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Research Article

Economic Risk of Bee Pollination in Maine Wild Blueberry, *Vaccinium angustifolium*

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Abstract

Recent pollinator declines highlight the importance of evaluating economic risk of agricultural systems heavily dependent on rented honey bees or native pollinators. Our study analyzed variability of native bees and honey bees, and the risks these pose to profitability of Maine's wild blueberry industry. We used cross-sectional data from organic, low-, medium-, and high-input wild blueberry producers in 1993, 1997–1998, 2005–2007, and from 2011 to 2015 ($n = 162$ fields). Data included native and honey bee densities (count/m^2/min) and honey bee stocking densities (hives/ha). Blueberry fruit set, yield, and honey bee hive stocking density models were estimated. Fruit set is impacted about 1.6 times more by native bees than honey bees on a per bee basis. Fruit set significantly explained blueberry yield. Honey bee stocking density in fields predicted honey bee foraging densities. These three models were used in enterprise budgets for all four systems from on-farm surveys of 23 conventional and 12 organic producers (2012–2013). These budgets formed the basis of Monte Carlo simulations of production and profit. Stochastic dominance of net farm income (NFI) cumulative distribution functions revealed that if organic yields are high enough (2,345 kg/ha), organic systems are economically preferable to conventional systems. However, if organic yields are lower (724 kg/ha), it is riskier with higher variability of crop yield and NFI. Although medium-input systems are stochastically dominant with lower NFI variability compared with other conventional systems, the high-input system breaks even with the low-input system if honey bee hive rental prices triple in the future.

Key words: lowbush blueberry, fruit set, yield, net farm income, native bee

Recent declines in the populations of honey bees and native bees have been a concern to the blueberry industry in the United States, particularly the wild blueberry industry in Maine (National Research Council [NRC] 2007). The wild blueberry (also referred to as lowbush blueberry) is the predominant complex of blueberry species cultivated in Maine (predominantly *Vaccinium angustifolium* Aiton; but also: *Vaccinium myrtilloides* Michx, *Vaccinium pallidum* Aiton, *Vaccinium boreale* I.V.Hall & Aalders, *Vaccinium angustifolium* × *Vaccinium corymbosum*) and accounts for about 97% of U.S. wild blueberry total production (Strik and Yarborough 2005, Yarborough 2009, Jones et al. 2014). Recent challenges in maintaining pollinator populations is of particular concern for Maine's wild blueberry industry, as the crop is close to 100% dependent on bees for pollination (Usui et al. 2005, Bell et al. 2009, Yarborough 2012). Population declines in both managed and native bees are caused by a multiplicity of factors, namely, fragmentation and degradation of habitats, reduction in resource diversity, pests and pathogens of pollinators, competition from introduced pollinators, climate change, reduced genetic diversity, pesticide use, and colony collapse disorder among other causes (Kluser and Peduzzi 2007, Breeze et al. 2011, Garibaldi et al. 2011, Rucker et al. 2012).

Maine is the largest producer of wild blueberry, *Vaccinium angustifolium* Aiton, in the United States. The plant is a perennial shrub that spreads by underground rhizomes, with aerial shoots occurring every 2–30 cm, and are not generally planted but establish after cutting forested landscapes. New shoots can take 6–8 wk to come into full production and can remain for 50 yr or more (Barney et al. 1992). Managed wild blueberry fields operate on a 2-yr cycle where half of the total area produces fruit each year (Hunt et al. 2006). Fields are pruned by mowing or burning during the fall after harvest or in the spring of the following prune year to ensure new growth and improved yields during the harvest year.

Wild blueberry plant yields are impacted by a number of factors, but the most important is bee pollination, measured by fruit set. The plant requires insects, predominantly bees, to cross-pollinate flowers. Greater bee visitation to flowers form more seeds, resulting in larger fruits that ripen earlier and more evenly (Usui et al. 2005, Yarborough 2012). Compared with honey bees, 59 native bee species associated with wild blueberry are very efficient and effective pollinators (Drummond 2002); however, many have shorter travel distances which make pollinating the centers of large wild blueberry field monocultures challenging. The honey bee is predominantly used to pollinate blueberry fields because of its greater foraging distance compared with native bees, availability and pricing in established markets, and ease of management and transport of honey bee hives (Drummond 2002, Yarborough 2009). Conserving native bees and their habitats are also important for the wild blueberry industry in Maine (Drummond and Stubbs 2003) owing to global pollinator decline resulting from habitat loss, pesticides, invasive species, parasites and diseases, climate change, and predators (Gleer 1999, NRC 2007).

Reductions in both wild and commercial bee populations could negatively impact the sustainability of the blueberry industry in the United States, and Maine, in particular, because wild blueberry has the second largest honey bee hive rental following California almonds with 74,800 hives imported in 2013 (Jennifer Lund, Maine State Apiarist, personal communication). Increases in the cost of rented honey bee hives could limit profitability in the short run. Higher production costs cause producers to exit the industry in the long run, resulting in reduction of wild blueberry supply. This combined with global increases in demand for wild blueberries for their health benefits (Hu et al. 2009) may increase crop prices, thus offsetting these higher production costs.

The economics of pollination has been the focus of several recent studies, although much of this work has been from a global perspective. Economic vulnerability of bee-pollinated crops has been estimated (Gallai et al. 2009), and the economic value of bee habitat and biodiversity has been calculated for crop pollination (Pimentel et al. 1997, Ricketts et al. 2004, Venturini et al. 2017a). However, the effects of uncertainty and risk that the variation in bee foraging density poses on net farm income (NFI) of specific crop enterprises is still largely unknown, with the exception of a few studies on specific crops (Kasina et al. 2009, Winfree et al. 2011). This paper will contribute to filling the gap in economic uncertainty knowledge by investigating the economics of bee count variability and the risk this poses to the profitability of the wild blueberry industry in Maine. The goal of this paper is to investigate the economic risk posed by differences in managed and native bees observed in Maine's conventional and organic wild blueberry systems. The specific objectives are to: 1) estimate fruit set and yield models of wild blueberries, and assess the relative importance of native bees and honey bees in these models, 2) estimate the risk associated with native bee and honey bee variation on the NFI of organic, low-input, medium-input, and high-input farming systems, and 3) estimate the impacts that honey bee hive rental cost and honey bee stocking density as well as native bee densities have on the relative profitability of these farming systems.

Materials and Methods

Data Sources and Description

This study uses cross-sectional data sampled from wild blueberry farms in Maine. The data collections were performed during 162 field samplings over 11 yr: 1993, 1997–1998, 2005–2007, and from 2011 to 2015. Using the farming system classification by Chen et al. (2017), wild blueberry production is grouped into organic and conventional (low-, medium-, and high-input) farming systems (Table 1) in increasing order of intensification and chemical use. Conventional systems unlike organic ones use synthetic chemicals.

Table 1. Distribution of wild blueberry farming systems for field survey data

	Farming systems			
	Organic	Low input	Medium input	High input
1993	0	24	8	2
1997	2	6	6	4
1998	1	5	6	4
2005	0	0	4	3
2006	0	8	0	0
2007	0	0	5	2
2011	3	3	3	3
2012	1	7	8	0
2013	4	4	5	3
2014	3	7	2	0
2015	4	4	5	3
Total	18	68	52	24

Native bees tend to be exclusively relied upon for pollination by organic producers owing to low capital requirements of this system and also because of the diverse floral resources that typically occur on and surrounding these types of farms that can enhance native bee populations (Drummond and Stubbs 2003, Drummond et al. 2009b). Conventional systems are likely to have fewer native bees associated with them owing to higher likelihoods of pesticide exposure to bees and intensified weed control which reduces alternate bee forage both before and after blueberry bloom (Drummond et al. 2017, Yarborough et al. 2017). This in addition to larger scales of production cause conventional producers to mostly rely on honey bees for their pollination needs, usually at stocking densities of 4.5–12.5 honey bee hives per hectare (ha; Drummond 2002).

In field-surveyed commercial blueberry fields, sampling was done for bee population abundances and density. An index of bee abundance was estimated for each field two to three times during bloom. At each visit from 1993 to 2015, 10–20-m^2 quadrats of blooming crop (representing 10–20 clones at each sample date) were arbitrarily selected, and for 1 min, the number of honey bees and wild native bees foraging on the bloom were counted and recorded. In 1993, for the first sampling period, five to seven 100- by 1-m belt transects were used to estimate native bee and honey bee abundance. Bees were counted and the time taken to survey the transect length was recorded. The abundance of bees from these transects were converted to bees/m^2/min, so that they could be averaged with square quadrat counts. Bee abundance for each of the 10–20-m^2 sampling quadrats were averaged for each visit and over all the visits for each field. The sampling of bee abundance was only conducted between 0900 and 1500 hours and when the weather was at least partly sunny and warmer than 10 °C, with average wind speed less than a maximum of 30 km/hr. Yields were obtained for each field from wild blueberry producers and converted to kg harvested per ha.

Wild native bees were not identified to species or family, but in Maine wild blueberry, native bees comprise almost 100 species (ranging from 5 to 42 species per field) representing the families *Apidae*, *Andrenidae*, *Halictidae*, *Colletidae*, and *Megachilidae*. Hand collections on blueberry flowers and bee bowl-trapping of the

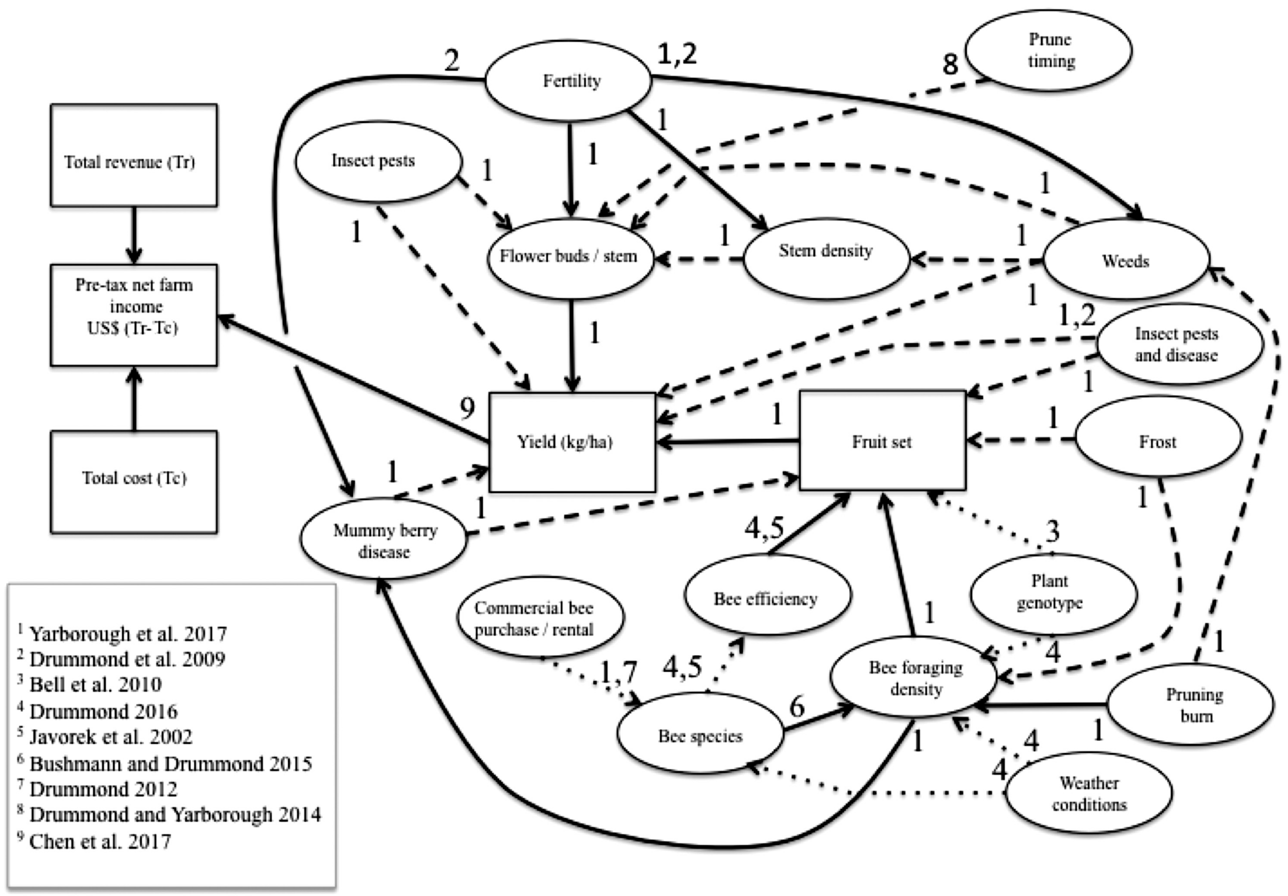

Fig. 1. Conceptual model of wild blueberry bloom (solid arrows are positive causal relationships, dashed arrows are negative causal relationships, and dotted arrows are positive or negative relationships depending upon the independent factor; numbers at base of arrows are literature citations documenting relationships).

bee communities in each field during this study have been partially reported by Bushmann and Drummond (2015), Drummond et al. (2017), and (F.A.D., unpublished data). The relative abundances of the major bee taxa groups found in blueberry fields during this study are bumble bee queens (8–22%), *Andrena* spp. digger bees (15–45%), sweat bees or Halictidae (12–24%), leafcutting and mason bees or Megachilidae (2–5%), and Colletidae (1–3%).

Theoretical Framework

Wild Blueberry Production

Other factors that affect the yield of wild blueberries are weed competition and shading (Yarborough 2009, 2011), soil structure and texture (preferably, 45.72 cm or more of well-drained soils; Barney et al. 1992), pH (Yarborough 2008) and fertilizer needs, especially di-ammonium phosphate fertilizers (Yarborough 2009), irrigation (Hunt et al. 2006, Yarborough 2012), diseases, especially botrytis blossom blight (*Botrytis cinerea* Pers.) and mummy berry (*Monilinia vaccinii-corymbosi* Reade), insect pests, especially blueberry maggot (Strik and Yarborough 2005, Rodriguez-Saona et al. 2015) and more recently *Drosophila suzukii* (Alnajjar 2016), spring frost or cold winter damage (Strik and Yarborough 2005, Rowland et al. 2008), and mulching (Hepler and Yarborough 1991, Yarborough 2009). A conceptual model of the factors that influence wild blueberry pollination is illustrated in Fig. 1. Although this model is supported by published literature, it does not include all the factors that might affect fruit set and yield. However, the model shows that both native wild bees (>120 species, Bushmann and Drummond 2015) and commercially managed honey bees and bumble bees, *Bombus impatiens* Cresson (Drummond 2012), are not the only factors that determine fruit set and subsequent yield.

In our conceptual model, we did not include larger spatial geographic effects on bee community abundance and diversity driven by the landscape structure and function surrounding blueberry fields (Groff et al. 2016). However, within blueberry field effects are numerous. Stochastic factors such as plant genotype composition, weather conditions, and field topography that may determine risk of frost affect fruit set and yield. Also, deterministic factors such as farm management practices impact densities of weeds, insect pests, disease, and fertilization and pruning methods that affect stem density, flower buds and stem, and berry size which contribute to fruit set and yield, and thus economic income and profit in wild blueberry agro-ecosystems. Because farm management is a significant factor, we incorporated farming system for each field to account for these effects on fruit set and yield with our econometric modeling.

Econometric Model

The following framework was used to estimate the parameters of the blueberry yield and fruit set models. As previously discussed, many factors can affect the yield and fruit set of wild blueberries. However, owing to a lack of data availability, many of these variables were not included in our models. The wild blueberry yield and fruit set models are specified as follows:

$$Y_i = \beta \boldsymbol{X} + u_i \quad (2.1)$$

$$FS_i = \alpha \boldsymbol{Z} + v_i \ (2.2) \quad (2.2)$$

$$u_i \sim N(0, \sigma_u^2); \ v_i \sim N(0, \sigma_v^2)$$

where,

Y_i is the yield of wild blueberries per ha for the i[th] farm; $\boldsymbol{X}$ is a vector of independent variables in the yield model, which is composed of the fruit set of the i[th] farm (FS_i), a set of farming system dummy variables representing high-, medium-, and low-input systems. The base dummy is organic with a set of farming season dummy variables (with 2015 as the base dummy) that present 1993, 1997–1998, 2005–2007, and 2011–2015 production seasons; $\boldsymbol{Z}$ is a vector of regressors that include the square root of native bee density, the square root of honey bee density, an interaction term of honey bee and native bee density, and a set of wild blueberry system and production season dummy variables as explained above; β and α are the parameters to be estimated in the model; u_i and v_i are the models' error terms with expected values of zero with errors normally distributed with constant variance. Incorporating farming system into the models essentially controls for variation in field size and honey bee stocking density. Honey bee stocking densities and field size increase with increasing input intensity from organic to high-input wild blueberry systems.

The omission of other variables in the models can potentially cause the coefficients of native bee and honey bee densities to be biased and inconsistent, especially when those factors are correlated with the fruit set of wild blueberries and at the same time with native bee and honey bee counts (Woodbridge 2010). To mitigate this, the system dummy variables in the model account for production-related variables, such as pesticide/fertilizer/herbicide applications, and other cultural practices. Also, the season dummies account for spatial and weather-related factors potentially affecting wild blueberries yield. These are appropriate because the agronomic and weather variables could potentially affect both fruit set and bee pollination. Also, data unavailability did not allow for the right instruments to be used for instrumental variable or two-stage least square estimators, if one or more of the explanatory variables are endogenous. The assumption of homoscedasticity, or constant error variance, was verified in the models using a White test (Woodbridge 2010). Violating the assumption of homoscedasticity can result in unreliable model inferences.

For each specific wild blueberry yield simulation for organic, low-, medium-, or high-input systems, a distribution is specified for each system's native bee density. This can be used to predict fruit set from the estimated fruit set model. As predicted fruit set varies, the predicted yield of wild blueberries will also vary, as fruit set is a proxy for bee pollination. Thus, the variation in predicted fruit set indirectly captures variations in native bee density. Honey bee density was fixed at the average level for the low-input farm, to allow for an unbiased partial analysis of the effect of the variation in native bee density on NFI.

To run risk analyses through wild blueberry system budget models, we defined a model estimating honey bee hive stocking density based on observed production season data (1993, 1997–1998, 2005–2007, and 2011–2015) for honey bee density:

$$SD_i = \gamma \boldsymbol{Z_i} + w_i \quad (2.3)$$

$$w_i \sim N(0, \ \sigma_w^2)$$

where,

SD_i is the estimated stocking density of honey bee hives on the farm; $\boldsymbol{Z_i}$ is the observed honey bee density (count/m^2/min); γ is the parameter to be estimated in the model; and w_i is the error term.

Crop Enterprise Budget Model

The goal of most wild blueberry producers in Maine is to maximize profits. Profit is a random variable, influenced by wild blueberry yield and price of as well as the cost of inputs. The costs incurred during wild blueberry production in Maine have historically been provided through crop budgets based on a few cooperating producers (D'Appollonio and Yarborough 2011). These budgets were upgraded for more detailed revenue and variable and fixed cost accounting through in-depth budget development based on budget interviews of 23 conventional and 12 organic wild blueberry producers. All interviews took place and farm-specific budgets were engineered between 2012 and 2015. Individual farm budget data were summarized and used to construct representative budget models for the different types of wild blueberry farms (organic, low-input, medium-input, and high-input) shown in Supp. Tables 1–3 (online only), respectively. Intermediate farm sizes of 30.35 fruiting hectares for conventional and 5.06 fruiting hectares for organic wild blueberry were used for budget models corresponding to medium-sized farms with typical mechanical and hand equipment typically used by both farm types, respectively.

The most important factor in estimating profit is marketable wild blueberry yield, which is a result of crop fruit set as influenced by the densities of managed or rented honey bees and native bees on the farm. Fruit set in this paper is defined as an index for capturing bee pollination service. Bee densities, fruit set, and wild blueberry yields were measured or obtained from farmers during field studies. Other factors impacting crop yield (Fig. 1) were not directly surveyed from producers and farms such as rainfall during berry ripening and bulking, field renovation and weed pressure, soil structure and soil pH, weather conditions conducive for disease, and timeliness of harvest. So, these additional drivers of yield were not formally included in our wild blueberry fruit set and yield models. However, 10-yr average wild blueberry crop yields per area were obtained from the 35 producers surveyed during budget interviews in addition to 45 other wild blueberry producers surveyed between 2012 and 2013 ($n = 80$) as part of a shorter pollination practices survey.

The yield model was used to predict yield to estimate crop revenues and profits. Actual wild blueberry yields obtained from producers were used to adjust yield model estimates for budget calculations. In estimating the total revenue (predicted yield multiplied by unit price of wild blueberries), the price of processed frozen wild blueberries was used for the simulation analysis of conventional farms, as about 99% of the Maine wild blueberry crop is frozen and sold as processed compared with about 1% that is sold fresh (Yarborough 2009). Organic lowbush blueberries enjoy a price premium, which was accounted for in our whole-farm budget for organic fresh-pack. Thus, we built such a premium into our enterprise budgets and risk analyses.

Total cost is the sum of both variable and fixed costs. Variable costs, such as rented hives, labor, and fuel, change with the quantity of wild blueberries produced. The price of honey bee hives was set to an average of US$104.20/hive for conventional and US$94.62/hive for organic producers surveyed during economic interviews (2012–2015). Yield-dependent variable costs such as berry transportation after harvest were engineered into enterprise budgets (Kay et al. 2016) associated with each farming system. Wild blueberry tax is also yield dependent and is the product of the unit tax per kilogram (kg) of wild blueberries (US$0.0165/kg) times yield. Berry transportation from the field to the processor gets more expensive when wild blueberry yield increases. Fixed costs such as equipment depreciation do not change in the short-run time horizon of an annual budget. Net farm income (NFI) is obtained by subtracting total cost from total revenue and is a long-run measure of profits, as it accounts for both variable and fixed costs. Return over variable costs (ROVC) is a short-run profitability measure, as it only subtracts variable costs from revenues.

Native Bee and Honey Bee Risk Analysis

The task of simulation modeling is to quantify the production and profitability risk associated with uncertainties in the availability of native bees and honey bees, as well as the price of honey bee hives. The usual measure of risk in the financial literature is variance or standard deviation (Benassay 2011), while more complex analyses involve comparing cumulative distribution functions (CDF's) of contrasted agricultural system profits (measured as NFI) to determine their comparative stochastic dominance (Hardaker et al. 2004). Cumulative distribution functions that are exclusively to the right of others are economically preferable from a stochastic dominance perspective, as all NFI outcomes are greater.

Using both farm data from field sampling and the @Risk simulation software (Palisade 2016), actual observed wild blueberry yields combined with rented honey bee hive density observed at each farm in each field season were used to calculate NFI using representative budgets. Net farm income (NFI; US$/hectare) over the seasons for the different wild blueberry systems were each graphed as a CDF, where system A is first-order stochastically dominant to system B if its CDF is entirely to the right of system A with higher profits. However, if the CDF's for both A and B cross, second-order stochastic dominance is determined by comparing the areas under both functions, where x* is the maximum NFI value for each CDF:

$$\int_{-\infty}^{x*} F\mathrm{A}(x)dx \leq \int_{-\infty}^{x*} FB(x)dx \qquad (2.4)$$

In other words, if the area under the CDF for system A is less than the area under the CDF for system B, A is preferred to B from an economic risk perspective. Even though the mean NFI of system B may be greater than system A, it is assumed farmers are risk adverse, which means they are willing to accept a lower average NFI if this means less variability in profit outcomes. Thus, a wild blueberry system is less risky if the cumulative profit outcomes under the CDF is less subject to variability and is smaller than a system that is more at risk. Both first- and second-order stochastic dominance assume farmers are risk averse. Additional stochastic dominance with respect to a function analyses can be conducted where different levels of risk aversion or risk taking can be assumed (Hardaker et al. 2004).

For stochastic dominance simulation comparisons for organic and all three conventional systems, declining exponential functional forms were fit to both honey bee and native bee densities (count/m^2/min) for all four systems using @Risk. Using the fruit set equation (2.2) and wild blueberry yield equation (2.1) we econometrically estimated, @Risk was set to randomly sample (1,000 times) from the declining exponential functional forms specified to fit bee densities to stochastically generate both fruit set and crop yield. Equation 2.3 that was also econometrically estimated for honey bee hive stocking density used the same 1,000 random draws of field-sampled honey bee density (count/m^2/min) to generate honey bee hive stocking densities.

Stochastically generated crop yields (part of total revenue) and honey bee hive stocking densities (impacting variable cost) were then run through our budget models to generate 1,000 NFI values in total, per ha, and per unit of crop production volume (liter). Simulated NFI values for all four systems were then comparatively graphed using @Risk. Conventional (low-, medium-, and high-input) systems used the fruit set equations we estimated for honey bees, while organic used the fruit set equation we estimated for native bees. Stochastic simulations had crop yield adjusted to the average yield calculated from field-sampled fruit set over all 11 field seasons. Also, as wild blueberry crop yield is impacted by other factors (weeds, disease, precipitation, etc.) not included in our yield equation (2.1), stochastically simulated yields were also adjusted to 10-yr average crop yields surveyed during budget interviews with cooperating producers for all four systems. These yields were lower than those averaged over all 11 field experiment years.

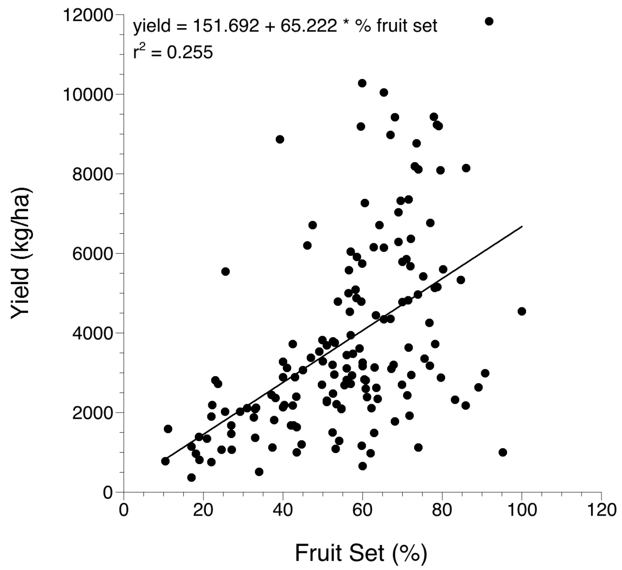

Fig. 2. Relationship between wild blueberry yield, and fruit set.

Results and Discussion

Descriptive Analysis

There is a positive relationship between yield and fruit set (Fig. 2; $F_{(1,156)} = 54.831$, $P < 0.0001$, $r^2 = 0.255$). This is expected because fruit set is a determinant of the potential yield of wild blueberries (Fig. 1). Also, there are positive relationships ($P < 0.05$, r^2 ranged from 0.081 to 0.102) between fruit set and bees/m^2/min for honey bees (Supp. Fig. 2 [online only]), native bees (Supp. Fig. 3 [online only]), and total bees (Supp. Fig. 4 [online only]; native bee and honey bee densities are square-root transformed in our fruit set predictive model). The effect of the square root of native bee density on fruit set is 2.43 times greater than that of the square root of honey bee density (see Table 2; slopes are 6.122 and 14.880, respectively, for square root honey bees and square root native bees), suggesting that native bees on an average are more efficient pollinators than honey bees on a per bee basis, despite native bees being sampled at lower densities than honey bees (Supp. Fig. 6 [online only]).

An analysis of variance (square-root transformed honey bee densities, ($F_{(3,158)} = 49.841$, $P < 0.0001$) shows that the high-input system had the highest mean count (14.68 bees/m^2/min) of honey bees, followed by the medium-input (3.5 bees/m^2/min). Low-input (1.1 bees/m^2/min), and organic at 0.33 bees/m^2/min were not significantly different from each other, but lower than the medium input system (Supp. Fig. 7 [online only]). This is expected, as theoretically high-input farms rely mostly on honey bees compared with the crop systems. Organic farms at the other extreme do not typically use rented honey bees.

Table 2. Wild blueberry fruit set regression model

Variable Dep. Variable: Fruit Set (percent)	Coefficient	Standard error	*P* - values
Intercept	37.0861	4.188539	<0.0001
Dummy_1993	1.2936	2.92904	0.659
Dummy_1997	−14.1111	4.59677	0.003
Dummy_1998	−11.9996	3.777587	0.002
Dummy_2005	−15.0067	5.978717	0.013
Dummy_2006	17.5508	5.268242	0.001
Dummy_2007	1.4891	5.617996	0.791
Dummy_2011	−2.0510	4.213999	0.627
Dummy_2012	−12.8323	3.710656	0.0007
Dummy_2013	3.1900	3.699573	0.390
Dummy_2014	17.5065	4.183071	<0.0001
High input system dummy	4.1931	3.901514	0.284
Low input system dummy	−4.5188	2.471251	0.069
Medium input system dummy	4.6038	2.052077	0.026
Square-root honey bees (Count/m^2)	6.1217***	1.553611	0.0001
Square-root native bees (Count/m^2)	14.8804***	5.141989	0.004
Interaction of (native bee)$^{0.5}$ and (honey bees)$^{0.5}$	−5.4018	3.146658	0.089

Number of observations = 162, Adjusted R-square = 0.39.
***, **,* denote significance at 1%, 5%, and 10%, respectively.

An analysis of variance conducted to determine the cropping system effect on native bee densities suggested that there was no significant effect ($P = 0.406$). Native bee counts/m^2/min (Supp. Fig. 8 [online only]) for organic were 0.47/m^2/min, high-input were 0.52/m^2/min, medium 0.61/m^2/min, and low were 0.62/m^2/min. It is generally expected that organic farms will have the highest count of native bee density per m^2, followed by low-, medium-, and high-input systems mainly owing to lower pesticide exposure and access to alternative pollen and nectar forage plants (Yarborough et al. 2017). However, this pattern of no difference, on an average, in native wild bee foraging densities among wild blueberry cropping systems was corroborated previously in wild blueberry by Bushmann and Drummond (2015). An explanation of this result may be owing to the findings of Groff et al. (2016) that show that habitat surrounding wild blueberry fields significantly affects native bee community abundance within fields. An exception to this is that large areas of contiguous wild blueberry fields, independent of the cropping system, tend to have significantly lower densities and richness of native bees (Bushmann and Drummond 2015).

An analysis of variance showed that percent fruit set was significantly different among farming systems ($F_{(3,158)} = 5.374$, $P = 0.002$). Given that fruit set is an indicator of pollination service, it is not surprising that the high-input system has the highest mean fruit set (66.5%). Fruit set in the medium-input system (58.3%) was not significantly different from the high input and not significantly different from low-input (51.2%) and organic at 49.1% which were both different from high input (Supp. Fig. 9 [online only]). Wild blueberry mean yield is highest ($F_{(3,154)} = 26.261$, $P < 0.0001$) for high-input (6,167 kg/ha), followed by medium-input (4,610 kg/ha), and then by low-input (2,675 kg/ha), which was not significantly different from organic producing 2,092 kg/ha (Supp. Fig. 10 [online only]).

Fruit Set Model

Year, cropping system, and native bee and honey bee density are significant predictors of fruit set ($F_{(16,145)} = 7.209$, $P < 0.0001$). The fruit set model indicates native bee and honey bee densities (square-root transformed) both have positive and significant ($P < 0.05$) effects on the fruit set of wild blueberries (Table 2). The model explains 39% of the variation in percent fruit set. The interaction term between native bees and honey bees is negative, although not significant. It has been observed in other ecosystems that honey bees can suppress pollen foraging of certain native bees such as bumble bees (Huryn 1997, Thomson 2004). However, flight cage studies in wild blueberry has shown that positive synergistic effects can occur in pollen deposition on stigmas when honey bees visit flowers previously visited by bumble bee queens (Drummond 2016).

Year is also significant (relative to the base year of 2015). One would expect year to have a large effect of wild blueberry fruit set, as weather affects frost incidence, mummy berry flower infection, the number of suitable foraging days during bloom, nectar secretion, and length of stigma viability (Barker et al. 1964, Bell et al. 2009, Starast et al. 2012, Selås et al. 2015, Drummond 2016, Yarborough et al. 2017). In addition, because different fields were surveyed each year, the genetic structure of plants varies from field to field and this greatly affects fruit set (Bell et al. 2010). Cropping system also significantly affects fruit set. This is not surprising as stem density and flower density per stem varies by cropping system, and the management of insect pests that attack flowers, mummy berry disease, and weeds that might compete for pollinators all vary by cropping system (Yarborough et al. 2017). Across all of the cropping systems, the average portioned variance explained in fruit set (partial r^2) for year was 75.4%, for honey bees was 16.4%, and for native bees was 8.2%. Although year can be seen to drive the variance in fruit set (Table 2), bee foraging density is not totally independent of year as the model would suggest.

Yield Model

Bee foraging densities are not a good predictor of yield ($P > 0.05$). This is most likely owing to the numerous other factors that affect yield (Fig. 1, Yarborough et al. 2017; pests and pest management, fertility, irrigation, weather, and time of harvest). However, fruit set is a good predictor of yield, as it is a requisite of yield (Bell et al. 2009). The best predictive model for yield included fruit set, year, and cropping system ($F_{(14,143)} = 20.691$, $P < 0.0001$). The yield model indicates fruit set has a significant (1% level) positive effect on wild blueberry yield (Table 3). Also, yields in high-input were higher than the medium-input farming system, and both of these systems had comparatively higher yields than the low-input and organic systems (see Supp. Fig. 10 [online only]). The yield model explains 63.7% of the variation (adjusted r^2) in wild blueberry yield (kg/ha). The partitioned variance explained in yield (partial r^2) was as follows: year, 39.3%; cropping system, 48.9%; and fruit set, 11.8%.

Honey Bee Hive Stocking Model

The honey bee stocking density model is also significant. Here, the number of hives stocked per ha by growers predicts the foraging force of honey bees in the field (the number of honey bees/m^2/min, was square-root transformed to provide homogeneity of variance). The observed honey bee hive density explains about 55.5% of the variation in observed honey bee foraging density for each field surveyed ($F_{(1,160)} = 199.51$, $P < 0.0001$). This model suggests that for every increase in a hive stocked per ha, the square root of foraging honey bees/m^2/min is 0.191 ± 0.014 (se; Supp. Fig. 5 [online only]). Using a nontransformed model for ease of interpretation (hives/ha vs. honey bees/m^2/min), an increase in a hive stocked per ha results in an increase in foraging honey bees/m^2/min of $0.931 + 0.081$ (se).

The proportion of growers that did not stock honey bees in our study was 23.5% ($n = 38$). They mostly constitute growers that operate organic and low-input farming systems. Some of the growers that do not stock honey bees have fields adjacent to those growers who do stock (F. Drummond personal observation), although we have no data that allows us to estimate the proportion. The average hive stocking density by those that did rent hives was 6.4 hives/ha (range: 0.2–23 hives/ha). Current hive stocking recommendations by the Cooperative Extension (Drummond 2002) is 5 hives/ha for fields with adequate native bee densities and 10 hives/ha for fields that have very low native bee densities.

The 23.5% of growers not renting honey bee hives may benefit from pollination owing to spillover of honey bees from neighboring producers also stocking honey bee hives. We suggest that spillover is almost entirely owing to neighbor's hives (managed colonies), as in Maine, feral colonies with >1-yr persistence are rare (Drummond, personal communication). Spillover honey bee foraging density was not directly estimated. However, honey bee foraging density was recorded on farms that did not stock honey bees and is easily estimated by the regression model as a proxy for spillover foraging honey bees. The mean density (back transformed from square root) of honey bee foragers/m^2/min is 0.301 in fields that had no honey bees stocked. This compares with a density (back transformed from square root) of 0.547 honey bees/m^2/min for fields that had a stocking of ~1.0 hive/ha. Therefore, on an average, growers who do not stock honey bees are provided a benefit of 1.0 hive/ha by their neighbors, and this relates to an average increase in fruit set of about 1% (or if this was the only source of pollination, a fruit set of 38.4%) and an average increase in wild blueberry yield of about 0.5%. Because growers do not pay for such spillover pollination from their neighbors, this amounts to an average increase in NFI of US$27.65/ha across all three conventional systems, which is 26.54% of the value of such spillover (1 hives/ha × US$104.20/hive = US$104.20/ha) based on the 2012–2013 surveyed average price for honey bee hive rentals.

Table 3. Wild blueberry yield regression model

Variable Dep. Variable: Yield (kg/ha)	Coefficient	Standard error	*P*-values
Intercept	1,228.1982	442.9019	0.006
Dummy_1993	−1,312.213	281.529	<0.0001
Dummy_1997	−184.9415	338.5379	0.586
Dummy_1998	−290.8469	358.9828	0.419
Dummy_2005	−1,400.959	571.6445	0.016
Dummy_2006	−948.4375	527.0967	0.074
Dummy_2007	−86.74533	530.4166	0.870
Dummy_2011	654.8426	407.362	0.110
Dummy_2012	170.1641	390.3622	0.664
Dummy_2013	2,596.338	358.5678	<0.0001
Dummy_2014	−530.6673	465.567	0.256
High input system dummy	1,805.23	283.0383	<0.0001
Low input system dummy	−403.0334	223.973	0.074
Medium input system dummy	765.369	207.429	0.0003
Fruit set (percent)	44.08039	7.543015	<0.0001

Number of observations = 158, Adjusted R-square = 0.64.

System Risk Comparisons

Comparison of agricultural production and profit risk for organic, low-, medium-, and high-input wild blueberry systems using yield estimates from our fruit set and yield models based on observed fruit set data ($n = 162$) only show clear first-order stochastic dominance, and thus clear economic advantage of medium-input and high-input systems over low-input (Fig. 3), as CDF's for high- and medium-input are both to the right of that for low-input. Organic has higher average net farm income (NFI = US$11,222/ha) than the other systems (−US$1,434 to US$3,610/ha), but a wider variance of profitability outcomes that suggest it is characterized by more risk than any of the conventional systems. Likewise, the high-input is more risk laden than medium-input, as the area under the high-input CDF is greater than the area under the medium-input CDF.

Although 2012 wild blueberry prices received for organic fresh-pack (US$8.58/kg) are 434% higher than the typical conventional

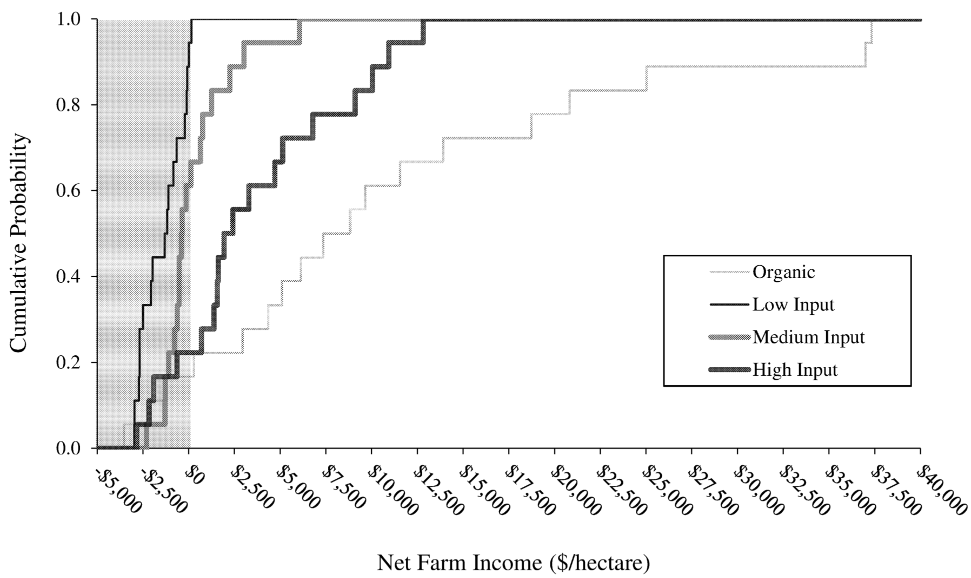

Fig. 3. Stochastic dominance comparisons of wild blueberry system models estimated solely on observed fruit set field data. Negative NFI is shaded.

Table 4. Wild blueberry yields estimated from field data and surveyed from producers during budget interviews

Wild blueberry		Conventional		
Yield (kg/ha)	Organic	Low-input	Medium-input	High-input
Estimated from field data	2,345	2,998	5,167	6,912
Surveyed during budget interviews	724	2,707	3,431	5,433

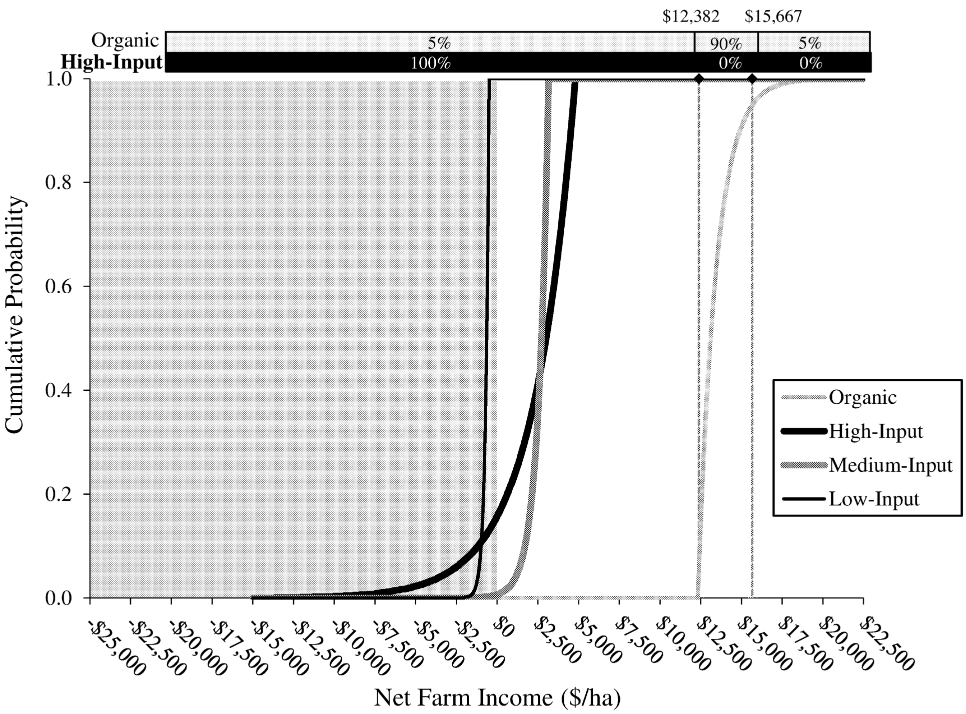

Fig. 4. Field study average crop yield data used for stochastic dominance comparisons of wild blueberry system profitability (US$/ha). Light gray headers indicate 90% of organic NFI distribution is between US$12,382 and US$15,667/ha, while black headers indicate 100% of high-input NFI is <US$12,382/ha. Negative NFI is shaded.

frozen price (US$1.61/kg) for low-, medium-, and high-input models based on our 2012–2013 producer surveys, estimated yields for organic based just on fruit set measured in the field were lower (2,345 kg/ha) compared with the range of simulated conventional yields (2,998–6,912 kg/ha) for low-, medium-, and high-input. Only one cooperating organic grower, of 12 interviewed, had a yield greater than our recorded estimated yield for the organic production system. This organic grower's high yield was likely owing to meticulous hand control of weeds. The 10-yr average wild blueberry yield from surveyed organic growers was only 724 kg/ha (Table 4). The 10-yr average yield from surveyed conventional growers was also lower than the yields that we measured in the field. These differences between measured in-field yields and grower survey estimated yields could be owing to different efficiencies in harvesting fields (mechanical harvested fields generally result in lower efficiency and yields [Drummond personal communication]), grower survey estimates based upon several fields over varying numbers of years, grower survey estimates based upon harvested berries after winnowing operations conducted in the field, or yields reported to growers by processors after sorting and culling fruit not meeting U.S. no. 1 grade. Thus, we evaluated the economic risk for both yield estimates from field data and those surveyed during grower interviews.

Comparing Monte Carlo simulations (1,000 iterations) of all four wild blueberry systems demonstrates clear first-order stochastic dominance of profitability distributions for organic and medium-input systems over low-input when comparing NFI per hectare (Fig. 4) and per liter of wild blueberries (Fig. 6) when higher surveyed crop yields from field-study years are used. The CDF's for medium-input and high-input cross; however, medium-input is less economically risky owing to higher average NFI as well as lower variability of NFI compared with that for high-input. However, when lower crop yields are used from our economic grower surveys, CDF's for all four systems cross (Figs. 5 and 7). Low-input systems have negative NFI across all of their cumulative distributions, whereas medium-input maintains positive NFI more consistently compared with the other three systems with the least variable yields and profitability.

Organic wild blueberry, owing to higher prices received per kg for fresh-pack, is first-order stochastically dominant, and thus economically preferable to all conventional systems when assuming average yields based on field experimental data (2,345 kg/ha), as shown in Figs. 4 and 6. Organic production has 90% of its simulated NFI between US$12,382 and US$15,667/ha (US$3.45–3.72/liter) and only 5% of NFI values <US$12,382/ha (US$3.45/liter), as indicated by the light gray bars above the graph; high-input has 100% of its NFI values <US$12,382/ha (US$3.45/liter) as indicated by the black bars above the graph, while this is true for only 5% of organic NFI values.

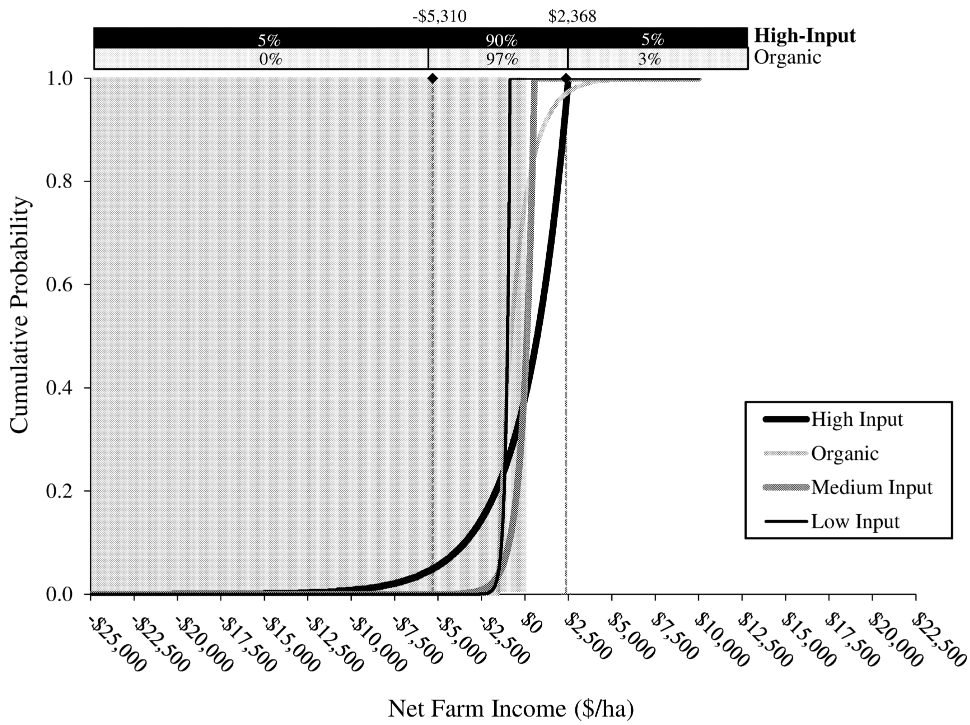

Fig. 5. Producer survey average crop yield used for stochastic dominance comparisons of wild blueberry system profitability (US$/ha). Black headers indicate 90% of high-input NFI distribution is between −US$5,310 and US$2,368/ha, while light grey headers indicate 97% of organic NFI is <US$2,368/ha. Negative NFI is shaded.

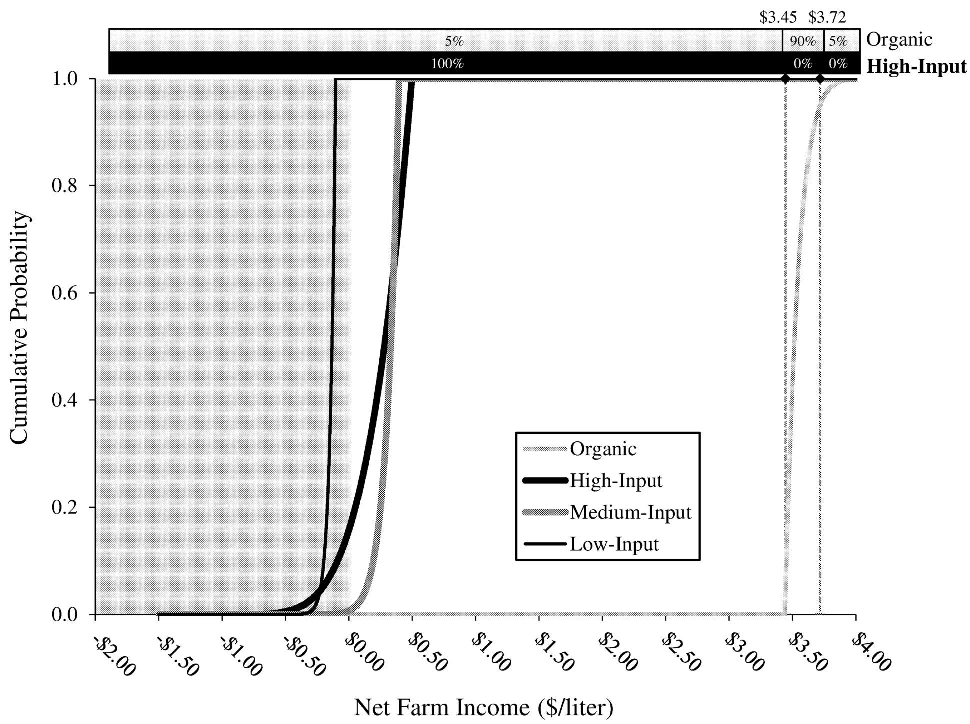

Fig. 6. Field study average crop yield data used for stochastic dominance comparisons of wild blueberry system profitability (US$/liter). Light gray headers indicate 90% of organic NFI distribution is between US$3.45 and US$3.72/liter, while black headers indicate 100% of high-input NFI is <US$3.45/liter. Negative NFI is shaded.

However, organic production is not preferable from an economic risk perspective if average yields (724 kg/ha) from cooperating growers surveyed during budget interviews are used (Figs. 5 and 7). Here, owing to the greater variability in crop yields from the 12 organic growers surveyed, the NFI per hectare and per liter CDF's for the organic system cross those for all three conventional systems (Figs. 5 and 7). Organic only has 90% of its simulated NFI between −US$1.56 and US$1.11/liter, as indicated by the light gray

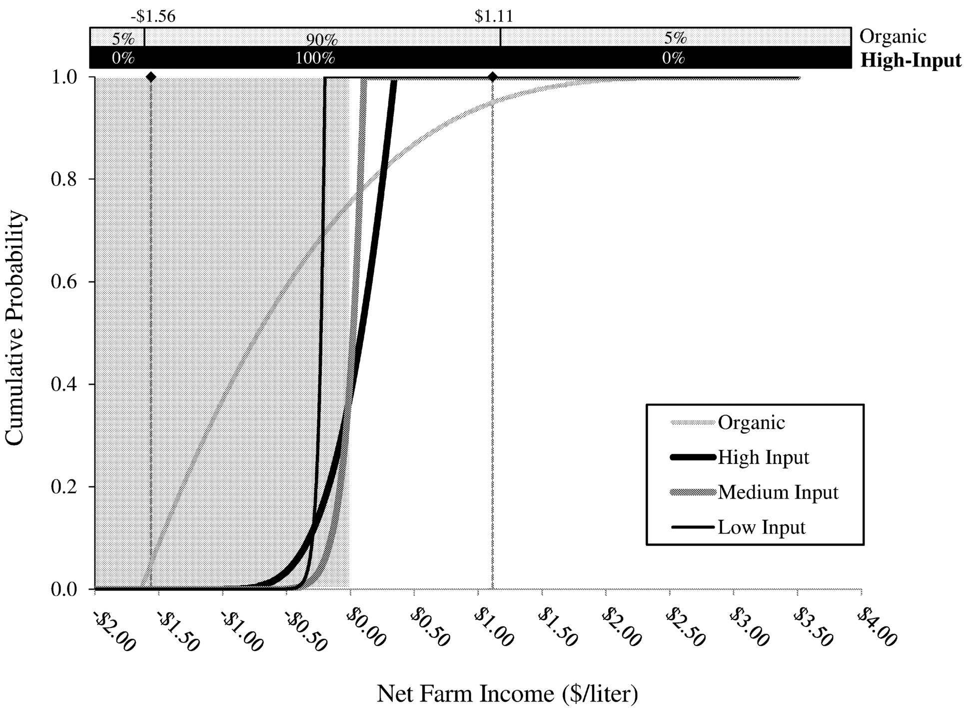

Fig. 7. Producer survey average crop yield used for stochastic dominance comparisons of wild blueberry system profitability (US$/liter). Light grey headers indicate 90% of organic NFI distribution is between −US$1.56 to US$1.11/liter, while black headers indicate 100% of high-input NFI is within this range. Negative NFI is shaded.[TQ3]

bars above the graph, whereas high-input has all NFI values within this range as indicated by the black bars above the graph.

In cases of CDF's that cross each other, second-order stochastic dominance (SSD) is evaluated by comparing the areas under each CDF. Assuming farmers are risk averse, smaller areas under the CDF are preferred which are indicative of less variance in profitability. When comparing both NFI/ha and NFI/liter using higher yields from field studies, medium-input is less profitable than organic, while being more profitable than low-input. Medium-input demonstrated SSD over high-input with a 16% smaller area under its CDF of NFI/ha (Fig. 4). When using lower yields from budget surveys, medium-input has a 55–91% smaller area under its CDF than other conventional and organic systems (Figs. 5 and 7). Thus, organic systems are first-order stochastically dominant (FSD) assuming higher crop yields over all conventional systems. However, when lower wild blueberry yields are assumed, medium-input has FSD over low-input as well as SSD over high-input and organic owing to lower variability in NFI compared with all other systems.

In conclusion, pollination by both native bees and honey bees is essential for wild blueberry fruit set and profitable yields. A one-unit increase in the foraging density of native bees and honey bees ($\sqrt{}$ [bees/m^2/min]) will increase fruit set by 14.9% and 6.1%, respectively; or with untransformed bee densities (bees/m^2/min) fit to the same model, 11.0% and 0.8%. A study conducted by Blitzer et al. (2016) found increasing numbers of wild native bees have an 11.5% marginal impact on seed set in apple production. Fruit and seed set in apples, similar to blueberries, is highly dependent on bee pollination.

Also, the marginal impacts of native bee and honey bee densities on fruit set and yield (which were calculated at their means of 0.58 native bees/m^2/min and 3.8 honey bees/m^2/min, respectively; Supp. Figs. 2 and 3 [online only]) showed that honey bees contribute more to fruit set than native bees owing to their greater numbers outweighing their lower pollination efficiency on a per bee basis (Drummond 2016). Eaton and Nams (2012) also showed that native bee populations have relatively smaller effects on fruit set and yield of wild blueberries than honey bees when one considers the total foraging densities that are present throughout fields during bloom. The marginal impacts are highly dependent on the mean values used in the calculations. For instance, when the means are normalized to 1 (for both native bees and honey bees), a unit increase in the count of native bees and honey bees, increase fruit set by 7.44% and 3.1%, respectively. This means the abundance of bees (native bee and honey bee densities) will have differential impacts on fruit set. Both types of bees are important to fruit set and ultimately yield of wild blueberries. Our study shows that a 1% increase in fruit set will cause a 44.1 kg/ha increase in the yield of wild blueberries when averaged over all production systems and years. Native bees will most likely contribute a greater contribution to pollination of "less pollinator-dependent crops" (i.e., crops with lower flower density/ha, wild blueberry fields average 9,011/m^2 (Bajcz and Drummond 2017)), such as red rape for seed (Ladurner et al. 2002), watermelon (Winfree et al. 2007), and sweet cherry (Holzschuh et al. 2012). In addition, native bee populations should contribute more to crop pollination than honey bee populations if native bee habitat or pollinator reserves are prevalent adjacent to the crop fields (Kremen et al. 2004; Ricketts et al. 2008; Groff et al. 2016; Venturini et al. 2017a, 2017b).

Although organically managed wild blueberries may be more profitable from an agricultural risk perspective, especially if yields are kept competitive to those for low-input systems, there are challenges to the more widespread adoption of this system. Organic systems rely on hand pulling weeds and reducing soil pH from application of sulfur to create an environment less suitable to weeds, as mechanical cultivation is not possible in this system (Drummond et al. 2009a). Although some low-input and medium-input producers use sulfur, hand pulling weeds is replaced by conventional post- and presprout emergent herbicide application(s) and manual or mechanical wiping of weeds with Roundup (glysophate). There are only 60–75 organic wild blueberry growers in Maine (F.A.Drummond, personal communication), which are about 10–18% of all lowbush blueberry producers managing 0.66% of wild blueberry crop area in the state (United States Department of Agriculture, National Agricultural Statistics Service [USDA, NASS] 2010–2013, Rose et al. 2013, Hanes et al. 2013). Challenges to adoption of organic practices for wild blueberry also extend to pollination.

Organic wild blueberry farms also predominantly rely on native bees that can be subject to fluctuating populations and subsequent variability in pollination efficacy. This can cause more variable wild blueberry fruit set, yield, and profit compared with conventional systems relying upon honey bees (Figs. 5 and 7). Assuming organic wild blueberry yield is higher based on field survey data (2,345 kg/ha) from producers with higher than average yields, native bee densities could tolerate a 30% reduction and still be as profitable as the high-input system. In fact, native bee densities in a single field (Winterport, Maine) followed over a 27-yr period suggest that annual fluctuations from the long-term average density 39.2 ± 5.7% with the most extreme fluctuation from one year to the next being 89.75% (Dibble et al. 2017). However, if organic yield is lower (724 kg/ha), more representative of an average organic yield surveyed from producers during budget interviews, native bee densities need to be 54% greater in order for organic to break even with high-input.

The high-input system is not as economically favorable owing to diminishing marginal impacts on fruit set, wild blueberry yield, and profit from adding more honey bee hives beyond what University of Maine Extension recommends (4.5–12.5 hives/ha; Drummond 2002). In years with ideal weather conditions for pollination, overstocking honey bee hives increases costs while not having an appreciable impact on fruit set, crop yield, and revenue. However, there may be certain years and situations where having higher than recommended stocking densities of honey bee hives can be worthwhile. In the past 10–15 yr, weather conditions for pollination have been less ideal with the number of open pollination days in May reduced by half (Dibble et al. 2017). Therefore, stocking higher than recommended densities of rented honey bees may have more positive impacts on wild blueberry profitability in the future if this trend of poor weather conditions continues.

Some low-input and medium-input farms have also over the past couple of decades diversified into having some component of their sales as fresh fruit (referred to as fresh-pack in the industry). Our risk analysis assumes selling to the conventional frozen market that processes 98.8% of wild blueberries sold in Maine (USDA, NASS 2010–2013). Because conventional fresh-pack price (US$4.96/kg) received for berries are higher than prices received for conventional frozen berries (US$1.65/kg) in Maine (USDA, NASS 2010–2013), risk profile CDF's for low-input systems may be more economically competitive relative to the medium-input system. Profitability was greater for individual farmer budgets the more sales were devoted to fresh-pack rather than local freezers. However, the recent establishment of *Drosophila suzukii* has presented challenges for producers processing fresh-packed berries (especially those that are conventional "nospray" not using inorganic chemical insecticides or those that are organic) owing to the additional costs of insecticide applications and other controls such as agricultural fabric covers used during the harvest season.

It is important to remember that NFI is a long-term profit measure that subtracts fixed costs such as equipment depreciation in addition to variable costs like those for labor, sulfur, and fuel. If low-input systems are simulated as having negative NFI (Figs. 4–7), this does not necessarily mean that farmers in this system have no short-run profits or ROVC, as ROVC is positive for low-input (Supp. Figs. 11–14 [online only]). For example, the low-input system budget model using the surveyed average yield (2,707 kg/ha) from cooperating farmer budget surveys has a ROVC of US$1,604/ha while having a negative NFI of –US$1,143/ha. A positive ROVC indicates that the farm is covering all of its variable costs of production on an average, so there is money in the farm's checking account. However, if NFI is negative, capital like equipment cannot be replaced in the long run exclusively from cash flow from crop sales. Our analyses suggest low-input producers could be more profitable in the long run if they transition from conventional to organic, as an average NFI for organic is greater than low-input even though variability of profits can be greater with negative NFI in some years if the farm has low yields. Our budget results for NFI are consistent with wild blueberry producers surveyed who indicated industry anticipated profits over 5 yr as positive for 2 yr, breakeven for 1 yr, and negative for 2 yr.

Although high-input farms are more favorable from an economic risk perspective, their high dependence on rented honey bee hives leave this system open to greater potential uncertainty in terms of profitability. Total annual honey bee hive mortality was about 45% in 2012–2013 owing to colony collapse disorder (CCD) and other factors (Lee et al. 2015). Future potential aggravation of CCD could increase prices for rented hives above the 2012–2013 crop-area weighted average (US$104.20/hive) we surveyed for conventional Maine wild blueberry producers. Because hive rentals are 46% of variable costs for our high-input model, a 205% increase in rented honey bee hive prices to US$317.32/hive would result in the high-input system breaking even with the low-input system. Alternatively, high-input would have higher fruit set, crop yield, and revenues from stocking 36.1 hives/ha to also break even with low-input.

Future analyses should focus on economic budgeting and risk comparisons at small and large sizes for organic (2 ha and 10 ha) and conventional (10 ha and 400 ha) systems in addition to the medium size modeled here as well as on exploring conventional fresh-pack. Economic risk comparisons can also be made between the organic fresh-pack berries modeled here to the recently established organic frozen market where producers receive an organic price premium for their berries over frozen conventional berries but a lower price per kg relative to organic fresh-pack. Organic and low-input farm size tend to be smaller than medium- and high-input. Such lack of economies of scale contributes to unfavorable economic risk. Blueberry consumers have been shown to be willing to pay a 11–16% premium (US$0.51–0.74/liter; Stevens et al. 2015) for berries advertised as being pollinated by native bees, which may offset the lower profits of low-input, high-input, and low-yielding (724 kg/ha) organic relative to medium-input, as this premium is 4–17 times greater than these lower profits per liter relative to the medium-input system.

Our results can help wild blueberry producers know the risk associated with relying on native bees and honey bees on their crop's profitability. This can provide them with insight into managing these risks with appropriate pollination insurance measures such as alternative commercial pollinators: bumble bees, alfalfa leaf cutting bees, native and exotic *Osmia* spp. leafcutting bees; and actively installing pollinator plantings to enhance native pollinator populations (Venturini et al. 2017b). Such risk management can ensure reasonable certainties in their net profits or losses for future planning purposes. It could also assist policy makers and implementers of pollination security practices on farms to propose the appropriate policies and strategies to conserve bees and to sustain the wild blueberry industry in Maine, United States.

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