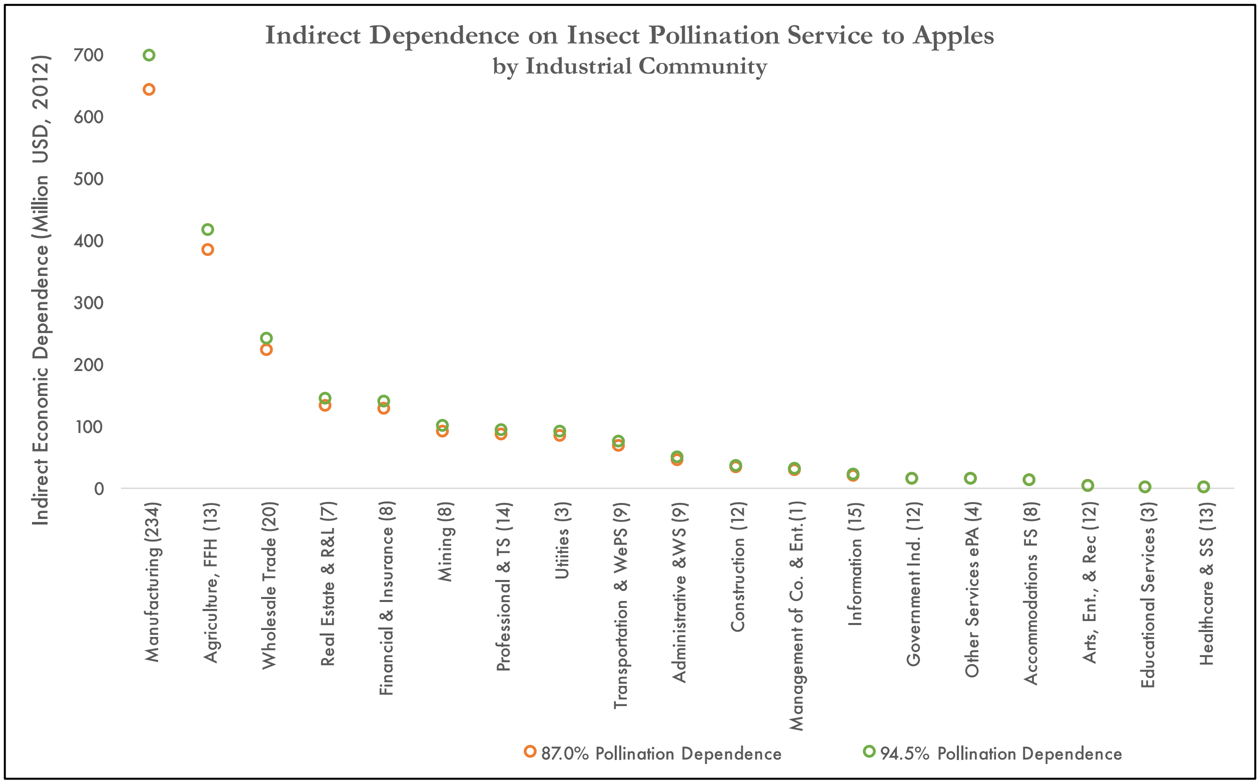


Figure 8. Indirect dependence on insect-mediated pollination service to apples aggregated by industry communities (labeled on x-axis) for the low and high 95% confidence interval of the apple dependence coefficient as determined by Jordan *et al.*, 2020. The number of industry sectors represented in each industrial community is shown parenthetically by the community name.

There is additional economywide indirect economic dependence attributable to insect pollinators resulting from linkages from the apple farming sector to other industry sectors. This *indirect pollination dependence* is determined by the IO model and for apples equals 2.0 billion-

2.2 billion USD. The indirect economic dependence aggregated by industry community can be seen at the extremes of this range in ***Figure 8***. The total dependence on insect-mediated pollination service throughout the entire economy to apples is 5.1 to 5.5 billion USD in 2012, an increase of 64 to 67 percent compared to the direct dependence alone.

While the Manufacturing has the greatest indirect economic dependence as a community of 234 sectors, the community does not include the sector with the greatest indirect economic dependence, Support Activities for Agriculture and Forestry (NAICS 115000) (***Figure 9*** & ***Figure 10***). While this sector may be expected to have high dependence on farming sectors including apple farming, other sectors with high indirect dependence do not have such intuitive linkages to farming sectors (e.g. Insurance Carriers, except Direct Life and Other Real Estate (***Figure 9***). While these sectors have high indirect economic dependence, some, including Other Real Estate are incredibly large economic sectors, generally, and are not necessarily vulnerable to this kind of disruption. Similarly, the Manufacturing community has the highest indirect dependence on insect-mediated pollination service, however, this is a result of the Manufacturing community being the largest industry community of 234 sectors (***Figure 10***). Despite the high total dependence of the Manufacturing community, the individual sector with the greatest indirect dependence is Support Activities for Agriculture and Forestry (NAICS 115000) from the Agriculture, Forestry, Fishing, and Hunting Community (***Figure 10***).

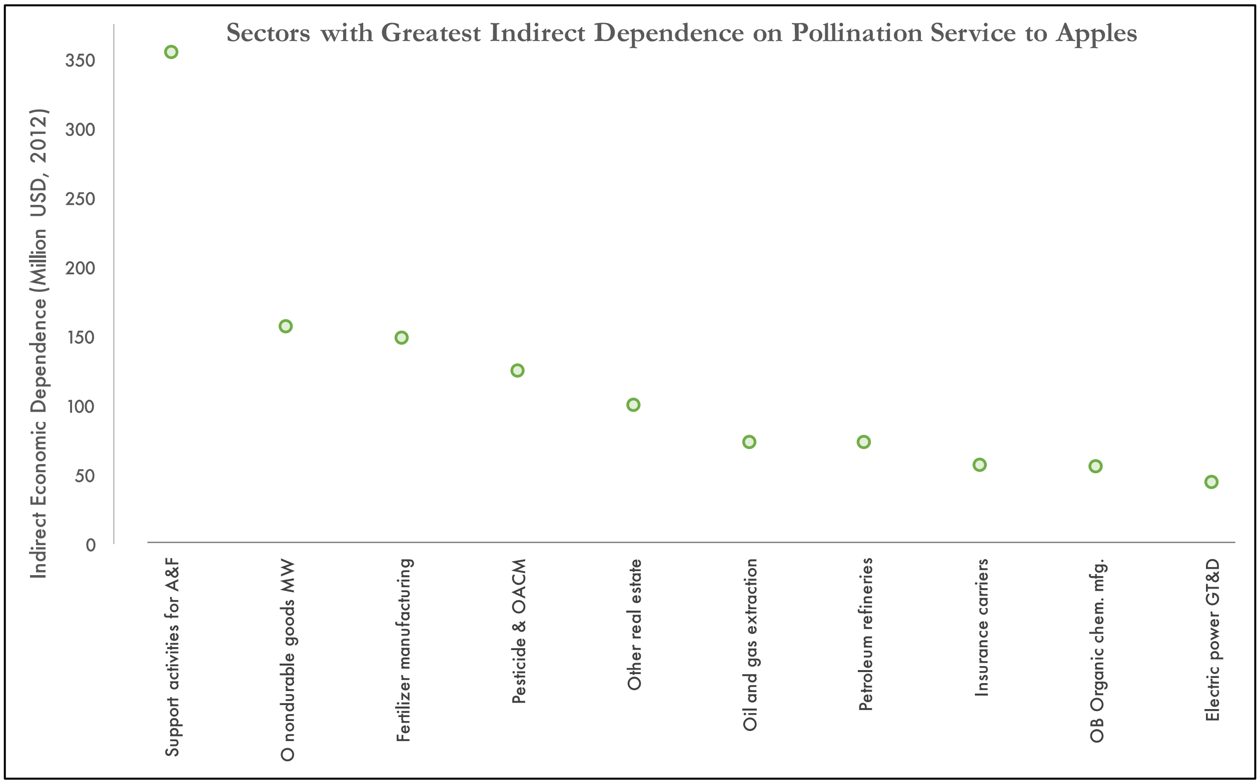


Figure 9. Top ten sectors with indirect dependence on insect-mediated pollination service to apples in 2012 in millions USD.

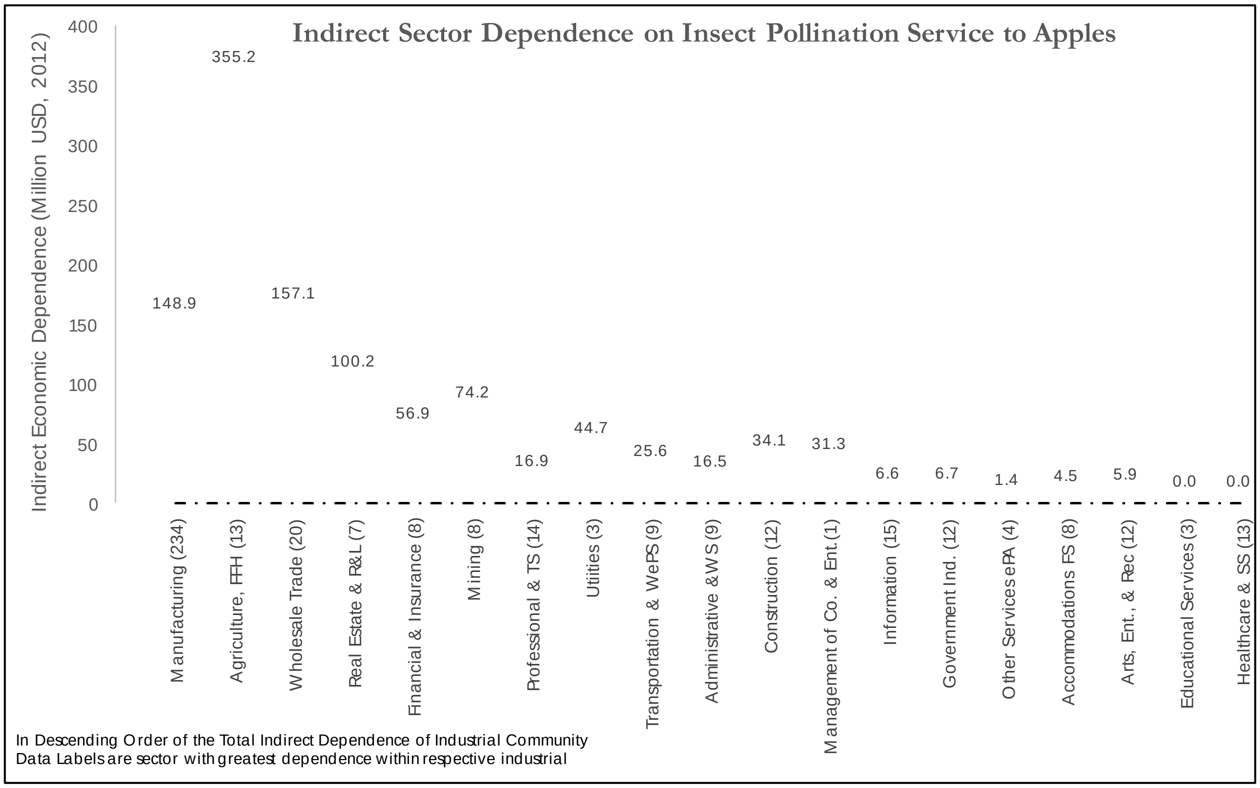
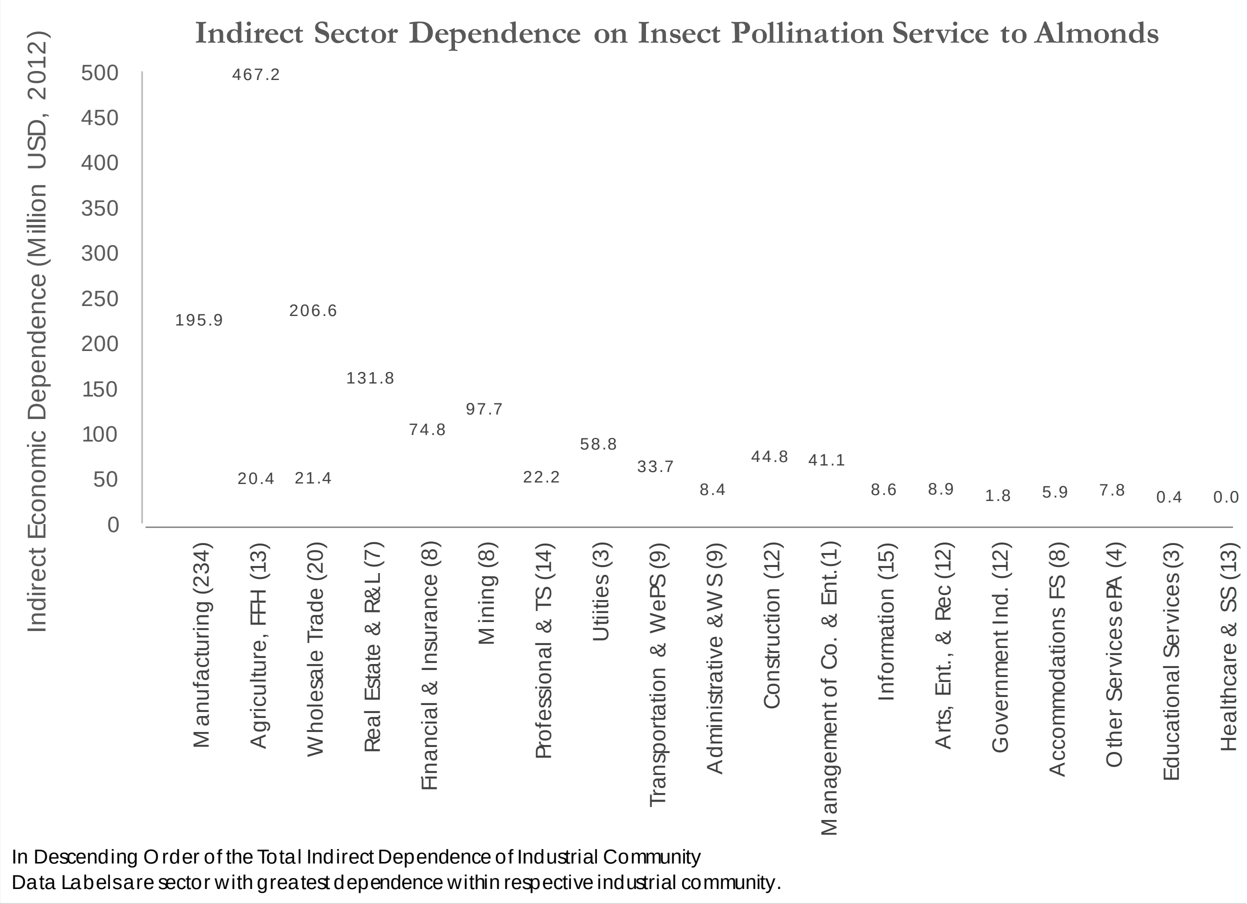


Figure 10. Indirect dependence of individual sectors grouped by industry community with regard to insect-mediated pollination service to apples at the upper extreme of the direct dependence for apples. Presented in descending order of total industry community dependence, data labels are the sector with greatest dependence within respective communities.

For almonds, we previously determined the direct dependence to be between 2.0 billion and 4.4 billion USD in 2012. In addition to this direct dependence, the IO model in the present work estimates between 1.3 billion -2.9 billion USD indirect economic dependence for almonds through linkages of almond farming sector with the rest of the economy. The total dependence on insect-mediated pollination service throughout the entire economy to almonds is 3.3-7.3 billion USD in 2012, an increase of 65 to 66 percent compared to the direct dependence alone. Apples and almonds share the same ten sectors with greatest indirect dependence and have similar overall distribution of indirect dependence. However, differences in the supply chain and downstream consumption of apples and almonds by various sectors do lead to some differences including a shift in the descending order by total industry community dependence (***Figure 10*** & Figure 11).



In Descending Order of the Total Indirect Dependence of Industrial Community
Data Labels are sector with greatest dependence within respective industrial community.

Figure 11. Indirect dependence of individual sectors grouped by industry community with regard to insect-mediated pollination service to almonds at the upper extreme of the dependence coefficient 95% CI for almonds, 0.9. Presented in descending order of total industry community dependence, data labels are the sector with greatest dependence within respective communities.

3.4.2 Changes in Final Demand of Apple and Almond Farming

A simulated disruption of economic output in the supply-constrained sectors (apple and almond farming sectors) resulted in substantial changes to endogenous final demand of those supply-constrained sectors. ***Table 5*** summarizes changes to the final demand of each farming sector for individual reduction in production from these sectors reflecting our knowledge of pollination dependence. Modeled changes to the output of the supply-constrained farming sectors, which is assumed to be due to the sectors' dependence on insect-mediated pollination service results in large negative shifts in final demand. We present a national model with only domestic final demand, and it is difficult to assess with certainty what this shift indicates. These changes in final demand in the short-term can imply a drastic shift to a reliance on importation of both apples and almonds following disruptions of this nature. Household lifestyles and farming practices may change to reflect production decreases of this nature, substitutions of these crops for others which may be more readily available or grown in the absence of pollinators, an increase of land, water, and other inputs to maintain production rates, but are implausible in the short-term.

Table 5. Changes to final demand following disruptions to apple and almond farming sectors determined by mixed model IO analysis.

		Final Demand (*Y*) of disrupted farming sectors		
	Production	***Y*** Million, US$, 2012	**Δ *Y*** Million, US$, 2012	**Δ*Y*** %
Apple				
No Disruption	100%	1217		
CI_{low} dependence	13%	-1814	-3031	-249%
CI_{high} dependence	5.5%	-2075	-3292	-271%
Almond				
No Disruption	100%	1682		
CI_{low} dependence	60%	-243	-1925	-114%
CI_{high} dependence	10%	-2649	-4331	-257%

3.4.3 Structure of indirect dependence

Indirect dependence of the economy on insect-mediated pollination service can result from multiple pathways. These pathways could be represented and interpreted as varying orders of linkages with the agricultural sectors that are directly dependent on insect pollinators. Influence at the first, second, and third orders are represented for the five main backwards pathways to the apple farming sector in ***Figure 12*.** Those sectors with the greatest impact include intuitive sectors such as Support activities for agriculture & forestry and Fertilizer manufacturing, but also less intuitive sectors like Tenant-occupied housing or Synthetic dye & pigment manufacturing. We present the five most influential pathways of apples for constraint of space. Sectors with first order influence flow directly into the apple farming sector have inputs from the sectors with second order influence. The sectors with second order influence flow directly into those with first order influence and have inputs from the sectors with third order influences. The sectors with third order influence flow directly into those with second order influence and have inputs from the sectors with fourth order influence and so on. The five (5^1) sectors with the largest influence at the first order are shown flowing into the apple farming sector. At the second order, 5^2 sectors with the largest influence are shown flowing into the first order sectors. At the third order, 5^3 sectors with the largest influence are shown flowing into the second order sectors. The five backward pathways represent 155 ($5^1 + 5^2 + 5^3$) arcs. For apples, these are represented across 36 sectors as some of the pathways involve the same sectors as others (***Figure 12***). The greatest first order connections are with Support Activities for Agriculture and Forestry, Biological Product (except Diagnostic) Manufacturing, Fertilizer Manufacturing, Petroleum and Petroleum Products, Tenant-Occupied Housing. This means that these five sectors feed directly into the Apple Farming sector with the greatest intensity (influence) (***Figure 12***). Here, we begin to see the structure of dependence upstream of Apple Farming and the beginning of the complexity of the interdependencies of economic sectors.

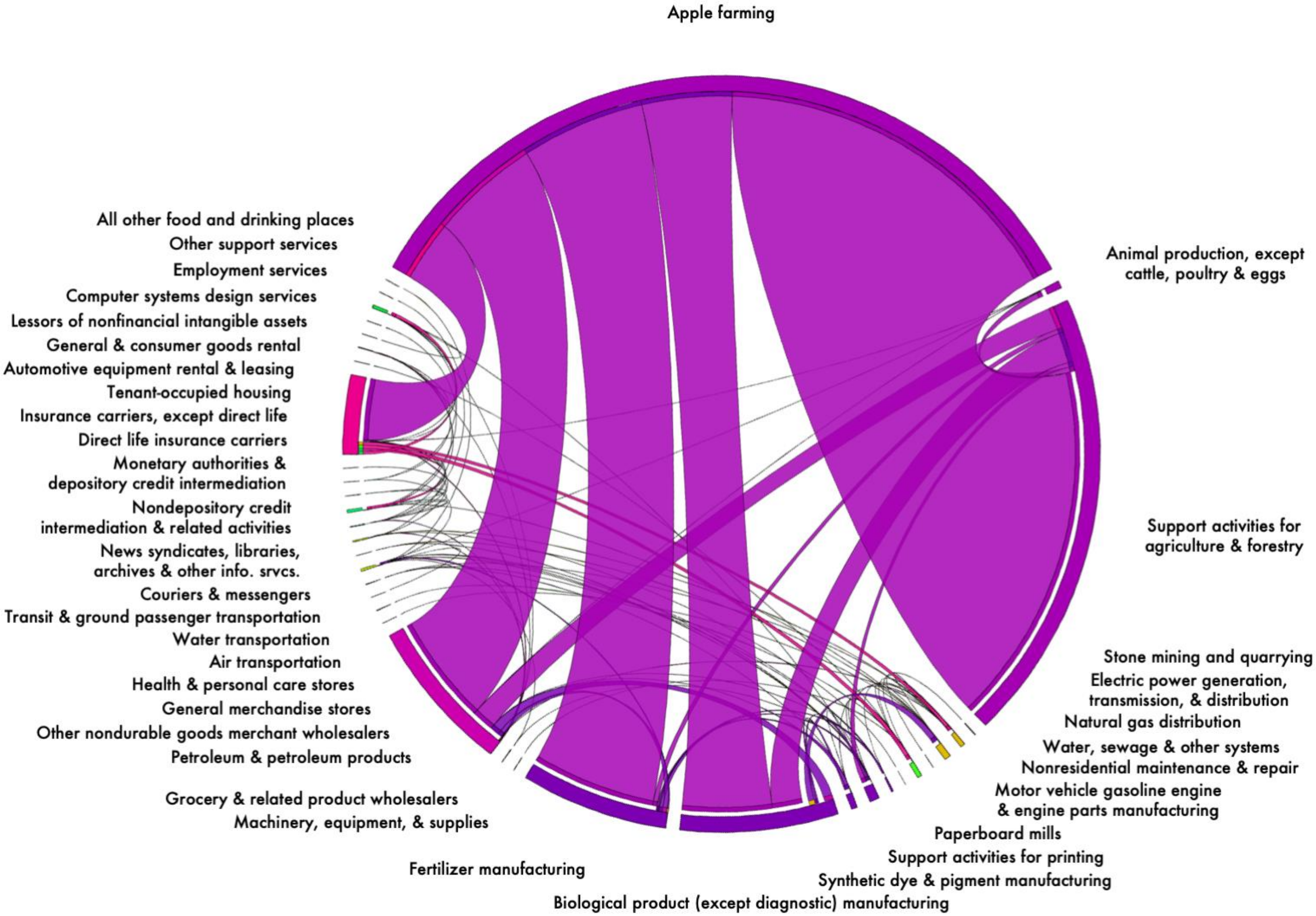


Figure 12. 1st, 2nd, and 3rd order influence for top five backwards pathways to the apple farming sector by relative influence determined by structural path analysis (SPA). Size of exterior bar represent relative total influence to sector, and color represents grouping by industry community. Size of arc tail is relative to size of impact in each connecting sector.

3.5 Discussion

The results of this study, as with all IO modeling, offers a static snapshot of the immediate effects of an initial disruption (e.g. loss or deterioration of key ecosystem service) on crop farming sectors and the rest of the economy based on their interdependence. It is not an explanation of events to occur following loss or decline of insect pollinators. It is quite difficult to assess what would definitively happen in absence of insect pollinators or what adaptations might emerge. Even dynamic models cannot predict future events with certainty. However, what this model details is that the overall dependence of US economy on insect pollinators is not straightforward nor restricted to agricultural sectors. Based on empirical economic data and best available information on crop pollination dependence, these results capture the economywide dependence on insect pollination service.

In terms of direct dependence, pollination-dependent crops have individual and varying levels of dependence on insect-mediated pollination service quantified by dependence coefficients. With regard to indirect dependence, this work reveals there are hidden dependencies on insect-mediated pollination service that exist in the economy due to supply chain structures and interdependencies between industry sectors. The findings of the SPA expand those of IO analysis by assessing influence at several orders of supply-chain pathway. We observe that the impact of pollination service to apples and almonds in both cases extends well beyond agricultural sectors and widely spreads throughout the economy. Further, each pollination-dependent crop will be used differently downstream and puts different magnitudes of demand on its unique supply chain. High-level aggregation of pollination-dependent crops in economic models improperly estimates our direct and indirect dependence on pollination service. Accounting for indirect, greater economy impacts of ecosystem services is an important piece of understanding the overall value of those services.

Including the indirect dependence of the economy on insect-mediated pollination service is a meaningful part of assessing its value. However, it still does not account for non-economic benefits of pollination service or the insects mediating the service. Loss of pollinators would be a detriment to ecosystem function and biodiversity[9]. In fact, many pollinator species with no agricultural production value are necessary to ecosystem function[12]. Other benefits such as upholding biodiversity, building ecosystems, having cultural and social significance or pollinating other species with that cultural or social significance or which are necessary for recreational activities have value that is difficult to quantify. The present work and subsequent valuations can have the potential to motivate conservation efforts as well as social and economic development.

Some mitigation of economic loss due to pollinator loss may be mitigated by price changes, increased inputs, or increased production. Including price information can improve an existing IO framework and allow for more detailed evaluation of risks of pollination service decline or loss[120]. However, a requirement of increased physical inputs (land, water, fertilizer, etc.) and therefore increased production leads to additional associated environmental impacts.

Though not the focus of this manuscript, insect pollinators have intrinsic value and value to humans recreationally, culturally, and socially in addition to other ecosystem services they provide. Pollinators structure ecosystems, provisioning food and habitat resources by facilitating plant reproduction or as prey for other organisms. Pollinators are critical to biodiversity of insects as well as angiosperms (flowering plants) which is essential to the ecosystem resilience. The value of these benefits provided by insect pollinators are not trivial and merit future studies.

Unintended and unexpected impacts of pollination dependence are identified in this work, however, there are others unaccounted. Previous work has argued that a lack of pollinators would increase the intensity of water and other inputs such as fertilizer, pesticides for crop production [7, 121, 122]. To achieve the same yields necessary to meet demand of pollination-dependent crops, agriculture intensification and additional land use may be necessary in the event of pollinator decline. For water intensive crops like almonds growing in already water-scarce regions, this is no trivial concern. Additional chemical inputs may lead to further negative impacts on the health and fitness of insect pollinators and entire ecosystems in a positive-feedback loop wherein negative impacts on health and fitness require more chemical inputs which cause increased negative impacts and so forth [121, 123, 124]. This work highlights a need for detailed crop-specific supply chain information as well as downstream usages. Lacking this detail in a full-scale study incorporating all crops would leave the model vulnerable to inaccuracies which undermine the valuation of indirect dependence on this and other ecosystem services. A complete disaggregation is not possible at present, but will only benefit future work. In addition, this will allow the knowledge of the full impact of this ecosystem service.

4.0 Accounting for ecosystem services in life cycle thinking: integrating insect pollinators into life cycle assessment

The following chapter is based on an article to be published in a peer-reviewed journal with the citation:

Alex Jordan, Kevin Padgett, Harland M. Patch, Christina M. Grozinger, and Vikas Khanna. *Accounting for ecosystem services in life cycle thinking: integrating insect pollinators into life cycle assessment.*

4.1 Chapter Summary

Ecosystem services and processes are often overlooked in life cycle analyses despite their impact in industrial production and processes. Creating an environmental vector for pollination service mediated by managed honey bees, this work provides methodology for valuing this important ecosystem process, bridging the critical gap between pollination intensity and life cycle analysis. Here, an environmentally-extended input-output (EEIO) methodology frames the creation of an environmental vector of managed honey bee hives utilized in the economic production of farming sector output and subsequently all industry sectors of the US economy. Results are effective, allowing for the integration of pollination service mediated by managed honey bees into existing life cycle assessment tools and for the account of this critical ecosystem process within product and process life cycle analyses.

4.2 Introduction

Ecosystem services are benefits derived from ecosystems such as water, food, and cultural or spiritual value. These services and the ecosystem processes that produce them are critically important to the welfare of humans as well as human industrial activity. One of these vital processes is pollination, the transfer of pollen from the anther of one flower to the stigma of the same (self-) or another flower (cross-). Almost all (85 percent) of wild flowering plants and more than 75 percent of global food crops depend on animal-mediated pollination, in some capacity, for either yield or quality[3, 94]. The majority of pollination service by animals is performed by insects including widely managed *Apis mellifera* and *Apis cerana* (honey bees), bumble bees, stingless and solitary bees as well as many more wild, unmanaged pollinators[3]. These crops are used as inputs for or are produced using inputs from other industries which have linkages with agricultural and non-agricultural industries. When a product is created in most any industry, therefore, it can be reliant upon pollination at some point in its life cycle. In fact, while there is an estimated 34.5 billion USD as of 2012 dependent upon insect-mediated pollination service in farming sectors alone[100], downstream linkages can account for an additional 65 percent of this direct dependence value for certain crops[125]. Due to the number of linkages between insect pollination and various sectors, it is of paramount importance that pollination be included in life cycle assessment therein.

4.2.1 Life Cycle Assessment Models

Life cycle assessment or analysis (LCA) gives one a framework for assessing a product or system through all parts of its life cycle including materials extraction, materials processing, manufacturing, use, and waste phases as well as potential remanufacturing, reuse, or recycling stages therein[126]. It is important to use this and other systems-level perspectives to consider environmental impacts that may not be encompassed by more limited approaches. Though all relating to systems thinking, there are several approaches to LCA, each with a unique lens with which to view a product or system. The subset of LCA may be chosen for a given analysis to reflect the individual aims of that analysis. Regardless of aim, in terms of sustainability, the main objective of LCA cannot be achieved by exclusion of ecosystem goods and services. Largely, in LCA this exclusion has been the *status quo*, while some branches have begun to build toward inclusion. Crenna, *et al.* attempt to quantify drivers affecting pollinators with the aim of assessing the impacts of various life cycles of processes and products on pollinator communities[28]. This work is fundamental in representing pollinators in life cycle impact assessment (LCIA). Our work attempts to represent pollinators from another dimension of LCA, through the representation of pollinators as an environmental vector in products and processes.

4.2.2 Environmentally-extended Life Cycle Assessment Models

An environmentally-extended IO model, Economic Input-Output Life Cycle Assessment (EIO LCA) developed at Carnegie Mellon University builds from existing economic input-output modeling by combining the economic relationship matrix of EIO with environmental and energy flows[24, 29]. This is done by adding an environmental effects vector to the economic input-output model developed from the work of economist Wassily Leontief[30, 125]. The model takes final demand estimates (***Y***) and direct/indirect economic requirements (***X***) from the EIO model and combines them with an environmental impacts sector[29].

This environmental sector (***E***) is defined by the following:

$$\boldsymbol{E = RX = R\,[I\text{-}A]^{-1}\,Y} \qquad [\,6\,]$$

and is illustrated by the following conceptual representation:

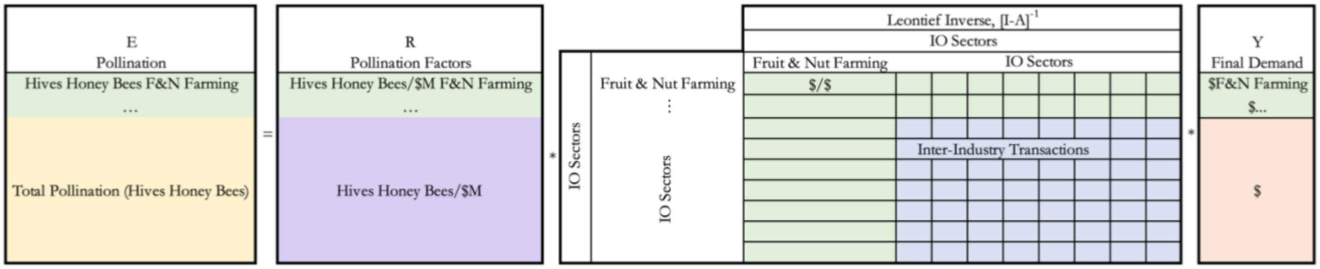


Figure 13. Conceptual representation of EEIO framework using disaggregated Leontief Matrix

In *Equation 6*, ***R*** is a matrix with diagonal elements representing the environmental impact per dollar of output in each sector[29]. The ***R*** matrix has units of environmental burdens per dollar of output (e.g., kg CO_2/$). This matrix is multiplied by vector ***X***, the output of each sector in dollars. Vector ***X*** is defined by $[I\text{-}A]^{-1}$ (*Equation 2*) the total requirements matrix, multiplied by ***Y***, the vector of desired output or final demand[29, 30]. It is called the *total* requirements matrix (sometimes the Leontief inverse[30]) because to calculate the term, $[I\text{-}A]^{-1}$, all direct and indirect purchases are totaled[29]. The total environmental burden, vector ***E***, includes both direct and indirect environmental effects with units of burdens (e.g., kg Co_2) by sector[24, 29]. In the case of this research, units of hives of honey bees are captured by vector ***E***.

The EIO-LCA model can include an array of environmental burdens such as air pollutant emissions, global warming potential, ozone depleting substances, or estimates of resource inputs such as fuels, fertilizers, or electricity[24, 29]. As indicated in *Equation 6*, these burdens are calculated using economic output data from each sector (***X***) and the ***R*** matrix. The values for the ***R*** matrix from which these burdens are derived comes from public datasets or field studies that report these burdens on a sector-level (e.g. how many hives are used in fruit and nut farming). Many burdens are not represented for lack of data or because they are not incorporated into the framework of the model.

4.2.3 Ecosystem Services in EIO-LCA

Particular to the present research, ecosystem services, such as pollination, go ignored in LCA including Carnegie Mellon University's online tool for EIO-LCA described above[24]. All ecosystem goods and services, including pollination, are overlooked in this model. Ecosystem services are often considered free and with infinite supply; however, the renewability of these resources has limitations[31, 32]. This limit has been made apparent for many of these resources including fisheries which have seen significant decline due to overfishing and pollination, where pollinators have faced significant decline due to many factors including industrial use of pesticides[31]. The impact industry sectors have on these resources are unexplored compared to finite or nonrenewable sources. This research aims to close this critical gap in knowledge with regard to insect-mediated pollination. As a resource, "Pollination," exists in EcoLCA, an IO-LCA tool developed by The Ohio State University, however, the vector is not developed and exists as a placeholder in this tool at present[25]. The present work creates a new environmental burden vector entirely for pollination service, specifically provided by honey bees, to be incorporated into these tools and fill this need. This can facilitate more complete life cycle analyses that account for this crucial ecosystem service and sets a precedence for the incorporation of ecosystem goods and services into process-based product life cycle assessments.

4.2.4 Eco-LCA

Ecologically-based Life Cycle Assessment (Eco-LCA) is a framework for accounting both the direct and indirect role of ecosystem services in LCA by including them within an expanded LCA boundary[127]. This approach is similar to other LCA methodology but includes an Eco-LCA inventory which defines the role of ecosystem goods and services in the economy. For services like renewable energy, land, water, and fossil fuels, direct accounting can be achieved through easily quantifiable bio-physical units. However, for other ecosystem services which do not have a measurable parameter that can entirely represent the complexity of the service, quantification and accounting can be quite challenging. Pollination is one such service which can be challenging to include in LCA. Additionally, lack of sufficient data on a measured parameter can exacerbate challenges associated with quantification even further.

Zhang *et al.* describe the importance of accounting for natural capital and renewable resources in life cycle analysis and discuss Eco-LCA and the functional unit of hive-days to represent pollination service as an impact vector in LCA[23]. Our work, however, finds that capturing the time for which insect pollinators should be present is not possible. Although there is an indication of overall bloom period (i.e. Almonds: late January to late March), the many varieties have various timings and often for crops it is recommended to plant several varieties for cross-pollination. Even if we know how many days each variety is blooming (which is not necessarily true depending on the crop), calculating hive-days would require knowing how many acres of a given crop were dedicated to a particular variety. In terms of producing acres, this can vary from year to year. Thus, we would have to know these variety proportions for 2012. Maintaining this information is impractical. For this reason, our study develops an impact category with the units of hives (of honey bees).

4.3 Materials & Methods

To support an EEIO framework in the present work, the ***R*** matrix is created using an extensive review of available literature on pollination requirements for all 75 pollination-dependent crops grown in the United States (***Figure 2***). First, estimates of honey bee hive stocking rate, or the number of honey bee hives recommended to pollinate a pollination-dependent crop per acre grown were extracted from existing literature for each crop. The average of the stocking rate recommendations was multiplied by the total number of acres of each crop grown annually per the Agricultural Census reported by the USDA National Agricultural Statistics Service, for which the latest data is available (2012). The product of this calculation is the honey bee hives required to produce each crop annually. The estimate of honey bee hive requirements for each crop were summed according to the sector in which they are aggregated by the Bureau of Economic Analysis (BEA) (***Table 8***) and divided by the total throughput ($\boldsymbol{X}$) for that sector. Throughput is reported every five years by the BEA and is published as input-output account data. This quotient quantifies $\boldsymbol{R_i}$ for each sector ($\boldsymbol{i}$) growing pollination-dependent crops. An $\boldsymbol{R}$ matrix is derived using the vector of $\boldsymbol{R_i}$ along the diagonal of a square matrix of zeroes of size $\boldsymbol{n}$ (the number of economic sectors).

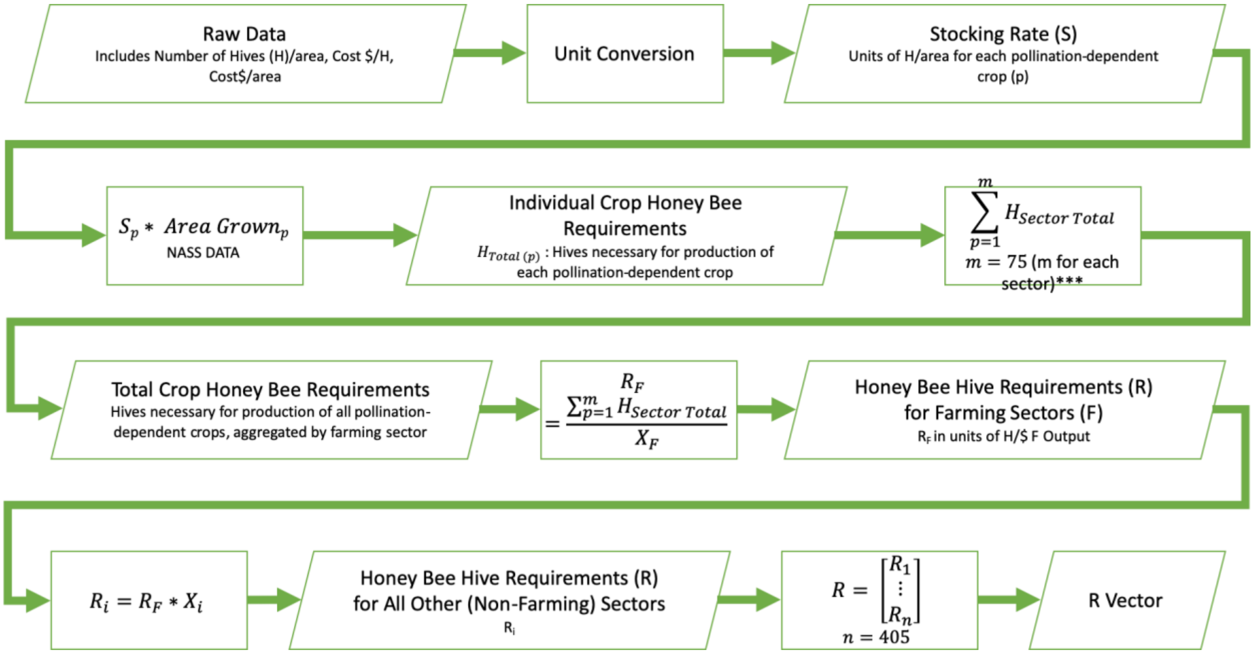


Figure 14. Flowchart depicting methodology for calculation of R vector.

Hives per millions of dollars are used to correspond with the units of the BEA IO tables. In 2012 Input-

Output Accounts data, there are 405 sectors defined by the BEA, however, the Oilseed Farming and Grain Farming sectors are oft aggregated and the division of crops among them is unclear. For this reason, the present work aggregates Oilseed and Grain Farming into one sector therefore defining disparate 404 sectors. The newly derived ***R*** matrix is used with the Leontief inverse and a final demand for each sector of $1 million USD to calculate the environmental vector, ***E***, (*Equation 6*).

4.4 Results

The resulting vector, ***E***, is presented below in ***Table 6***. Oilseed and grain farming crops, including beans, buckwheat, canola, lentils, peanuts, rapeseed, safflower, sesame, soybeans, and sunflower, demand the most managed colonies of honey bees. It must be considered that these crops are also the topic of debate with regard to their dependence on pollination mediated by insects. Although soybeans are pollination-dependent, the degree to which they rely on insect pollinators in agricultural settings is thought to be less than usually described in field studies[46, 52-55].

Table 6. Environmental vector and hive requirements by economic sector

NAICS Code	**Sector Description**	**Environmental Vector or E** ***[hives per million USD Final Demand]***	**R (Hive Requirements)** ***[total hives per sector throughput]***
111100	Oilseed & Grain farming	3402	379
111200	Vegetable and melon farming	225	195
111300	Fruit and tree nut farming	477	240
111900	Other crop farming	1870	1001

The stocking rate recommended in the literature for maximizing yield of a given crop varies (***Figure 15***) as does the availability of data for this parameter in existing literature. The summary of stocking rates recommended by available literature (***Figure 15***) indicates that crops may have varying needs for pollination by honey bees. Much of the difficulty in pinpointing pollination service requirements is due to variability in pollinator efficacy which is dependent on many factors including weather, climate, pollinator fitness, landscape, crop fitness, plant-pollinator interaction, and pollinator anatomy. For this reason, some variation is expected. One of the most accepted and most recent resources for stocking rate is a book, Crop Pollination by Insects written by Keith S. Delaplane and Daniel F. Mayer[46]. This book updated foundational resources that predated it[45, 128]. For many crops, Delaplane and Mayer report a "literature average" derived from available primary field studies at the time (***Figure 16***). While there are some well-studied crops, ***Figure 17*** shows the distribution of current literature available on stocking rates of hives of honey bees for crops. Stocking rates provided in the literature may or may not correlate with dependence. If a crop is highly dependent on insect pollinators, the literature may also recommend a high stock of honey bees (such is the case with onions), or the literature may not recommend a relatively high stock of honey bees (such is the case with pumpkins). This may seem counterintuitive, however, honey bees may be more or less effective at pollinating various crop flowers. In fact, honey bees are often not the most effective pollinator as they were bred as honey producers first. They are instead generalist pollinators that do a satisfactory but not outstanding job at pollinating a great variety of plants. In addition, some crops are more or less dependent on wild insect pollinators as wild insects may be more effective at pollinating the flower of that crop than honey bees. This is the case with pumpkins and squash which highly depend on squash bees rather than honey bees.

Pollination-dependent crops are classified as either Fruit & Tree Nut, Vegetable & Melon, Oilseed & Grain, or Other according to the aggregation of BEA sectors following NAICS code guidelines (***Table 8***). Only farming of these four sectors have direct pollination input and therefore direct burden, given as colonies (hives) necessary to produce one million USD (2012) commodity output for that sector (***Figure 17***). Stocking rate data is not possible to aggregate with formal statistical analysis for minimal sample size. Farming of crops classified as, “Other,” has the greatest direct and indirect pollination intensity, using 1070 hives per million USD directly and another 1120 hives per million USD indirectly. Oilseed and Grain farming follows as the second-most intense, with a direct burden of 380 hives per million USD and an indirect burden of 420 hives per million USD. Considering the indirect burden associated with a sector can increase the impact on pollination services significantly, approximately doubling the total burden from just the direct burden alone. The inclusion of indirect burdens provides an important addition to assessments and underscores the significance of big-systems thinking.

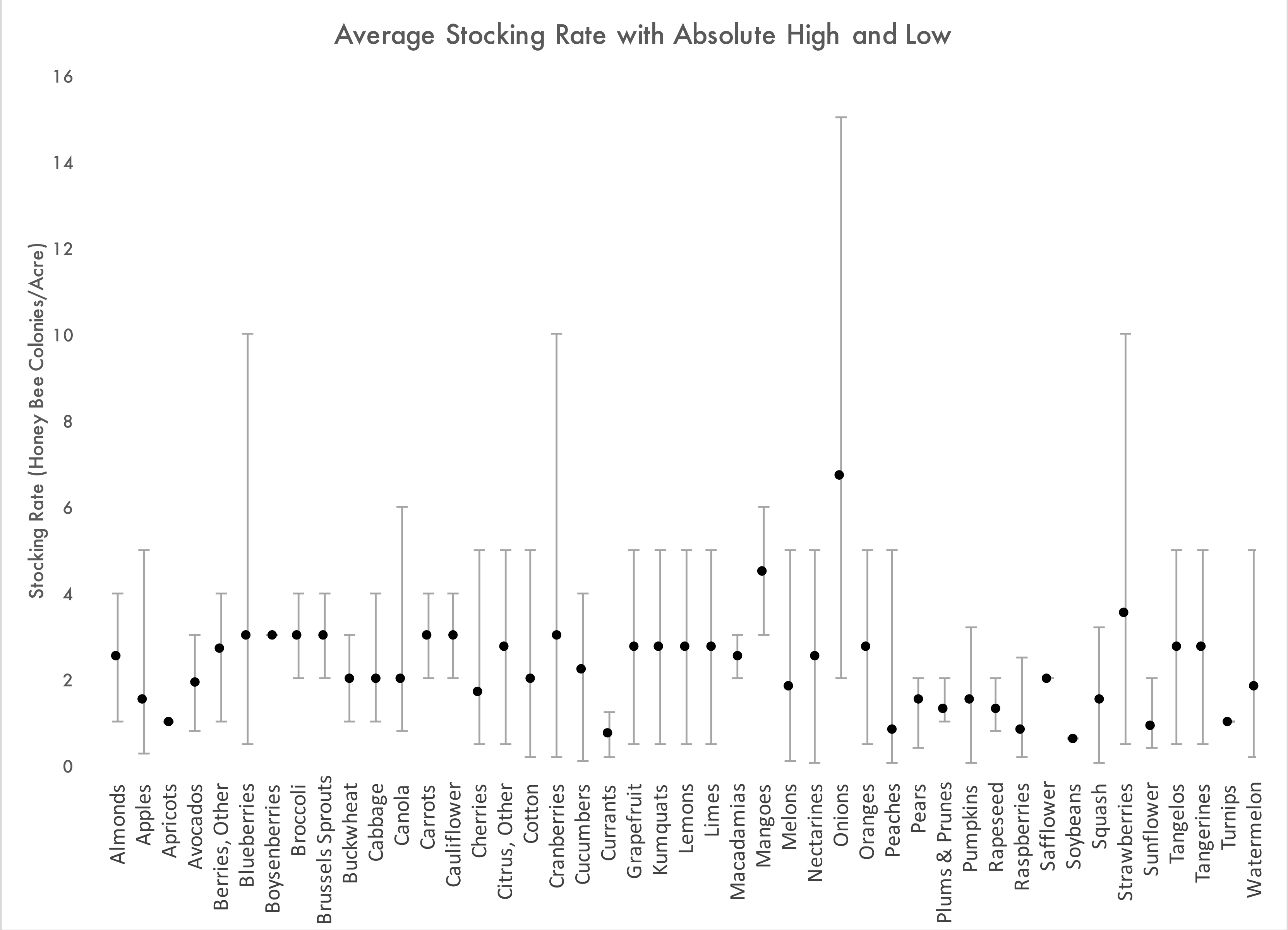


Figure 15. A summary of stocking rate data in available literature (circles). Bars represent the absolute high and absolute low stocking rate reported.

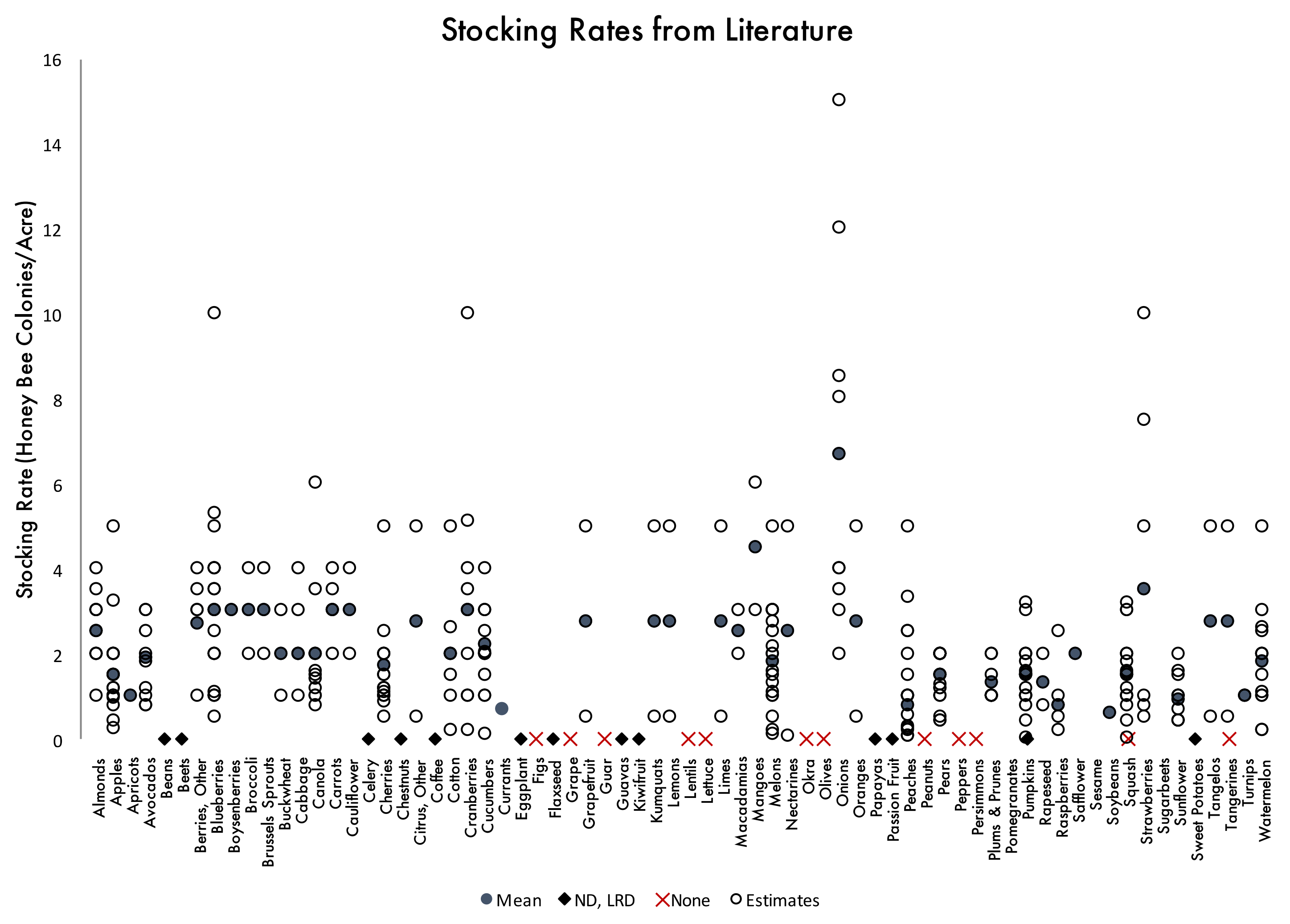


Figure 16. Stocking rates reported by the literature. Each point is represented by an empty circle. Mean (filled circle) represents the literature average calculated by Delaplane, Mayer, and Mayer (2000) from individual sources or the average of the range of data when this was not available. No recommendation, lack of research and data (NR, LRD; diamond) indicates that the literature generally had a lack of research on a particular crop and therefore could not recommend a stocking rate. None (X) indicates that there was no literature available regarding stocking rate on the particular crop.

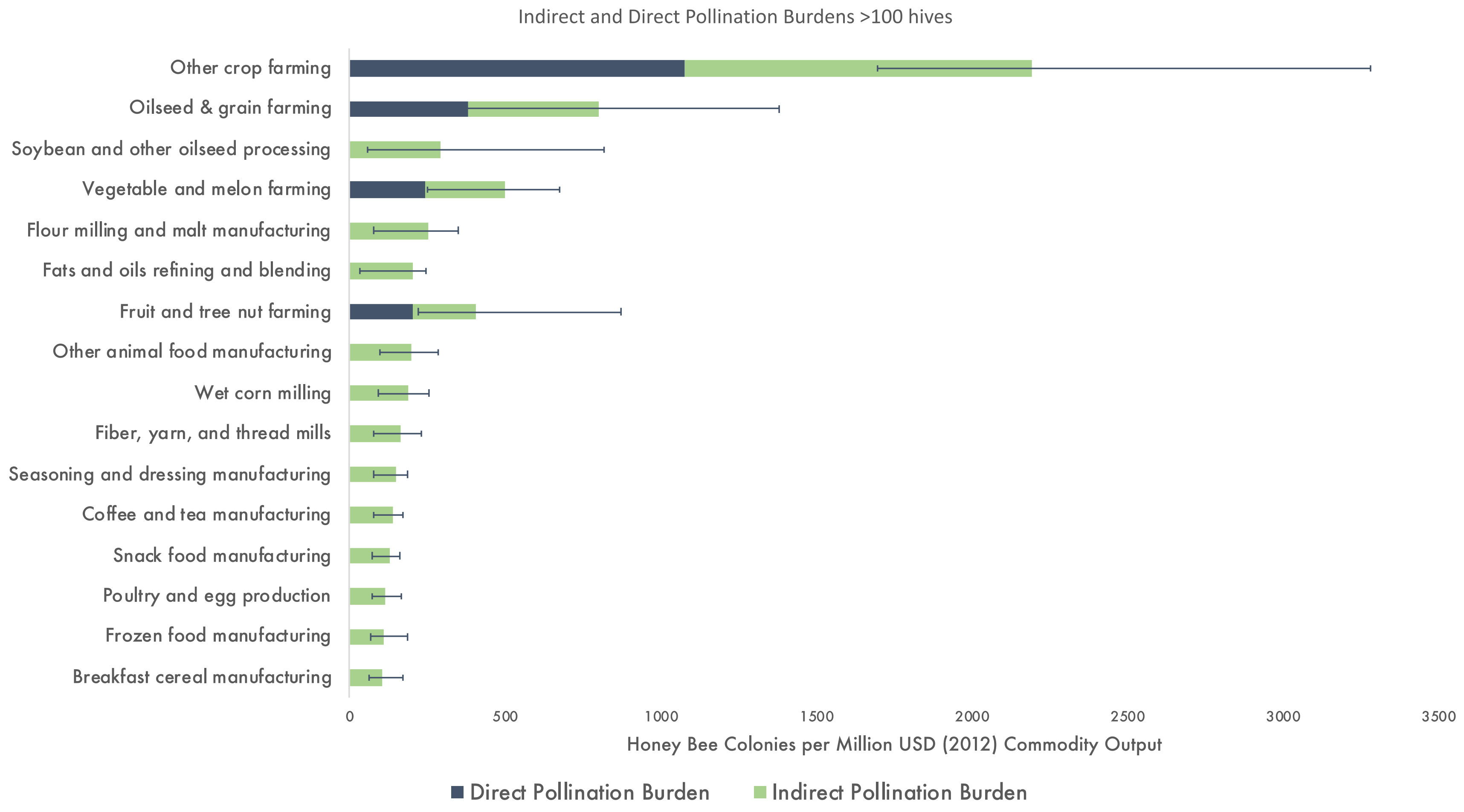


Figure 17. Greatest indirect and direct pollination burdens (>100 managed honey bee colonies) per million USD, 2012, commodity output by sector. Direct (left, blue) burdens are associated with farming sectors growing pollination-dependent crops. Indirect (right, green) burdens result from linkages to the farming sectors. Error bars were determined using the absolute minimum and maximum stocking rates reported by the literature and represent those limits of the total (direct and indirect) burdens.

4.5 Discussion

Because BEA data is highly aggregated, contributions are also aggregated. Reported as BEA input-output tables (IOTs), the transactional data of the US economy is reported between 404 industry sectors, and all produced crops are aggregated into four farming sectors. Due to this aggregation, if a downstream sector uses any crop from a farming sector, it will be identified as having used pollination service, despite that it may only be using inputs from non-pollination-dependent crops. Here, we aggregate total economic output dependent on insect pollinators after first calculating the contributions to each pollination-dependent crop in the farming sector in order to negate misattributions of this nature. Best practice for future endeavors requires further disaggregation of pollination-dependent crops from these farming sectors as manual adjustments to the BEA input-output tables.

There is limited data on the requirements of honey bee hives for the growth of pollination-dependent crops. The present research assumes that recommendations for stocking rates of honey bee hives are synonymous with the required pollination service to these crops by managed species. However, honey bee pollination dependence is variable across landscapes and cultivars and is impacted by many factors including the composition and abundance of the wild pollinator community and climate. While there are limits to the available data with regard to honey bee hive requirements, to our current knowledge, there is a complete lack quantification on the required pollination services mediated by wild insects to specific crops.

Despite understanding that wild insects are important and significant contributors to crop pollination[4, 86, 88], quantification of the amount of wild insects utilized by a crop for production is difficult to ascertain. For this reason, our study includes managed honey bees only. Expanding this research to create a pollination vector for wild pollinators would be an important step toward valuing these essential members of the ecosystem, however, the inability to include them now is not entirely surprising. First, managed honey bees are well-studied, especially compared to both wild insect pollinators as well as other managed pollinators such as mason bees (*Osmia*) or bumble bees (*Bombus*). Second, honey bees are social insects with hierarchy and structure that supports the ease of management, transport, and subsequently quantification of their contributions to pollination. And lastly, honey bees are well-documented, having a beekeeping industry that keeps and maintains colonies and has evident transactional relationships with agricultural sectors.

Despite data limitations, this research creates an environmental impact category for integrating honey bee pollination service into existing EIO-LCA tools to facilitate more complete life cycle analyses. This new impact category lays a foundation for the incorporation of ecosystem goods and services into life cycle assessment. In addition, it provides support for the value of pollination services, pollinators, and other ecosystem services, contributing to efforts to conserve ecosystem health and biodiversity.

Loss or further decline of pollinators will be significant and extensive, having impacts directly in agriculture, indirectly in non-agricultural industries and human culture, and finally in essential ecosystem function[9, 38, 44]. Creation of this environmental impact category and its integration into life cycle analyses provides a better understanding of their role in production.

The preservation and restoration of pollinators are critical to the welfare of humans and ecosystems[32]. Already significant declines in abundance and biodiversity of pollinators has underscored a need for valuation of the benefits they provide. There are tools available for useful valuation of pollinators and pollination services from an economic perspective. However, the pollinators serve ecosystems indirectly through many pathways that ensure ecological and environmental resilience that cannot be accounted for in current economic methods.

In addition, many cultural, non-material benefits derived from pollinators may not ever be entirely captured by economics[32]. As with any valuation, it is critical to consider material and nonmaterial benefits and choose the scope of a valuation of pollinators and pollination service with care and always with clarification of limitations as the influence of a valuation can be far-reaching and highly influential. Although non-material benefits will not be captured in this work, this research adds significant weight to a body of work making a case for the preservation and restoration of insect pollinators. This research underscores the need to protect important material benefits of insect pollinators, and subsequently numerous vital non-material benefits will be aided.

5.0 Conclusions and Future Work

This research quantifies and extends existing research to better capture dependency of U.S. crops on insect-mediated pollination by both honey bees and wild pollinators with both estimation of economic value and associated uncertainty. In addition, it identifies primary economic vulnerabilities in the agricultural sector in a spatial way and higher-order economic vulnerabilities in at-risk industrial sectors. It is the recommendation of the author to extend the work performed in Chapter 2 to increase spatial resolution of the economic dependence even further to 30m to match the resolution of the USDA Cropland Data Layer (CDL) as well as update the values of agricultural production as the 2017 USDA Agricultural Census and NASS survey data become publicly available. The CDL is the source of the landcover evaluated by the Lonsdorf Model for nesting and forage suitability of wild bees. Increasing the resolution of the economic dependence to 30m, will increase the power of the comparison and combination of economic dependence data with other environmental factors or stressors such as forage availability, nesting suitability, pesticide application, and climate data. In addition, the framework outlined in Chapter 2 for evaluating the dependence of a given crop on insect-mediated pollination service successfully captures the uncertainty associated with dependence as many factors can influence the value of crop dependence. While this is an improvement upon previous methodology using rigorous statistical analysis, there is a general lack of field study data with which to perform the analysis in the existing body of literature. Performing field studies at the caliber and scale required to capture dependence variability (among varying cultivars, insect pollinators, landscapes, etc.) would be expensive financially and temporally especially for each pollination-dependent crop. Detailed field studies of all pollination-dependent crops would be impractical and in some cases unnecessary.

For crops which there is currently a lack of consensus in the literature regarding their dependence, especially those with high agricultural value (e.g. soybean, canola), it would be very useful to apply the outlined framework to understand the functional dependence of the crop in agricultural conditions.

This research also creates an environmental impact category for honey bee pollination service to be integrated in future work into existing EIO-LCA tools to facilitate more complete life cycle analyses. This new impact category builds the foundation for the incorporation of ecosystem goods and services into life cycle assessment. It is expected that the results of this research provide framework for the use of mixed IO models for analyzing ecosystem services. In addition, it provides support for the value of pollination services, pollinators (both wild and managed), and other ecosystem services, contributing to efforts to conserve ecosystem health and biodiversity.

Loss or decline of pollinators will be significant and extensive, having impacts directly in agriculture, indirectly in non-agricultural industries and human culture, and finally in essential ecosystem function. Creation and integration of this environmental impact category into life cycle analyses and systematic collection of data on managed pollinators provides better understanding of their role in production as well as the cultural and social benefits attributed to pollinators.

The preservation and restoration of pollinators are critical to the welfare of humans and ecosystems. Already significant declines in abundance and biodiversity of pollinators has underscored a need for valuation of the benefits they provide. There are tools available for useful valuation of pollinators and pollination services from an economic perspective. However, the pollinators serve ecosystems indirectly through many pathways that ensure ecological and environmental resilience that cannot be accounted for in current economic methods. In addition, many cultural, non-material benefits derived from pollinators may not ever be entirely captured by economics. In fact, if one were to consider all of the non-material benefits derived from pollinators, their value could be said to be infinite[33]. As with any valuation, it is critical to consider material and nonmaterial benefits and choose the scope of a valuation of pollinators and pollination service with care and always with clarification of limitations as the influence of a valuation can be far-reaching and highly influential. Although non-material benefits will not be captured in this work, this research adds significant weight to a body of work making a case for the preservation and restoration of insect pollinators. This research underscores the need to protect important material benefits of insect pollinators, and subsequently numerous vital non-material benefits will be aided.

Appendix A

Appendix A.1 Crop Selection

Globally, there are about 77 crops grown which depend directly or indirectly on pollination service mediated by insects (**Table 7**). Relevant US crops can be categorized as in **Table 8**. The top 25 crops according to the United Nations Food and Agriculture Organization (FAO) 2012 gross production value (GPV) were explored for analysis. Lettuce and chicory is excluded from the 25 highest valued crops due to its exclusion from Klein *et al.* (2007) dependence estimates. However, Southwick and Southwick (1992) do list lettuce as pollination-dependent. Indirectly-dependent crops are dependent on pollination for seed, but not for the commodity such as hay for alfalfa or bulb for onions. Indirectly-dependent crops are represented as italicized in **Table 9**. The economic value of pollination to indirectly-dependent crops is inherently more difficult to assess due to no direct measure of the commodity that is influenced by pollination. For example, fruit yield is measurable but not affected by pollination. Seed set is also measurable, but not the basis for the economic value of the commodity. Then, determining how much of the fruit yield is dependent on seed dependence on pollination is not possible.

Table 7. Crops dependent upon insect-mediated pollination service[1, 6, 7]. Lower-right italicized list of crops is indirectly-dependent upon pollination service; all others are directly-dependent upon pollination service.

- Almonds
- Apples
- Apricots
- Avocados
- Beans
- Beets
- Berries, Other
- Blueberries
- Boysenberries
- Brussels Sprouts
- Buckwheat
- Cabbage
- Citrus (other)
- Coffee
- Cranberries
- Cucumbers
- Currants
- Eggplant
- Figs
- Flaxseed
- Grape
- Grapefruit
- Guar
- Guavas
- Lettuce
- Limes
- Macadamias
- Mangoes
- Melons
- Nectarines
- Okra
- Olives
- Oranges
- Papayas
- Passion Fruit
- Peaches
- Persimmons
- Plums
- Plums & Prunes
- Pomegranates
- Prunes
- Pumpkins
- Rapeseed
- Raspberries
- Safflower
- Sesame
- Soybeans
- Squash
- Tangerines
- Tomatoes
- Turnips
- Watermelon
- *Alfalfa*
- *Broccoli*
- *Carrots*
- *Cauliflower*
- *Celery*
- *Clover*
- *Cotton*

Canola	Kiwifruit	Peanuts	Strawberries	*Onions*
Cherries	Kumquats	Pears	Sunflower	*Sugarbeets*
Chestnuts	Lemons	Peas	Sweet Potatoes	
Chicory	Lentils	Peppers	Tangelos	

Table 8. Categorization of US grown pollination-dependent crops.

Fruits and Nuts		Vegetables and Melons	Oilseed
Almonds	Lemons	Pumpkins	Sunflower
Apples	Limes	Broccoli	Canola
Apricots	Macadamias	Brussels Sprouts	Peanuts
Avocados	Mangoes	Cabbage	Rapeseed
Berries, Other	Nectarines	Cauliflower	Safflower
Blueberries	Oranges	Celery	Sesame
Boysenberries	Papayas	Cucumbers	Soybeans
Cherries	Passion Fruit	Eggplant	
Chestnuts	Peaches	Lettuce	**Other Crops**
Citrus, Other	Pears	Melons	Buckwheat
Cranberries	Persimmons	Okra	Beans
Currants	Plums	Peppers	Coffee
Figs	Pomegranates	Squash	Flaxseed
Grape	Prunes	Tomatoes	Guar
Grapefruit	Raspberries	Turnips	Sweet Potatoes
Guavas	Strawberries	Watermelon	
Kiwifruit	Tangelos		
Kumquats	Tangerines		

Table 9. Studies representing top 25 crops per gross production value, compiled for bootstrapping dependence ratio estimates.

Crop	Classification	Gross Production Value (2012, 100 Thousand USD)	Studies
Soybean	Oilseed	43796.4	12
Alfalfa	*Grasses and Fodder*	*10374.9*	*24*
Almond	Nuts	9413.6	45
Tomato	Vegetables: Fruit-bearing	8907.7	37
Cotton/Cottonseed	*Fiber*	*7721.1*	*9*
Grape	Grape	5663.6	16
Apple	Fruit: Pome/Stone	3362	41

Strawberry	Fruit: Berries	2705.6	21
Sugar Beet	*Sugar Crops*	*2332.7*	-
Oranges	Fruit: Citrus	2174.5	3 (citrus)
Groundnuts, with shell	Oilseed	2034.2	-
~~*Lettuce and chicory*~~	~~*Vegetables: Leafy Stem*~~	~~1628.5~~	-
Beans, dry	Leguminous Crops	1213.5	-
Onion	*Vegetables: Root/Tuberous/Bulb*	*1015*	*20*
Cauliflower/Broccoli	*Vegetables: Leafy Stem*	*972.1*	*3*
Blueberry	Fruit: Berries	854.2	55
Carrot/Turnip	*Vegetables: Root/Tuberous/Bulb*	*805.2*	*2/-*
Peach/Nectarine	Fruit: Pome/Stone	748.4	-
Sunflower Seed	Oilseed (temporary)	695	30
Rapeseed	Oilseed (temporary)	625	-
Pumpkin/Squash/Gourd	Vegetables: Fruit-bearing	617	20
Watermelon	Vegetables: Fruit-bearing	477.2	3
Cucumber/Gherkin	Vegetables: Fruit-bearing	444.5	-
Avocado	Fruit: Tropical and Subtropical	440.4	11
Pears	Fruit: Pome/Stone	436.8	-
Cranberry	Fruit: Berries	424.8	-
Total		**109883.9**	**352**
Total Represented by Studies		**99995.5**	

Appendix A.2 Dependence Coefficients

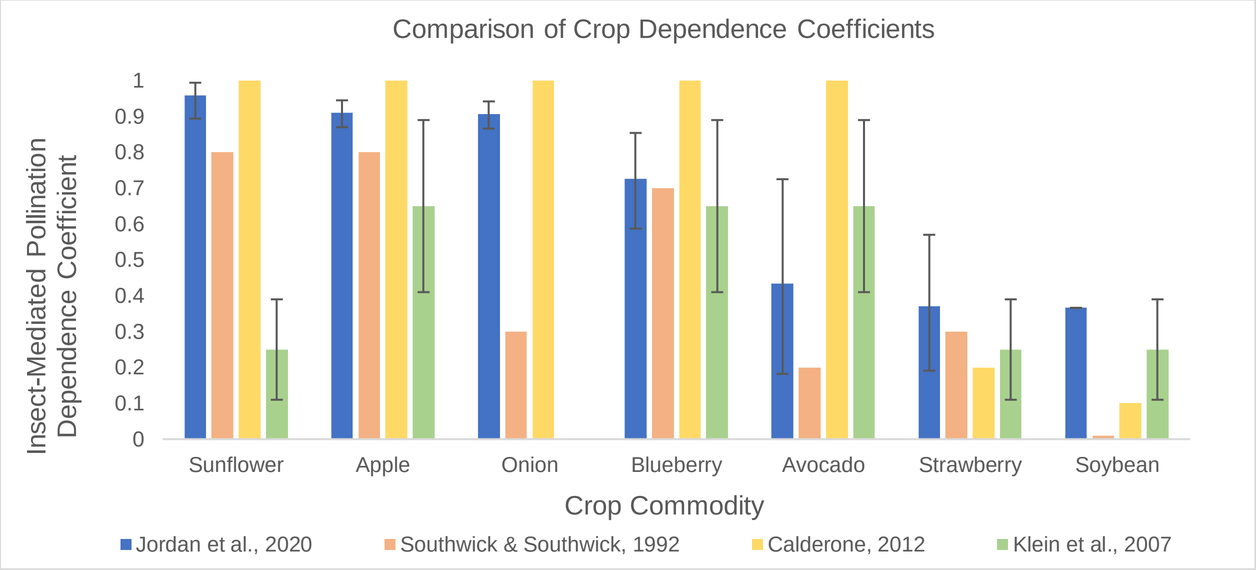


Figure 18. Comparison of average dependence coefficients between current study and prior literature sources. Error bars represent 95% confidence interval for bootstrapped estimate (Jordan *et al.*) and range low and high (Klein *et al.*).

Table 10. Dependence estimates from literature for US grown pollination-dependent crops. The letters I and D are abbreviations for indirectly pollination-dependent crops and directly pollination-dependent crops respectively. Commodity is the name of the crop as recorded by USDA NASS. Classes and subclasses are those defined by the Food and Agriculture Organization of the United Nations. K refers to Klein *et al.* 2007. SW refers to Southwick and Southwick (1992). Cald refers to Calderone, 2012. D_025 and D_975 represent the lower and upper bounds of the 95% CI respectively. The source column has identifies the source of the estimate utilized in the present work and the uncertainty column describes the method of uncertainty analysis.

Indirect or Direct	Commodity	FAO Subclass	FAO Class	K_Category	SW	Cald	Mean	D_025	D_975	Source	Uncertainty
D	Almonds	Nuts	Fruits and Nuts	great		1.00	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Apples	Pome/Stone	Fruits and Nuts	great		1.00	0.91	0.87	0.95	Klein *et al.* 2007	Monte Carlo
D	Apricots	Pome/Stone	Fruits and Nuts	great		0.70	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Avocados	Tropical and subtropical Fruits	Fruits and Nuts	great		1.00	0.43	0.18	0.73	Field Studies	Bootstrapping
D	Beans	Beans	Leguminous Crops	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Beets	Sugar Beet	Sugar		0.10	0.10	0.10	0.10	0.10	Southwick/Calderone	Monte Carlo
D	Berries, Other	Berries	Fruits and Nuts	great		0.80	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Blueberries	Berries	Fruits and Nuts	great		1.00	0.73	0.59	0.85	Field Studies	Bootstrapping
D	Boysenberries	Berries	Fruits and Nuts	great	0.70	0.80	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
I	Broccoli	Leafy or Stem Vegetables	Vegetables and Melons		0.90	1.00	0.95	1.00	0.90	Southwick (Low)/ Calderone (High)	Monte Carlo
D	Brussels Sprouts	Leafy or Stem Vegetables	Vegetables and Melons		0.90		0.90			Southwick	Point Estimate, No Uncertainty Analysis
D	Buckwheat	Other Cereals	Cereals	great			0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Cabbage	Leafy or Stem Vegetables	Vegetables and Melons		0.90		0.90			Southwick	Point Estimate, No Uncertainty Analysis
D	Canola	Other temporary oilseed crops	Oilseed Crops	great		0.50	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
I	Carrots	Root, bulb, or tuberous vegetables	Vegetables and Melons		0.60	1.00	0.80	0.99	0.61	Southwick (Low)/ Calderone (High)	Monte Carlo
I	Cauliflower	Leafy or Stem Vegetables	Vegetables and Melons		0.90	1.00	0.95	1.00	0.90	Southwick (Low)/ Calderone (High)	Monte Carlo
I	Celery	Leafy or Stem Vegetables	Vegetables and Melons			1.00	1.00			Calderone	Point Estimate, No Uncertainty Analysis

D	Cherries	Pome/Stone	Fruits and Nuts	great		0.90	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Chestnuts	Nuts	Fruits and Nuts	modest			0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
D	Chicory	Leafy or Stem Vegetables	Vegetables and Melons							Klein *et al.* 2007	Monte Carlo
D	Citrus, Other	Citrus Fruits	Fruits and Nuts	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Coffee	Beverage Crops	Beverage and spice crops	modest			0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
I	Cotton	Fiber Crops	Other Crops	modest		0.20	0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
D	Cranberries	Berries	Fruits and Nuts	great		1.00	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Cucumbers	Fruit-Bearing Vegetables	Vegetables and Melons	great		0.90	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Currants	Berries	Fruits and Nuts	modest			0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
D	Eggplant	Fruit-Bearing Vegetables	Vegetables and Melons	modest			0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
D	Figs	Tropical and subtropical Fruits	Fruits and Nuts	modest			0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
D	Flaxseed	Fiber Crops	Other Crops	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Grape		Fruits and Nuts	no increase		0.10	0.00	0.00	0.00	Klein *et al.* 2007	Monte Carlo
D	Grapefruit	Citrus Fruits	Fruits and Nuts	little		0.80	0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Guar	Beans	Leguminous Crops	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Guavas	Tropical and subtropical Fruits	Fruits and Nuts	modest			0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
D	Kiwifruit	Berries	Fruits and Nuts	essential		0.90	0.95	1.00	0.90	Klein *et al.* 2007	Monte Carlo
D	Kumquats	Citrus Fruits	Fruits and Nuts	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Lemons	Citrus Fruits	Fruits and Nuts	little		0.20	0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Lentils	Lentils	Leguminous Crops	no increase			0.00	0.00	0.00	Klein *et al.* 2007	Monte Carlo
D	Lettuce	Leafy or Stem Vegetables	Vegetables and Melons		0.03		0.03			Southwick	Point Estimate, No

											Uncertainty Analysis
D	Limes	Citrus Fruits	Fruits and Nuts	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Macadamias	Nuts	Fruits and Nuts	essential		0.90	0.95	1.00	0.90	Klein *et al.* 2007	Monte Carlo
D	Mangoes	Tropical and subtropical Fruits	Fruits and Nuts	great			0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Melons	Fruit-Bearing Vegetables	Vegetables and Melons	essential		0.80	0.95	1.00	0.90	Klein *et al.* 2007	Monte Carlo
D	Nectarines	Citrus Fruits	Fruits and Nuts	great		0.60	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Okra	Other	Vegetables and Melons	modest			0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
D	Olives	Permanent Oilseed Crops	Oilseed Crops	no increase		0.10	0.00	0.00	0.00	Klein *et al.* 2007	Monte Carlo
I	Onions	Root, bulb, or tuberous vegetables	Vegetables and Melons		0.30	1.00	0.91	0.87	0.94	Field Studies	Bootstrapping
D	Oranges	Citrus Fruits	Fruits and Nuts	little		0.30	0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Papayas	Tropical and subtropical Fruits	Fruits and Nuts	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Passion Fruit	Tropical and subtropical Fruits	Fruits and Nuts	essential			0.95	1.00	0.90	Klein *et al.* 2007	Monte Carlo
D	Peaches	Pome/Stone	Fruits and Nuts	great		0.60	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Peanuts	Groundnuts	Oilseed Crops	little		0.10	0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Pears	Pome/Stone	Fruits and Nuts	great		0.70	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Peas	Peas	Leguminous Crops	no increase			0.00	0.00	0.00	Klein *et al.* 2007	Monte Carlo
D	Peppers	Fruit-Bearing Vegetables	Vegetables and Melons	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Persimmons	Other	Fruits and Nuts	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Plums	Pome/Stone	Fruits and Nuts	great		0.70	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Plums & Prunes	Pome/Stone	Fruits and Nuts	great		0.70	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo

D	Pomegranates	Berries	Fruits and Nuts		0.10		0.10			Southwick	Point Estimate, No Uncertainty Analysis
D	Prunes	Pome/Stone	Fruits and Nuts		0.50	0.70	0.60	0.70	0.51	Southwick (Low)/ Calderone (High)	Monte Carlo
D	Pumpkins	Fruit-Bearing Vegetables	Vegetables and Melons	essential		0.90	0.95	1.00	0.90	Klein *et al.* 2007	Monte Carlo
D	Rapeseed	Other temporary oilseed crops	Oilseed Crops	modest		1.00	0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
D	Raspberries	Berries	Fruits and Nuts	great		0.80	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Safflower	Other temporary oilseed crops	Oilseed Crops	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Sesame	Other temporary oilseed crops	Oilseed Crops	modest			0.25	0.39	0.11	Klein *et al.* 2007	Monte Carlo
D	Soybeans	Soya Beans	Oilseed Crops	modest		0.10	0.37	0.37	0.37	Field Studies	Bootstrapping
D	Squash	Fruit-Bearing Vegetables	Vegetables and Melons	essential		0.90	0.95	1.00	0.90	Klein *et al.* 2007	Monte Carlo
D	Strawberries	Berries	Fruits and Nuts	modest		0.20	0.37	0.19	0.57	Field Studies	Bootstrapping
I	Sugarbeets	Sugar Beet	Sugar		0.10	0.10	0.10	0.10	0.10	Southwick/Calderone	Monte Carlo
D	Sunflower	Other temporary oilseed crops	Oilseed Crops	modest		1.00	0.96	0.89	0.99	Field Studies	Bootstrapping
D	Sweet Potatoes	Sweet Potatoes	Root,tuber crops with high starch or insulin content		0.10		0.10			Southwick	Point Estimate, No Uncertainty Analysis
D	Tangelos	Citrus Fruits	Fruits and Nuts	little	0.20	0.40	0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Tangerines	Citrus Fruits	Fruits and Nuts	little		0.50	0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo
D	Tomatoes	Fruit-Bearing Vegetables	Vegetables and Melons	little			0.05	0.10	0.00	Klein *et al.* 2007	Monte Carlo

D	Turnips	Root, bulb, or tuberous vegetables	Vegetables and Melons	great	0.65	0.89	0.41	Klein *et al.* 2007	Monte Carlo
D	Watermelon	Fruit-Bearing Vegetables	Vegetables and Melons	essential	0.95	1.00	0.90	Klein *et al.* 2007	Monte Carlo

Appendix A.3 Pollination Value

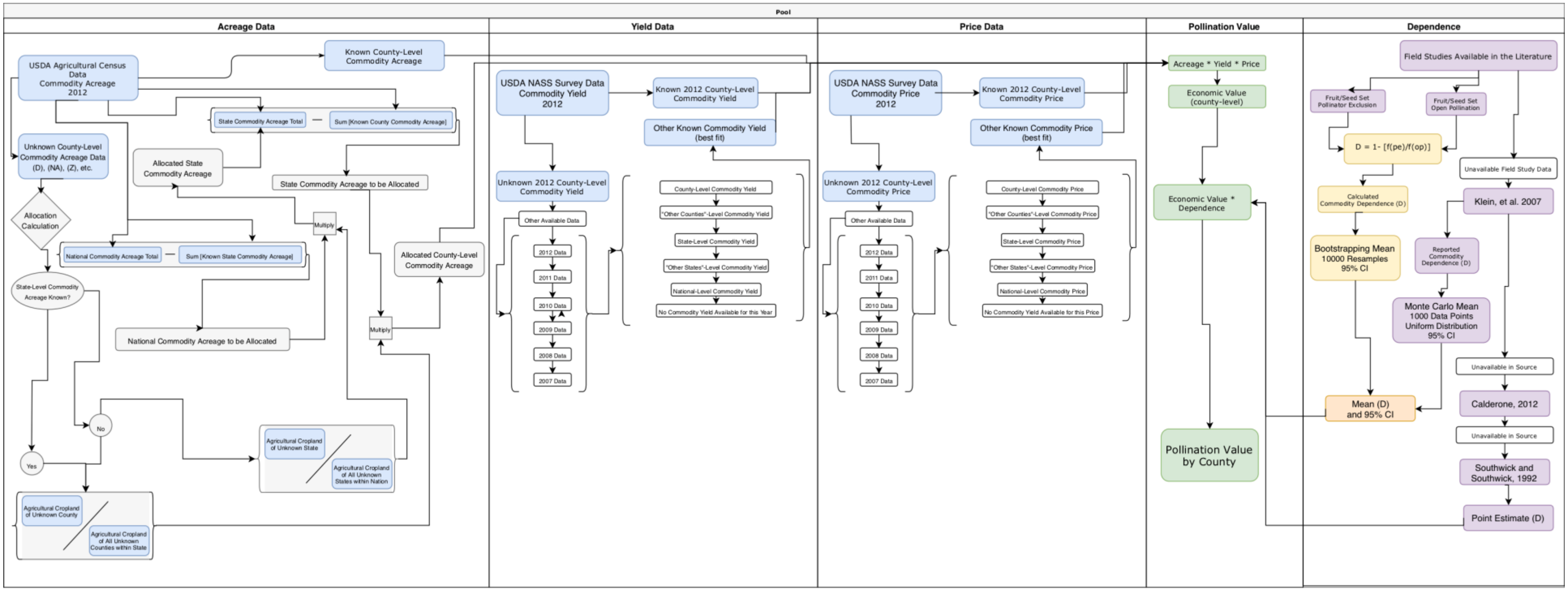


Figure 19. Flowchart depicting methodology to calculate county-level pollination value

Appendix B Spatial Analysis

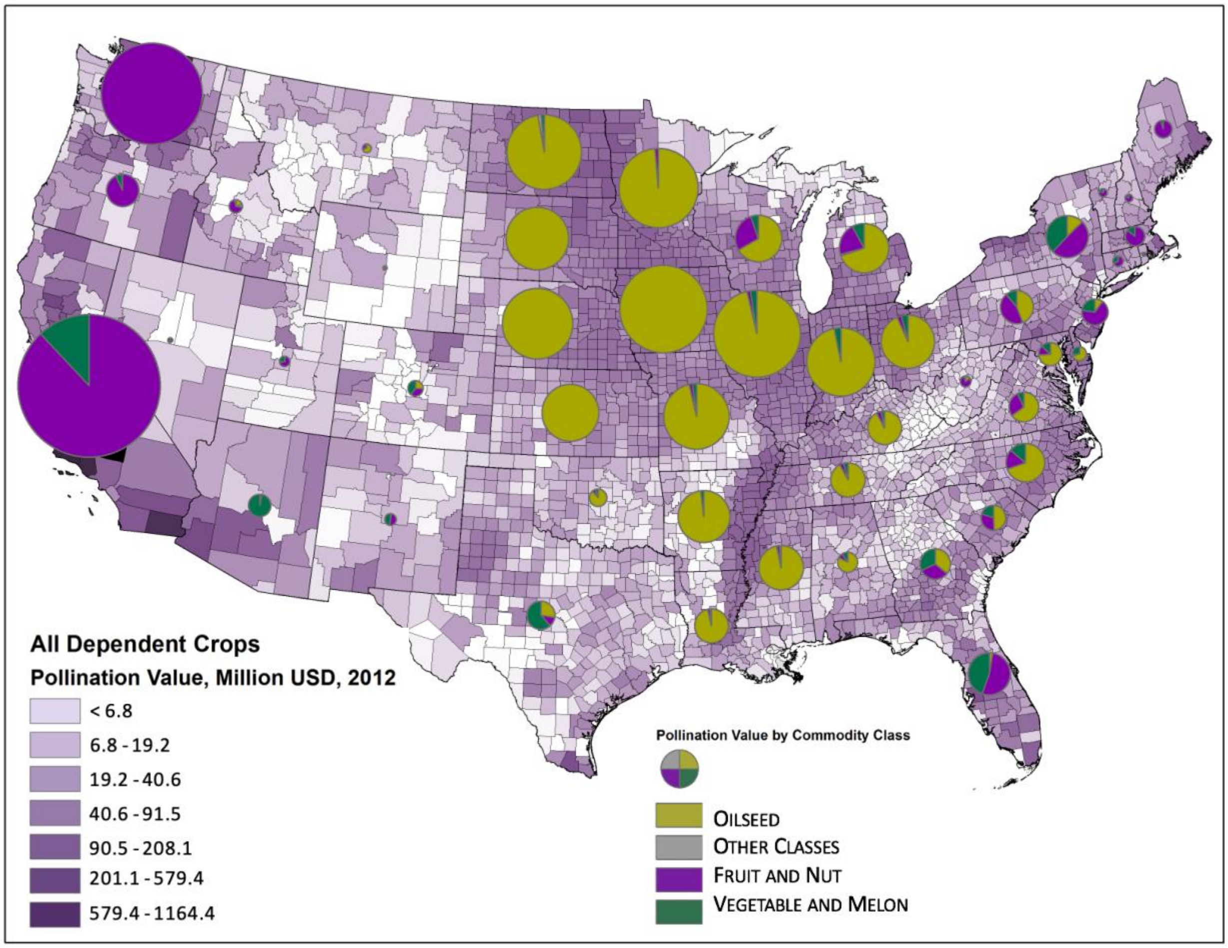


Figure 20. Average total pollination value mediated by insects both directly and indirectly, millions USD (2012) per county. White counties indicate a pollination value calculated from values that are lower than USDA reporting thresholds. Circle charts represent composition of commodity classes of crops represented in each county. Circle sizes are scaled by total county pollination value.

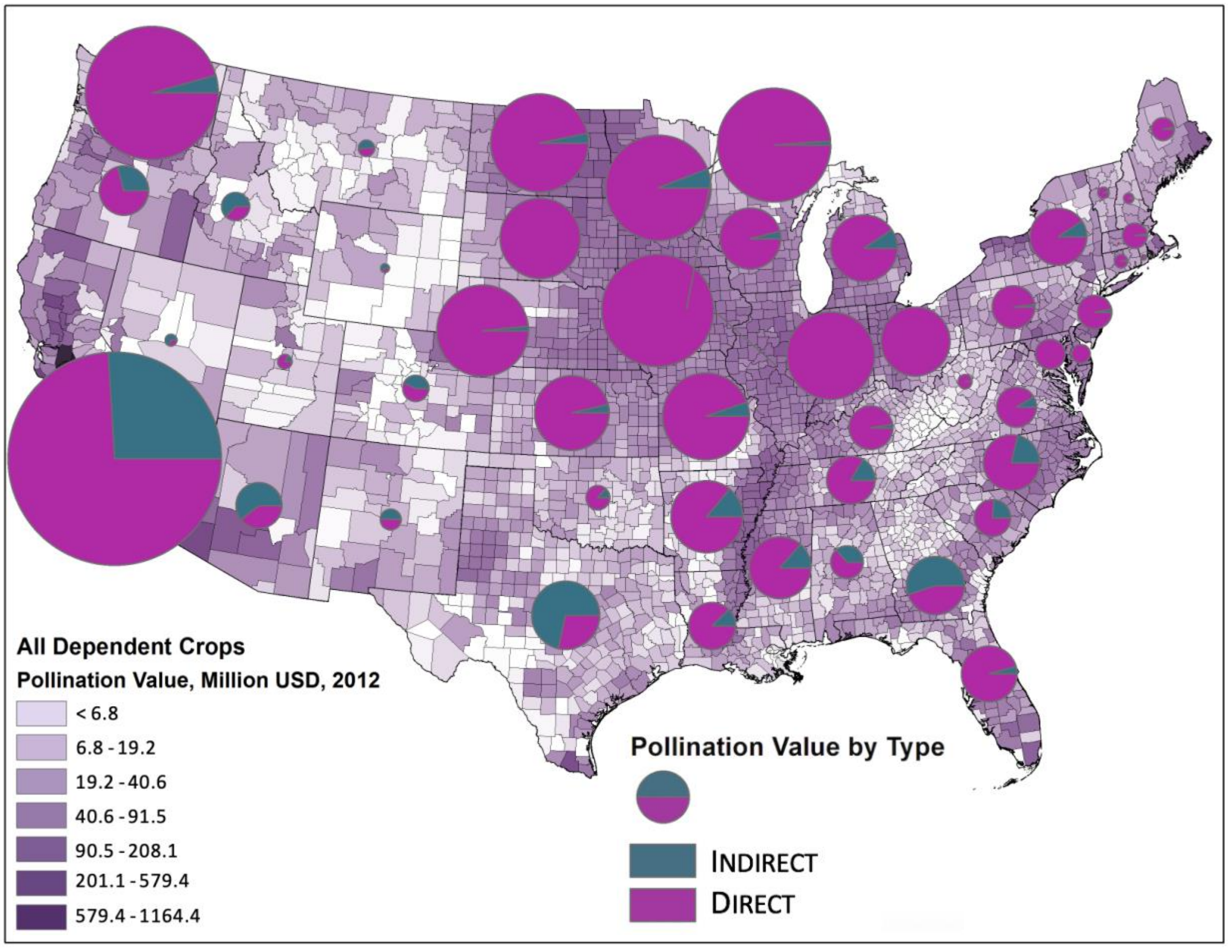


Figure 21. Average total pollination value mediated by insects both directly and indirectly, millions USD (2012) per county. White counties indicate a pollination value calculated from values that are lower than USDA reporting thresholds. Circle charts represent proportion of indirectly vs. directly pollinated crops represented in each county. Circle sizes are scaled by total county pollination value.

The county-level pollination value data best follow Pareto distribution (80 percent of total value is represented by 20 percent of the counties).

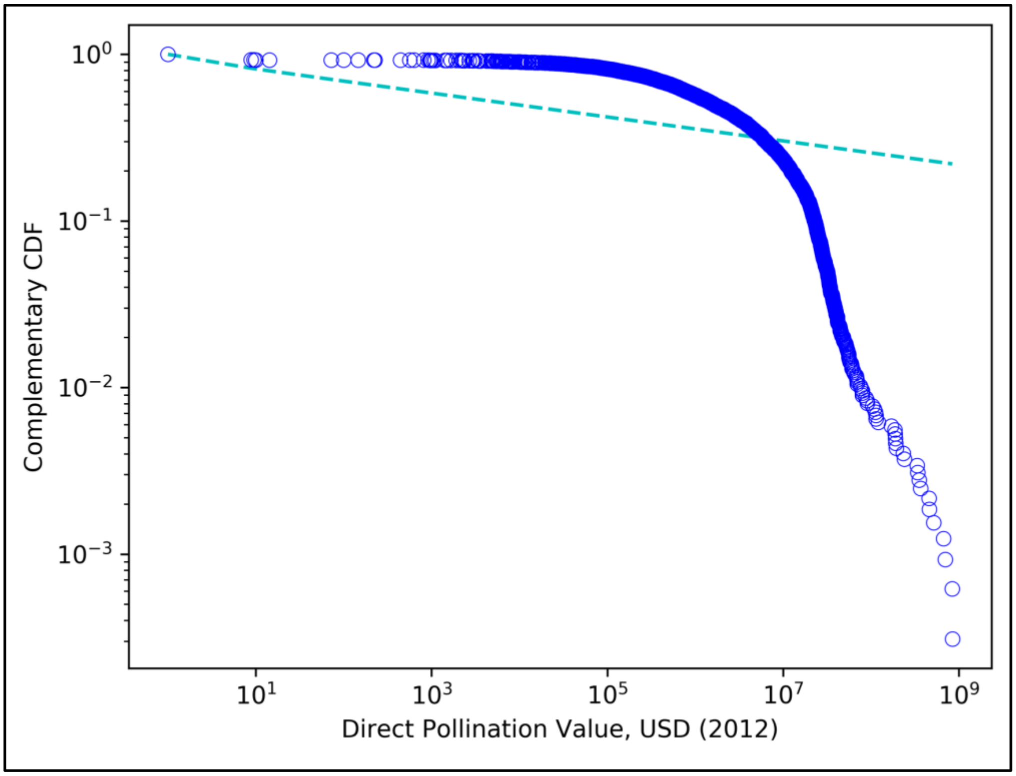
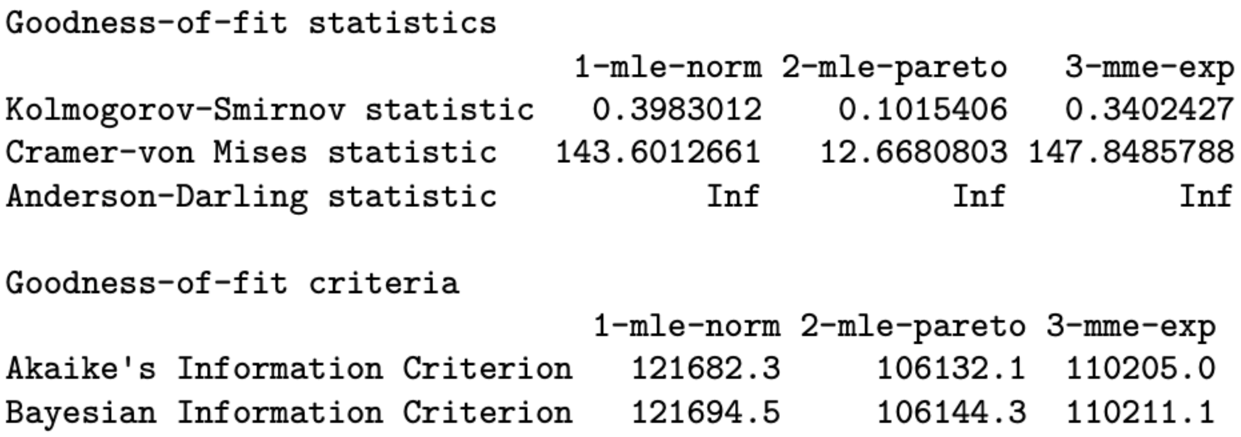


Figure 22. Cumulative distribution function of pollination value of directly-dependent crops (blue) and the maximum likelihood power-law fit (cyan, dotted) of the distribution for US counties in 2012 (alpha= 1.07, sigma= 0.0013).



```
Goodness-of-fit statistics
                             1-mle-norm 2-mle-pareto   3-mme-exp
Kolmogorov-Smirnov statistic  0.3983012    0.1015406   0.3402427
Cramer-von Mises statistic  143.6012661   12.6680803 147.8485788
Anderson-Darling statistic          Inf          Inf         Inf

Goodness-of-fit criteria
                               1-mle-norm 2-mle-pareto 3-mme-exp
Akaike's Information Criterion   121682.3     106132.1  110205.0
Bayesian Information Criterion   121694.5     106144.3  110211.1
```

Figure 23. Associated goodness-of-fit statistics for distribution testing of pollination value by county. The data were tested against normal, Pareto, and exponential distribution.

Appendix C Economic Details

County-Level Sums

Total pollination value (indirect and direct), sum of county-level data, using 95% CI lower bound, upper bound, and mean crop dependence coefficients:

Low: $30.496 billion 2012
High: $39.260 billion 2012
Mean: $34.873 billion 2012

Direct-pollination value, sum of county-level data, using mean dependence coefficients: $30.005 billion 2012

Indirect-pollination value, sum of county-level data, using mean dependence coefficients: $4.868 billion 2012

Appendix D

Appendix D.1 Additional Description of Mixed IO Model

If there are ***n*** sectors in the economy out of which the first ***k*** sectors are endogenous elements and the last ***(n-k)*** sectors are exogenous elements, this new mixed exogenous/endogenous variable IO model is defined as:

$$\begin{bmatrix} \boldsymbol{P} & \boldsymbol{0} \\ \boldsymbol{R} & -\boldsymbol{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{X} \\ \boldsymbol{Y} \end{bmatrix} = \begin{bmatrix} \boldsymbol{I} & \boldsymbol{Q} \\ \boldsymbol{0} & \boldsymbol{S} \end{bmatrix} \begin{bmatrix} \bar{\boldsymbol{Y}} \\ \bar{\boldsymbol{X}} \end{bmatrix} \qquad [7]$$

where:

P is the ***k*** × ***k*** matrix containing elements from the first ***k*** rows and the first ***k*** columns in ***[I-A]***;

R is the (***n- k***) × ***k*** matrix containing elements from the last (***n-k***) rows and the first ***k*** columns of ***[I-A]***;

X is the ***k***-element column vector containing elements X_1 through X_k, the total output of the non-supply-constrained sectors (to be estimated);

Y is the (***n- k***)-element column vector with elements Y_{k+1} through Y_n, the final demand of supply-constrained sectors (to be estimated);

Q is the ***k*** × (***n-k***) matrix of elements from the first **k** rows and the last (***n-k***) columns of –***[I-A]***;

S is the (***n-k***) × (***n-k***) matrix of elements from the last (***n-k***) rows and columns of –***[I-A]***;

$\bar{Y}$ is the ***k***-element column vector of elements Y_1 through Y_k representing exogenous final demands of non-supply constrained sectors (known); and

$\bar{X}$ is the (***n-k***)-element column vector of elements X_{k+1} through X_n, representing exogenous total outputs of the supply constrained sectors (agricultural)[30].

Rearranged, *Equation* 7 can be:

$$\boldsymbol{M}\begin{bmatrix}\boldsymbol{X}\\\boldsymbol{Y}\end{bmatrix}=\boldsymbol{N}\begin{bmatrix}\overline{\boldsymbol{Y}}\\\overline{\boldsymbol{X}}\end{bmatrix} \qquad [\mathbf{8}]$$

where

$$\boldsymbol{M}=\begin{bmatrix}\boldsymbol{P} & \mathbf{0}\\\boldsymbol{R} & -\mathbf{1}\end{bmatrix} \qquad [\mathbf{9}]$$

and

$$\boldsymbol{N}=\begin{bmatrix}\boldsymbol{I} & \boldsymbol{Q}\\\mathbf{0} & \boldsymbol{S}\end{bmatrix} \qquad [\mathbf{10}]$$

The total output (***X***) for the first ***k*** non-supply-constrained sectors and the final demand (***Y***) for the last ***n-k*** supply-constrained sectors can be determined using:

$$\begin{bmatrix}\boldsymbol{X}\\\boldsymbol{Y}\end{bmatrix}=\boldsymbol{M}^{-\mathbf{1}}\boldsymbol{N}\begin{bmatrix}\overline{\boldsymbol{Y}}\\\overline{\boldsymbol{X}}\end{bmatrix} \qquad [\mathbf{11}]$$

The mixed IO model is also known as the supply-constrained model and importantly allows for the exogenous definition of the disrupted sector, estimating impacts on non-supply-constrained sectors as above, given some disruption in the outputs of supply-constrained sectors[105]. With the mixed IO model, one can exogenously specify the final demand (***Y***) for some sectors and the total output (***X***) of remaining sectors. This is an important distinction between the mixed IO model and demand-driven models (i.e. Leontief's traditional model) or supply-driven models which only exogenously specify either final demand or value-added, respectively. The mixed model IO is linear by nature, assuming linear relationships between industries although this is not necessarily the case[30]. Increasing or decreasing outputs do not necessarily require proportionate increases or decreases in inputs or vice versa. The model is simplified in this way. For the size and scope of the data involved, this is a necessary simplification.

Appendix D.2 Model Crop Information

Almonds

Production Value:

4.875 billion USD

Direct Pollination Value:

1.950 billion - 4.388 billion USD, average 3.656 billion USD based on dependence coefficient 95% CI of 0.4-0.9

Indirect Pollination Value (IO):

1.272 billion -2.862 billion USD

Apples

Production Value:

3.527 billion USD

Direct Pollination Value:

3.069 - 3.334 billion USD, average 3.214 billion USD based on dependence coefficient 95% CI of 0.88-0.95

Indirect Pollination Value (IO):

2.004 billion- 2.177 billion USD

Appendix D.3 Additional Almond Results

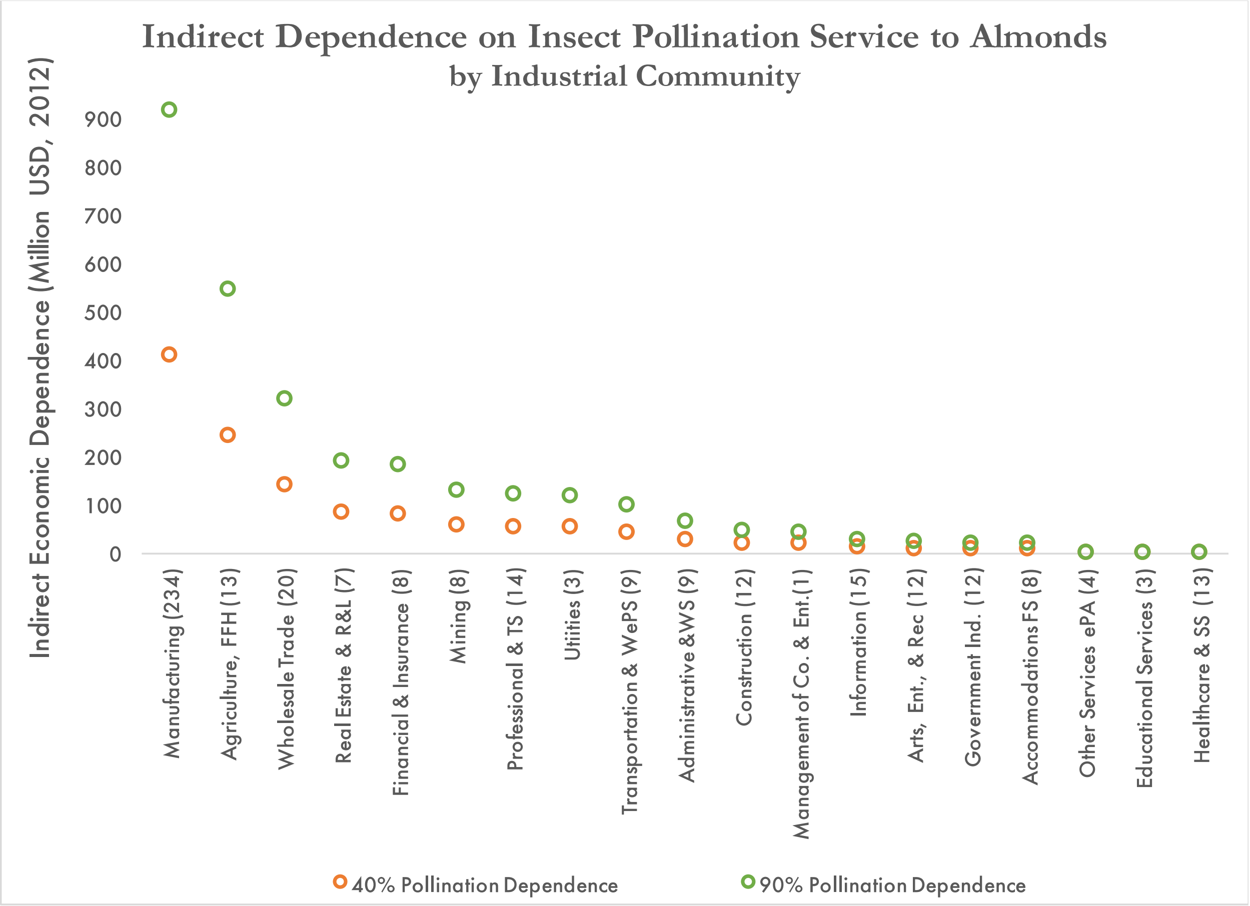


Figure 24. Indirect dependence on insect-mediated pollination service to almonds aggregated by industry communities (labeled on x-axis) for the low and high 95% confidence interval of the almond dependence coefficient as determined by Jordan et al., 2020. The number of industry sectors represented in each industrial community is shown parenthetically by the community name.

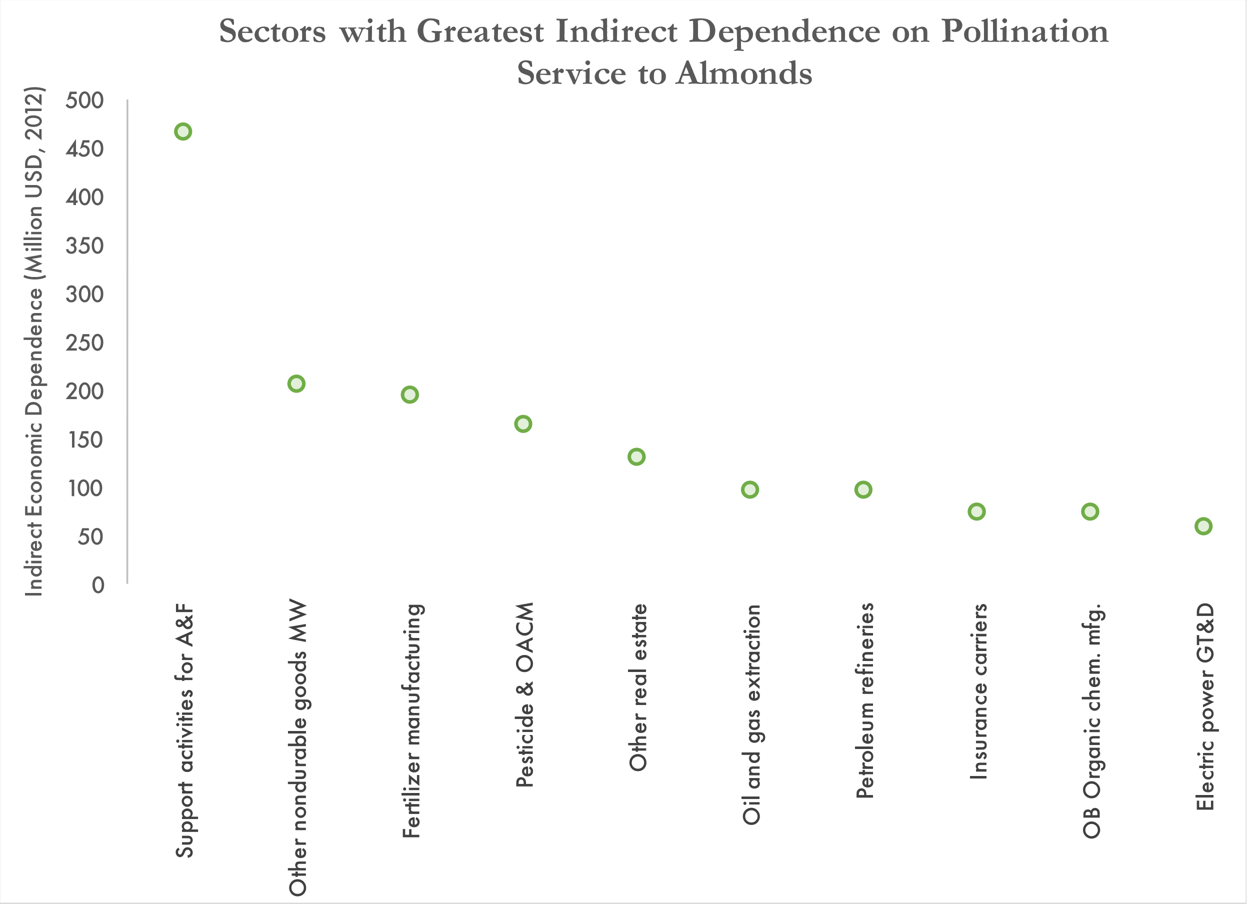


Figure 25. Top ten sectors with indirect dependence on insect-mediated pollination service to almonds in 2012 in millions USD.

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