Assessment of COVID-19 impacts on U.S. counties using the immediate impact model of local agricultural production (IMLAP)

Iman Haqiqi [a,*], Marziyeh Bahalou Horeh [b]

[a] *Department of Agricultural Economics, Purdue University, West Lafayette, IN 47906, United States of America*
[b] *Division of Resource Economics and Management, West Virginia University, Morgantown, WV 26506, United States of America*

ARTICLE INFO

ABSTRACT

CONTEXT: The COVID-19 pandemic has resulted in immediate and wide impacts on human and agricultural systems. While some of the positive and negative impacts of COVID-19 on the environment and economies are emerging, there is not a comprehensive understanding of the potential impacts of COVID-19 on the most vulnerable farmers.

OBJECTIVE: The purpose of this study is to evaluate the immediate impacts of COVID-19 on agricultural and food systems in the United States. Our aim is to quantify the impacts on labor productivity in crops and livestock production considering the heterogenous vulnerability of different farmworkers. We are interested in measuring the production that is not realized due to COVID-19.

METHODS: In this paper, we introduce IMLAP, Immediate impact Model of Local Agricultural Production. This model is an economic framework considering short-term agricultural production responses to economic, environmental, and policy changes. We investigate the potential impacts of COVID-19 on the farmers in the U.S. for each county with a special focus on female, Hispanic, black and African American, and small-scale producers.

RESULTS AND CONCLUSIONS: Considering the impacts of COVID-19 on labor, the findings of this study suggest a decline in agricultural output in all the U.S. counties ranging from 1.18% to 7.14% of total production. Our simulation results show that counties with a higher number of small-scale farms, non-white farmers, and female-operated farms are the most vulnerable to COVID-19. Also, we argue that the stimulus policies and support packages must target these communities of producers to ensure that their livelihood is protected. The findings suggest that productivity growth (technological improvements) and international trade can eliminate the negative impacts of pandemics.

SIGNIFICANCE: The proposed quantitative framework of this study is a simple yet novel model that empowers diverse research communities to provide a quick analysis of the impacts of unprecedented events. It offers a holistic framework to evaluate the response of agricultural production to changes in availability and productivity of labor, machinery & equipment, land, fertilizer, seeds, and other inputs. This study presents new foundations for agricultural research communities to provide solutions to agricultural resilience challenges and highlights the significance of demand drivers, technological growth, and international trade in strengthening the food system.

1. Introduction

Months after the beginning of the world-wide COVID-19 pandemic, the positive and negative effects on food and agricultural systems are being observed. Some of the positive effects of the pandemic on the environment are reduction in greenhouse gas (GHG) emissions (Hanna et al., 2020; Le Quéré et al., 2020; Venter et al., 2020), improved water quality, and less noise pollution (Diffenbaugh et al., 2020). The negative impacts of the pandemic on global poverty (World Bank, 2020), food production and supply chain (Barrett, 2020), welfare, and inequality (Diffenbaugh et al., 2020) are also emerging. While uncertainty is the nature of the agricultural system, COVID-19 has increased price uncertainty for the farmers. Due to challenges posed by the pandemic, farmers around the world are struggling to have a profitable production. Some farmers face higher production costs due to limits on labor; some others observe low sale revenues as the trade and storage margins on price are getting larger. On the global scale, food prices started high in 2020 and declined until June–May when the prices started to increase. Except for

some dairy products, the prices have been rising in August. This volatile situation can increase the risk of agricultural systems. A quantitative and informative analysis could help to identify the impacts on potentially vulnerable agricultural communities.

Labor has a significant role in the agricultural system. However, the impact of COVID-19 has been significantly different across different communities. Considering the effects of some risks such as COVID-19 on various producers is important to identify which groups of producers are more susceptible to the negative impacts of those risks. It is expected that COVID-19 hit hardest the Hispanic, black, and African American producers. These groups of farmers face more challenges relative to other farmers even in the absence of a pandemic (Leslie et al., 2019). Black farmers are disproportionally affected by COVID-19. The Centers for Disease Control (CDC) declares that people of color and black people are disproportionately represented in jobs which puts them at a greater risk of exposure due to factors such as not being able to work remotely (CDC, 2021a). Black farmers in the U.S. are older than other U.S. farmers (60.8 versus 57.5 years in 2017), operate on small-scale farms, and have difficulty obtaining credit (Taylor, 2018) which makes them more vulnerable to COVID-19. Moreover, in August 2020, the number of black or African American people employed in farm-related occupations decreased by about 70% compared to August 2019 while it declined by 6% for white people (BLS, 2020).

Female farmers may be impacted by COVID-19 more than male farmers. Woman farmers operate on a vast proportion of lands in the U. S. In 2017, The female-operated farms accounted for 38% of the U.S. agriculture sales and 43% of the U.S. farmland (USDA-NASS, 2019). Should they need aids to manage their finical hardship due to COVID-19, female producers are less likely to receive the subsidies compared to the male producers; mainly due to the fact that women engage more in the activities that are less likely to be subsidized such as small-scale farms (Leslie et al., 2019). Additionally, the female farmers are mostly the beginning farmer and have less access to credit and savings than the male farmers (30% of female farmers had farms 10 years or fewer while 25% of male producers owned farms 10 years or fewer). Also, female farmers are likely to face gender-based discrimination when they apply for loans to develop their operations.

We expect that the small-scale farmers and marginal producers are also among the most vulnerable to the pandemic. Some farmers have lost their local restaurant customers leading to extra marketing and delivery costs. On the other hand, large producers may benefit from this situation due to their better investment in storage and marketing power. The pandemic has decreased small farmers' incomes as a source of livelihood due to mobility restrictions, production disruptions, and a fall in regional demand for agricultural commodities. COVID-19 may also reduce the off-farm income that the small farmers use to cover their production and living expenses and manage their farm debts (USDA-ERS, 2021a).

In this paper, we suggest a simple yet informative approach to study the effects of COVID-19 on agricultural producers accounting for farmers' race, gender, and farm size. Our approach is similar to the Purdue Food and Agriculture Vulnerability Index (PFAVI) that quantifies the loss in production as a result of farmworkers' illness due to COVID-19 (Lusk, 2020). However, PFAVI does not report the loss in production considering different gender and races while we have accounted for race, gender, and farm size in our analysis. We also consider the differences in production technology and cost structure of different producers across the US.

Deploying numerical and economic models can be beneficial in different ways. Since COVID-19 is an unprecedented event, it is impossible to recognize all possible impacts on the economy and agricultural systems based on pure historical experience or conceptual models. The economic model that considers producer behavior can be used to measure the responses of each community/producer. The economic models can also be used to create simulations to test the hypothesis that cannot be anticipated otherwise. These models can be deployed to evaluate different policy interventions that can be designed to mitigate the impacts of COVID-19.

2. Methods

We introduce IMLAP, Immediate impact Model of Local Agricultural Production. This model is an economic model considering short-term agricultural production responses to economic, environmental, and policy changes. The agricultural production includes crops and animals and each location has its production structure. The major inputs in production function are labor, land, equipment and machinery, chemicals, seeds, and fertilizer as illustrated in Fig. 1.

The equilibrium price and quantity of each input or output commodity are determined in the model according to the interaction of agents in local markets. At each location (counties in the U.S.), the economic behavior for six types of agents is considered. This includes consumers, producers, landowners, capital owners, farmworkers, and the suppliers of agricultural inputs (seeds, fertilizer, chemicals, etc). Producers are categorized according to the farm size while farmworkers are classified based on ethnicity and sex. The demand and supply for each commodity are derived by solving the economic optimization behavior of each agent following microeconomic production theory (Klump et al., 2012; Kmenta, 1967; Lu and Fletcher, 1968).

2.1. Supply: labor, capital, land, and other agricultural inputs

The production function is a Nested Constant Elasticity of Substitution (Perroni and Rutherford, 1995; Prywes, 1986) system as shown in Fig. 2. In this system, all the production inputs are combined in various "nests". For example, the labor nest consists of different labor types and a parameter of substitution (σ3) governs the flexibility of replacing one type of labor with another. Then, another parameter, σ2, governs the flexibility of replacing labor with machinery. This is a standard framework widely used in agricultural economics for the assessment of agricultural shocks and policies like in SIMPLE-G (Baldos et al., 2020), GTAP (Corong et al., 2017), GCAM (Calvin et al., 2019), IMPACT (Rosegrant et al., 2012), AIM (Fujimori et al., 2017), ENVISAGE (Van Der Mensbrugghe, 2018), MAGNET (van Meijl et al., 2006), and EPPA (Jacoby et al., 2006). The Technical Appendix provides more details about the production function and its components.

Following the economic behavior of farmers discussed in the Technical Appendix, we derive the main analytical expression for this study which follows the SIMPLE-G logic (Hertel and Baldos, 2016). The following equation shows the main drivers of change in production by farm type and county.

$$q^y_{j,c} = \sum_i \theta^i_{j,c} \left(q^i_{j,c} + a^i_{j,c} \right) + \sum_l \theta^l_{j,c} \left(q^l_{j,c} + a^l_{j,c} \right)$$
$$+ \sum_n \theta^n_{j,c} \left(q^n_{j,c} + a^n_{j,c} \right) + \sum_k \theta^k_{j,c} \left(q^k_{j,c} + a^k_{j,c} \right) + a^y_{j,c} \quad (1)$$

here, $q^y_{j,c}$ is the percentage change in the production of output y, by farm type j in county c. While q shows the percentage change in the quantity of associated input or output, θ is the share parameter, and α is the productivity parameter. Then, i, l, n, k are indexes for intermediate inputs, labor, land, and capital, respectively. This equation shows an increase in the quantity of any input (q^i, q^l, q^k, q^n) can increase production given no reduction in other inputs and productivity. Also, it shows that an increase in productivity of any input can increase agricultural output given no reduction in other factors. However, if the use of other inputs is likely to change due to changes in relative prices (look at the Appendix for full functional forms), a computational framework is necessary to calculate the final impact. The final impact for the county is the weighted average of changes by farm size and producer type.
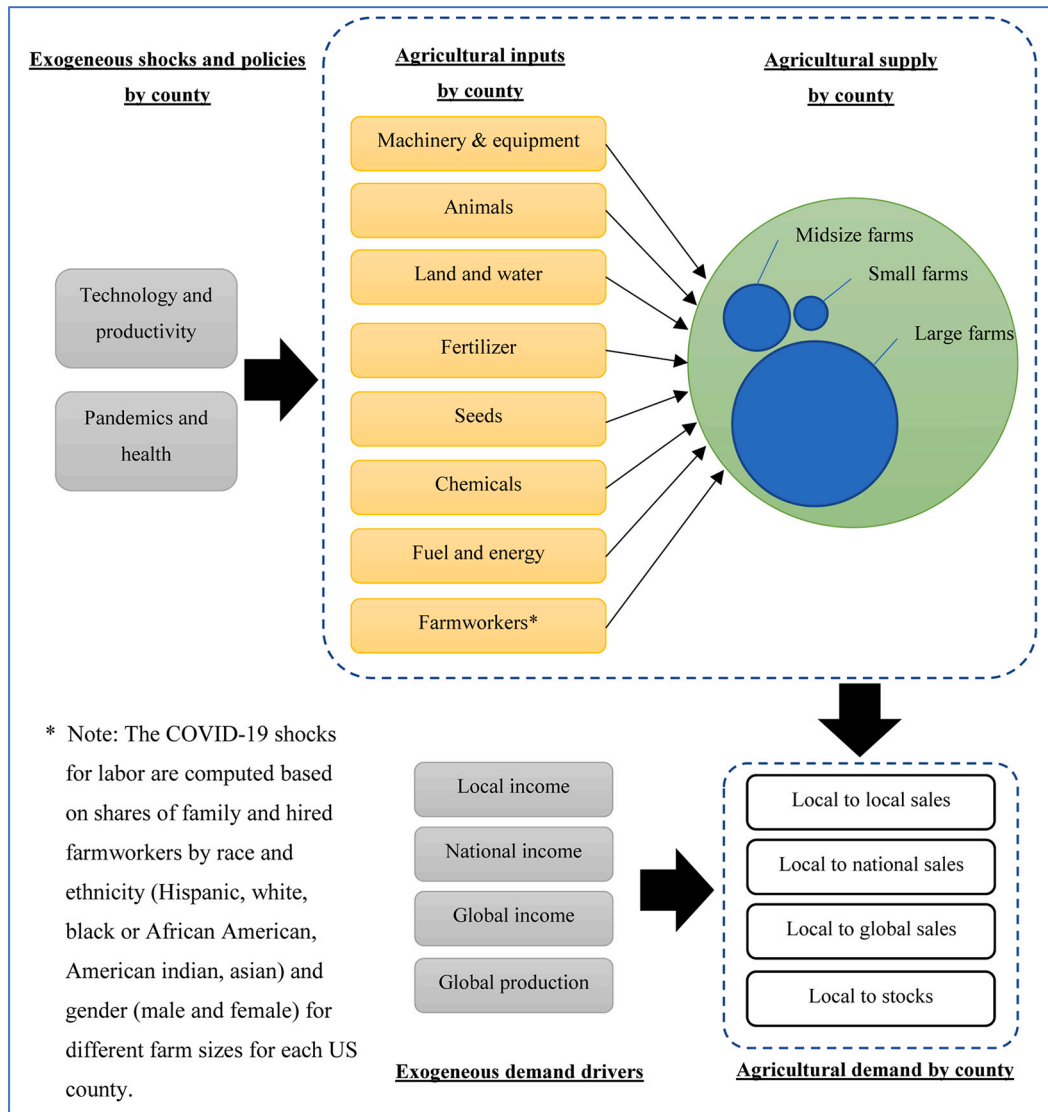
Fig. 1. Modeling the impacts of COVID-19 in IMLAP model.

2.2. Demand: local, national, and global drivers

The change in demand for agricultural products comes from four different sources including changes in direct local demand (qd^{local}), non-local domestic demand ($qd^{national}$), exports or global demand (qd^{global}), and stocks (qd^{stocks}). In this study, the changes related to demand are exogenous. The following equation shows major demand drivers of local production.

$$qd_c^{total} = \omega_c^{local} qd_c^{local} + \omega_c^{global} qd_c^{global} + \omega_c^{national} qd_c^{national} + \omega_c^{stocks} qd_c^{stocks} \qquad (2)$$

2.3. Model closure

To measure the short-run impacts of the COVID-19, the Leontief structure is considered for the top nests of the production function, and the Cobb-Douglas structure is assumed for lower nests (Miller, 2008). Other supply and demand parameters are calibrated for each location and each type of producer. Producers are categorized based on size and gender averaged at each county level. Labor types consist of different races and ethnicities to reflect different vulnerabilities to COVID-19. The county-level contributions by farm size are estimated using the United States Department of Agriculture (USDA) information on Production Expenses by county (USDA-NASS, 2019). We assume the demand for

agricultural products is exogenous to the model. Another assumption is that the relative wages of different labor types are unchanged. This ensures no major labor substitution across the labor types. Finally, we assume that the relative price of material inputs are also unchanged ensuring no major change in the composition of material inputs.

2.4. COVID-19 scenarios

A pandemic like COVID-19 can affect agriculture in multiple ways. Observations in April and May of 2020, suggest significant changes in the labor market and temporary food shortage. Following these observations, this study evaluates the potential impacts of COVID-19 on agricultural production in U.S. counties through a) changes in labor productivity, and b) changes in global food purchases. We also consider a scenario of continued productivity growth and yield improvements.

2.4.1. Scenario 1: lost labor productivity

Agriculture was considered an essential industry and was exempt during the U.S. lockdown (Torpey, 2020). Note that agricultural workers are not frequently exposed to infection at work (Hawkins, 2020). Thus the unemployment rate in farm-dependent metro and non-metro areas have been the lowest in the U.S. (Cromartie et al., 2020). However, there
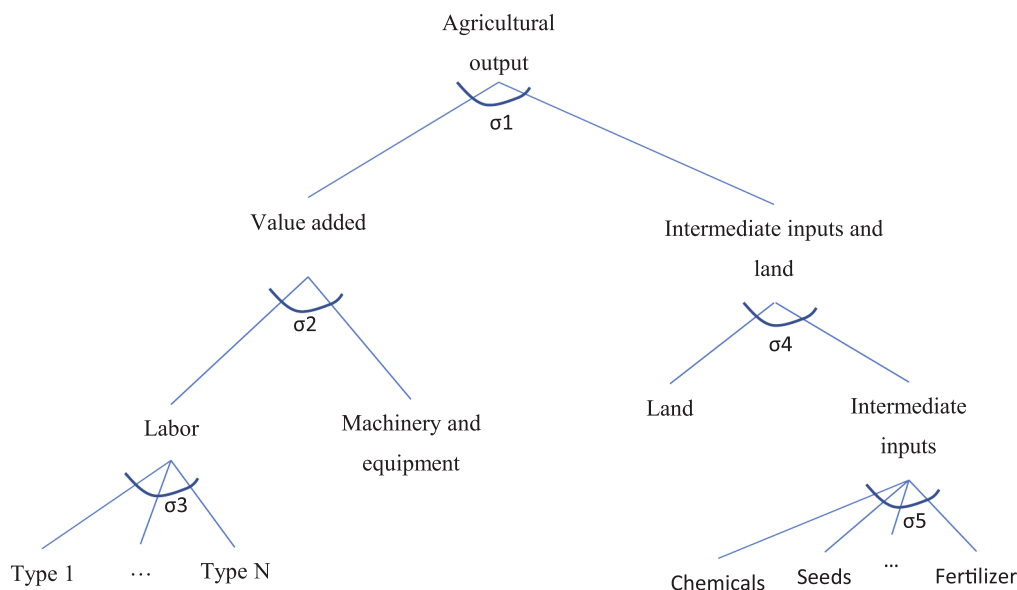
Fig. 2. Structure of local agricultural production.

are other ways that COVID-19 can affect labor productivity. This includes virus exposure out of the workplace, family and friend gatherings, shopping, outdoor dining, etc. Also, the illness of a family member or a friend can negatively affect productivity. In the U.S., livestock production suffered significantly in April and May of 2020 due to COVID-19 cases in slaughterhouses, processing plants, and meatpacking. This caused a temporary shortage and price increase. Here, we assume the reduction in labor productivity and capacity follows the pattern of hospitalization.

We cover all the counties in the Conterminous United States. For agricultural commodities we consider "crops total" and "animal totals-including produce". For producer types, we consider race/ethnicity (Hispanic, black and African American, American Indian, Asian, white, and others) and farm sizes. The share of each type is calculated based on the 2017 Census of Agriculture information obtained from USDA-NASS. The impact of COVID-19 on labor productivity is defined with a harm index based on the hospitalization rate of each labor type.

2.4.2. Scenario 2: exports

Not all the countries in the world were hit by COVID-19 simultaneously. China's quick recovery created opportunities for other countries to stay in the agricultural markets. Despite interruption in shipments, the U.S. soybean exports to China increased in 2020 as China's economy continued to grow. Also, the U.S. exports of animal products have increased. These changes are not considered to be associated with American domestic COVID-19 cases. However, it is the nature of pandemics to hit different regions at different points in time. USDA forecasts the volume of U.S. exports increased in 2020 (Kenner and Jiang, 2021). So, we associate a 1.4% change in U.S. agricultural exports due to COIVD-19 which is roughly equivalent to the increase of exports to China.

2.4.3. Scenario 3: continued productivity growth and yield improvements

Without COVID-19, total agricultural output was expected to grow following its recent trend. Regarding livestock and meat production, the average annual growth from 2016 to 2019 has been around 2.7%. However, its actual growth in 2020 has been around 1.1% compared to 2019. So, the 1.6% can be assigned to the growth not realized due to COVID-19. The potential growth is also expected for crops depending on weather conditions. U.S. corn yield in 2020 is estimated to be 2.7%

higher than the 2019 yields (USDA-NASS, 2021). Therefore, we assume around a 2.7% increase in total factor productivity for all production practices.

3. Results

Following a simple production model, this study estimates the likely impacts of COVID-19 on labor productivity and overall agricultural production. We report the impacts by U.S. counties, states, and farm sizes.

3.1. Lost labor productivity

According to CDC, around 22.85% of the population of 18 to 65 years old have been symptomatic for COVID-19 in 2020 (CDC, 2021b). Based on CDC estimates the average productivity lost is calculated for the US. Considering a two-week mandatory quarantine for the symptomatic person and people in close contacts, we estimate around 45.7% of people at this age had to stop working for two weeks, which is about 4% of total annual working days. In other words, around 1.9% of total labor hours had been lost due to COVID-19 in 2020. Table 1 shows the estimated impacts of COVID-19 on different farmworkers in crop and livestock production. Overall, the productivity of workers in livestock production is larger due to the Apr-May lockdown. Also, the productivity lost is the highest for Hispanic farmworkers followed by Black & African American farmworkers. This is the direct result of applying the CDC hospitalization factor for these communities.

Table 1
Estimated productivity lost due to COVID-19.

	Hispanic	Black & African American	White	Others
CDC hospitalization factor	3.2×	2.9×	1×	2.0×
Average productivity lost				
in crop production (%)	3.53	3.20	1.10	2.20
in livestock production (%)	6.72	6.09	2.10	4.20

3.2. National-level results by farm size

The findings suggest that the impact of COVID-19 on the agricultural system in the U.S. is equivalent to 2.63% of total agricultural production. This is around $10 billion worth of crops and livestock products. Fig. 3 summarizes the results by farm size in terms of the potential production not realized. In percentage change, the small farms are 20% more vulnerable to COVID-19 than large farms. However, in absolute values, the amount of production not realized due to COVID-19 is bigger in large farms as their share in agricultural production is higher.

3.3. State-level results

Considering county-specific labor composition (race and ethnicity) and production (crops and livestock), we calculate the production not realized due to COVID-19 by counties and aggregate it to states. Fig. 4 shows the change in farm production due to COVID-19, boosted exports, and continued growth in yields and TFP (total factor productivity) for major agricultural states. The yellow and blue colors show an increase in production and the red colors show a fall in production. The findings suggest that all the states will have lower agricultural production. The biggest damage is in California that may lose around $1.5 billion worth of agricultural outputs due to COVID-19. However, the increase in yields, the continued productivity growth, and boosted agricultural exports can eliminate the negative impacts and even cause an increase in production. Overall, the combination of all three scenarios can lead to a 1.47% increase in total agricultural production ($5.7 billion).

3.4. County-level results

On average, the model predicts a 2.63% lower agricultural output due to COVID-19 for the whole U.S. However, the impact is not uniform across space as shown in Fig. 5. The impact ranges from around −7.14% to around −1.18%. Note that this is average over the county. In other words, the within-county heterogeneity is not modeled here. The map shows the livestock producing regions such as South Dakota and Wyoming face high drops inoutput. These regions have also a high concentration of female-operated farms. Texas and Arkansas that have more black farmers than any other states also experience a reduction in their sales. On the other hand, Midwest and around Mississippi are less affected.

4. Discussion

The USDA has provided different estimates about U.S. agricultural production in 2020. According to USDA Farm Income Projections in February 2020, the net farm income was expected to grow 3.3% in 2020 from 2019 levels (Schnepf, 2020). In U.S. Farm Sector Financial Indicators released in February 2021, it was predicted that cash receipt has increased by 0.3% for all agricultural products, and increased by 5.5% for production of crops while it drops by 5.4% for animals and related products (USDA-ERS, 2021b). We estimate a 1.47% increase in production volume when combining COVID-19 impacts with yield and exports. There are several reasons for the difference with USDA forecasts. First, our model projects volume without looking at prices. The USDA forecast includes prices. This is important as farm-level cattle prices have declined by 4.9% in 2020 (USDA-ERS, 2021c). Also, we did not consider many other changes in the real world including changes in stocks, household consumptions, prices, and other demand components. With only three shocks (COVID-19, exports, and yields), we were able to predict the right direction of the change. One major factor can be the change in food spending. According to USDA, total food spending (including "food at home" and "food away from home") averaged $125.3 billion per month in Jan-Jun 2020, a 6.9% reduction from $134.7 billion per month in 2019. This is mainly a result of less spending on food away from home. Another reason can be un-identified changes in other agricultural inputs. Overall, the observed changes in other agricultural inputs are small and there is no robust evidence to show the linkage to COVID-19. The USDA estimated a small increase in the expenses of feed purchases, labor, fertilizer, seed, and rents in 2020 compared to 2019. However, total production expenses for 2020 are projected to be 1.3% lower than 2019 due to a decline in other expenses, especially interest payments (USDA-ERS, 2021d). With no robust evidence on the significant role of COVID-19 on other inputs, we assumed no covid-related shocks in other agricultural inputs. Thus, we considered the impact of COVID-19 on labor only, not other inputs. We expect that considering the changes in output prices and input costs may have a more uniform impact across the US. However, more information and further numerical analysis are required to do a comprehensive investigation.

The heterogeneous impact of COVID-19 on agriculture indicates a change in the organization of agricultural production. From small farms to large farms and from more labor contribution to higher
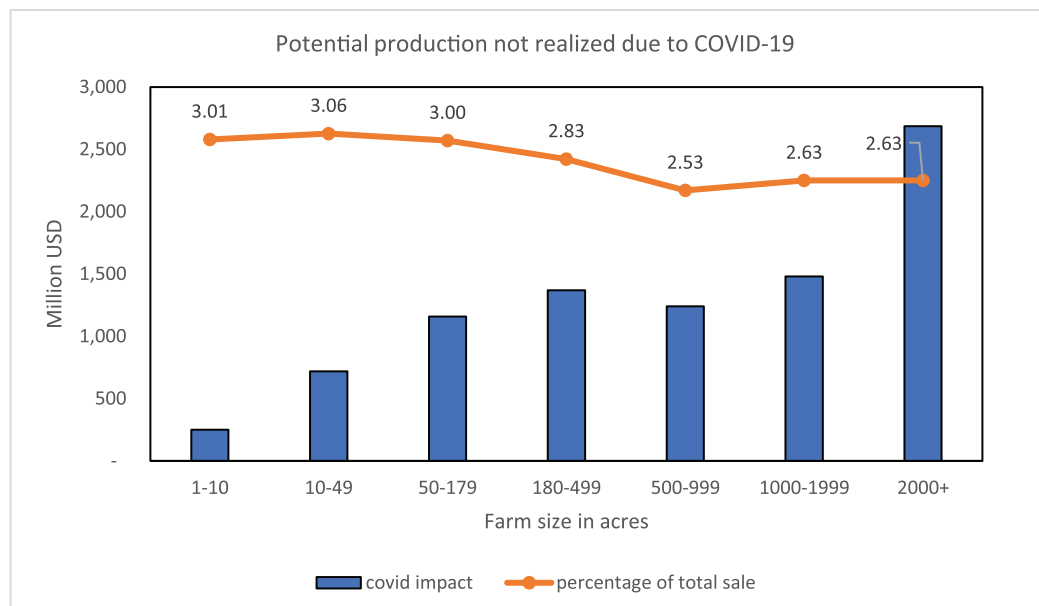

Fig. 3. Estimated share of production not realized due to COVID-19 by farm size.
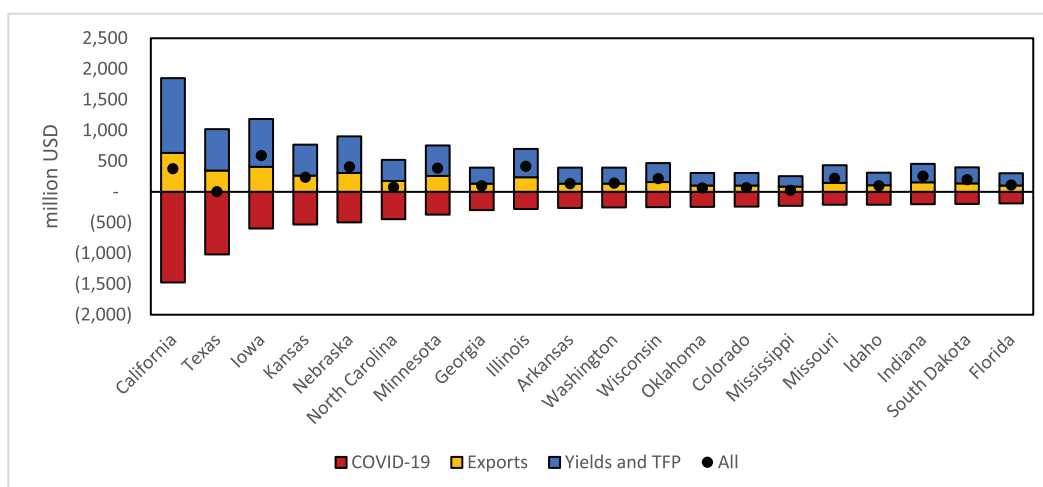
Fig. 4. Change in U.S. agricultural production in different scenarios for the major agricultural states.
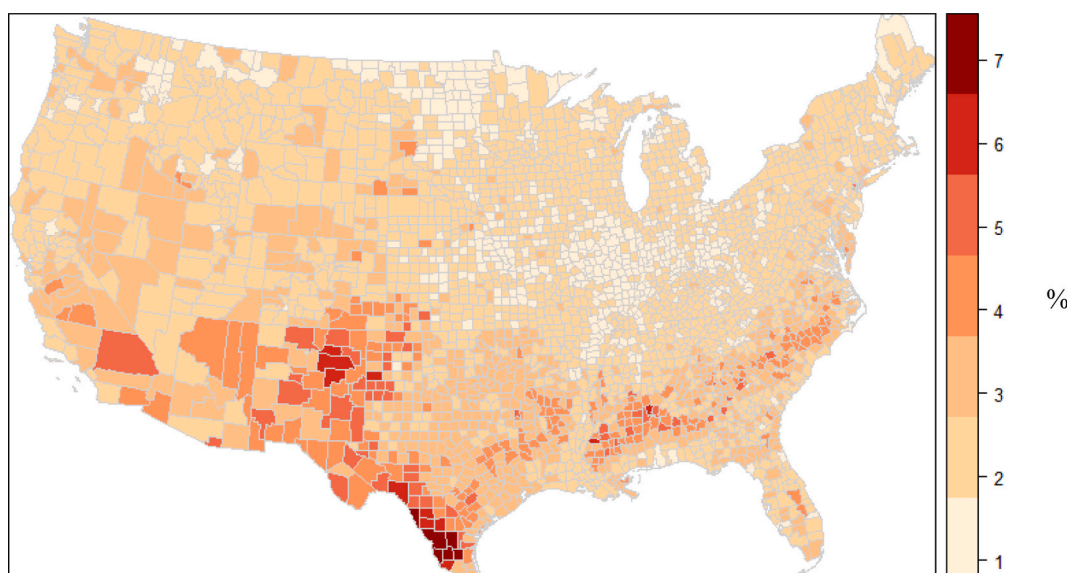

Fig. 5. Estimated share of production not realized due to COVID-19, by county. Source: simulation results.

mechanization and automation. This is in the short-term and just due to changes in the scale of production by heterogeneous farms. As small farmers are more affected, they may exit the market in the short-term or decide to change the production technology and strategies.

Also, supportive policies may have different effectiveness regarding the size of farms. Since tax payments contribute to a large proportion of total expenses for small farms (USDA-NASS, 2019), tax credits can be an effective policy for them. This suggests a policy for protecting agricultural systems via tax channel should target the small farmers. Moreover, labor contributes to a higher portion of expenses in small farms compared to large farms. An increase in labor costs due to protective concerns will shrink the profit margin for small farmers more than large farmers. Also, the share of cash rents is lower for small farms which means that they mostly own their land Thus, a rent-based supportive program will be less beneficial to small farmers. Finally, the share of fertilizer is lower for small farms (USDA-NASS, 2019). Thus, the fertilizer-based policies are more effective for large farms compared to small farms. In fact, due to the lower use of fertilizers by the smaller farms relative to the larger farms, the trade and price policies that can reduce the use of fertilizers can be effective in supporting the smaller farms.

5. Conclusion

Transformation to a more resilient and sustainable society in presence of a pandemic requires prioritizing the management of small-scale farms, consistent with the SDG 15 which demonstrates that: "Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss". In addition, sustainable small-scale farms can be greatly productive and produce a higher yield. Increased yield results in more agricultural income and more food security. It also leads to less pollution due to lower pesticide and fertilizer use (FAO, 2020). Therefore, protecting small-scale and marginal farms seems vital to achieve sustainable development goals. The government can support small-scale farmers by providing tax credits. Since tax payments contribute to a large proportion of total expenses for small farms, tax incentives can be effective tools to mitigate the negative impacts of COVID-19 on these farms.

In this paper, we introduced IMLAP, the Immediate Impact Model of Local Agricultural Production, to estimate the likely impacts of COVID-19 for U.S. counties. We considered the heterogeneous impacts on small farms and different farmworkers across the continental U.S. We

identified high-risk vulnerable communities. Our estimations suggest that COVID-19 may have a heterogeneous impact on the farmers operating on different farm sizes and farmers from different racial groups. The support policies and packages must target the most vulnerable communities including the female and non-white farmers to ensure that their livelihood is protected. Also, our estimations show that COVID-19 has a spatially heterogeneous impact. This means that policies must consider this regional heterogeneity to decrease the economic implications of COVID-19 and efficiently support the agricultural systems.

We find that improvement in yields is critical to offset the damage from COVID-19. Thus, natural disasters may intensify the negative impacts of COVID-19 and can change the spatial pattern of the damage. The direct impacts of the disasters are the loss of human lives, assets, and harvest or livestock, as well as lower food security. The indirect costs are the so-called higher-order costs (Hallegatte and Przyluski, 2010). Some of these indirect losses are due to the output loss that arise from a decrease in production, because of the disaster itself, or because of the reduction in the productivity of inputs of production including labor, capital, and land. Part of the indirect negative impacts is a result of the damages to the infrastructure, such as electricity and transportation. Some other negative impacts may be due to the disruption of supply chains. A compound disaster resulting from occurring pandemics and natural disasters can diminish the resilience of different economic sectors such as agriculture, environment, and energy (Bahalou Horeh and Haqiqi, 2020). The combined disaster augments disruptions in production, field crop, and livestock. It also can lead to higher prices of food and agricultural products relative to when the pandemic or the natural disaster happen individually. The coincidence of natural stress and pandemics may also lead to food security problems in more vulnerable regions. The proposed model of this study is an ideal framework for immediate assessment of such impacts.

In this paper, we discussed the immediate impacts of COVID-19 on agricultural systems. However, COVID-19 can have different impacts on a longer timescale. In the long-run, the farmers will move toward substituting labor-intensive technology with capital-intensive methods. Therefore, to minimize the impacts of risks and uncertainties similar to COVID-19, it is expected that farmers use less labor but more capital, fertilizer, seed, energy, and other inputs in their production process in the future.

This study shows the significance of labor productivity for creating the knowledge needed to evaluate the impacts of unprecedented changes in agricultural and food systems through data-intensive analysis and simple economic modeling. The knowledge provided by this approach is critical for integration with planning and policies to evaluate the benefits of potential solutions for agricultural resilience challenges. This paper calls attention to the significance of labor productivity responses when analyzing the impacts of pandemics like COVID-19. The important implication of the findings is that researchers should be aware of the significance of productivity growth and international trade and conduct a more careful analysis in a global context.

The outcomes of this study provide novel findings of the degree to which continued productivity growth, yield improvements, and international trade can eliminate the damages from COVID-19. It also expands a quantitative understanding of the underlying processes leading to changes in the food system. Thus, policymakers should consider technological growth and international trade in planning and choosing strategies to solve the challenging resilience problems. We have found that productivity loss varies by race and ethnicity. Therefore, a community-specific supportive policy can keep the agricultural production while meeting resilience goals.

Declaration of Competing Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

Appendix A. Appendix

This appendix describes the IMLAP model in more detail. The model considers demand and supply drivers for aggregate crops and aggregate livestock production. The producer goal is to minimize the cost of purchasing the inputs subject to the production function. The production function is a nested CES (constant elasticity of substitution) as illustrated in Fig. 2. The general from of a single nest CES system can be shown as the following set of equations:

$$\min_{Q_i} \sum_i P_i Q_i$$

$$\text{s.t. } Q = A\left[\sum_i \beta_i (A_i Q_i)^\rho \right]^{1/\rho}, \rho = \frac{\sigma - 1}{\sigma} \tag{A-1}$$

where, i is an index for inputs, P stands for price of output, P_i shows price of input i, Q is used for quantity of output, Q_i is the quantity of input, A is an index for total productivity, A_i is an index for input-specific productivity, β is the primal share coefficient, σ is the substitution elasticity, and ρ is called CES exponent. A solution to this system is described in many microeconomics textbooks and computational models (e.g. Van Der Mensbrugghe, 2018). Solving this optimization problem yields the demand for each input. There are two specific forms of this function as illustrated in Table A-1. The Leontief form assumes no substitution between inputs. This form is helpful for short-run analysis and specific technologies. The Cobb-Douglass form is equivalent to a substitution elasticity of one. This specification has constant expenditure shares irrespective of relative input prices (and changes in technology).

Table A-1
Solutions to different specifications of CES function.

CES	Leontief, σ = 0	Cobb-Douglas, σ = 1

Table A-1 (*continued*)

CES	Leontief, $\sigma = 0$	Cobb-Douglas, $\sigma = 1$
$Q_i = \beta_i (A_i A)^{\sigma-1} Q \left(\dfrac{P}{P_i}\right)^{\sigma}$	$Q_i = \beta_i (A_i A)^{-1} Q$	$Q_i = \beta_i Q \left(\dfrac{P}{P_i}\right)$
	$P = \dfrac{1}{A} \sum_i \beta_i \left(\dfrac{P_i}{A_i}\right)$	
$P = \dfrac{1}{A} \left[\sum_i \beta_i \left(\dfrac{P_i}{A_i}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$		$P = \dfrac{1}{A} \prod_i \left(\dfrac{P_i}{A_i}\right)^{\beta_i}$

With this introduction, we describe equations showing input use in agricultural production for the proposed nested CES form. The producers employ each input mainly based on relative prices and the scale of production. The demand is obtained by solving the cost minimization problem of the producer given its specific production possibility frontier and the nested CES structure. Four composite input bundles are introduced including the capital-labor bundle (*KL*), composite labor (*LT*), material-land (*MN*), and composite materials (*MT*). Let Q be the quantity and P show the price. The following equation shows the employment of machinery and equipment capital (*k*) for producer type *j* for county *c*:

$$Q_{j,c}^{k} = \beta_{j,c}^{k} \left(A_{j,c}^{y}\right)^{\sigma_1-1} \left(A_{j,c}^{k}\right)^{\sigma_2-1} Q_{j,c}^{y} \left(\frac{P_{j,c}^{y}}{P_{j,c}^{kl}}\right)^{\sigma_1} \left(\frac{P_{j,c}^{kl}}{P_{j,c}^{k}}\right)^{\sigma_2} \tag{A-2}$$

where, *k*, *y*, and *kl* are used to show the variables associated with capital, output, and the *KL* composite. Here, β is the CES parameter, A is the productivity index, σ_1 is the substitution elasticity between *KL* composite and *MN* composite, and σ_2 is the substitution elasticity between capital and labor. This equation shows the employment of machinery and equipment increases with an increase in the scale of production or a decline in the relative price of capital. A similar equation shows the employment of labor type *l* and includes the labor composite layer (*LT*) as shown in the following equation:

$$Q_{j,c}^{l} = \beta_{j,c}^{l} \left(A_{j,c}^{y}\right)^{\sigma_1-1} \left(A_{j,c}^{l}\right)^{\sigma_2-3} Q_{j,c}^{y} \left(\frac{P_{j,c}^{y}}{P_{j,c}^{kl}}\right)^{\sigma_1} \left(\frac{P_{j,c}^{kl}}{P_{j,c}^{lt}}\right)^{\sigma_2} \left(\frac{P_{j,c}^{lt}}{P_{j,c}^{l}}\right)^{\sigma_3} \tag{A-3}$$

where, all the notations are similar to the previous equation. Here, σ_3 shows the substitution elasticity between different labor types. The substitution parameter is important in this study as it provides a margin for adaptation when one category of labor is less productive. This equation implies the employment of each labor category depends on the scale of production, productivity, and relative wage, and other prices. The following equation shows the derived equation for land use, *n*, in county *c* for farm type *j*:

$$Q_{j,c}^{n} = \beta_{j,c}^{n} \left(A_{j,c}^{y}\right)^{\sigma_1-1} \left(A_{j,c}^{n}\right)^{\sigma_2-3} Q_{j,c}^{y} \left(\frac{P_{j,c}^{y}}{P_{j,c}^{mn}}\right)^{\sigma_1} \left(\frac{P_{j,c}^{mn}}{P_{j,c}^{n}}\right)^{\sigma_4} \tag{A-4}$$

where, *n* is used for land and *mn* for the material-land composite bundle. The demand for land also depends on the scale of production, the price index of composite materials, productivity, and substitution parameters. Here, σ_4 shows the substitution elasticity between land and materials (fertilizer, seeds, chemicals, etc). This parameter governs the intensifications in agricultural production. Finally, the use of material inputs for agricultural production is determined based on the following equation:

$$Q_{j,c}^{i} = \beta_{j,c}^{i} \left(A_{j,c}^{y}\right)^{\sigma_1-1} \left(A_{j,c}^{i}\right)^{\sigma_2-5} Q_{j,c}^{y} \left(\frac{P_{j,c}^{y}}{P_{j,c}^{mn}}\right)^{\sigma_1} \left(\frac{P_{j,c}^{mn}}{P_{j,c}^{mt}}\right)^{\sigma_4} \left(\frac{P_{j,c}^{mt}}{P_{j,c}^{i}}\right)^{\sigma_5} \tag{A-5}$$

where, *i* is used for material inputs, and σ_5 shows the substitution elasticity between other input materials (fertilizer, seeds, chemicals, etc).

The costs of production should not exceed the sum of revenues and other transfers (e.g. government supports). The following equation ensures that the zero-profit condition holds.

$$\underbrace{P_{j,c}^{y} Q_{j,c}^{y}}_{\text{total revenue}} + \underbrace{TR_{j,c}}_{\text{other transfers}} = \underbrace{\sum_i P_{j,c}^{i} Q_{j,c}^{i} + \sum_l P_{j,c}^{l} Q_{j,c}^{l} + \sum_n P_{j,c}^{n} Q_{j,c}^{n} + \sum_k P_{j,c}^{k} Q_{j,c}^{k}}_{\text{total costs}} \tag{A-6}$$

The price index of composite bundles is the weighted average of associated inputs. Let φ show the cost weight of each input in the bundle. The linear approximation of price indexes can be shown as the following equations.

$$p_{j,c}^{kl} = \sum_l \varphi_{j,c}^{l} \left(p_{j,c}^{l} - a_{j,c}^{l}\right) + \sum_k \varphi_{j,c}^{k} \left(p_{j,c}^{k} - a_{j,c}^{k}\right) \tag{A-7}$$

$$p_{j,c}^{mm} = \sum_i \varphi_{j,c}^{i} \left(p_{j,c}^{i} - a_{j,c}^{i}\right) + \sum_n \varphi_{j,c}^{n} \left(p_{j,c}^{n} - a_{j,c}^{n}\right) \tag{A-8}$$

$$p_{j,c}^{lt} = \sum_l \varphi_{j,c}^{l} \left(p_{j,c}^{l} - a_{j,c}^{l}\right) \tag{A-9}$$

$$p_{j,c}^{mt} = \sum_i \varphi_{j,c}^{i} \left(p_{j,c}^{i} - a_{j,c}^{i}\right) \tag{A-10}$$

where, *p* and *a* are defined as the percentage change in price and productivity, respectively. In other words, the percentage change in the price of an input bundle depends on the percentage change in the price of underlying inputs and their productivity changes. Thus, if prices are not changed and the productivity is unchanged, the price index of composite input will not change.

Combining eqs. A-2 to A-10, we can derive the main analytical expression for this study as shown in the following equation:

$$
\begin{aligned}
q^y_{j,c} = \sum_i \theta^i_{j,c}\left(q^i_{j,c} + a^i_{j,c}\right) + \sum_l \theta^l_{j,c}\left(q^l_{j,c} + a^l_{j,c}\right) \\
+ \sum_n \theta^n_{j,c}\left(q^n_{j,c} + a^n_{j,c}\right) + \sum_k \theta^k_{j,c}\left(q^k_{j,c} + a^k_{j,c}\right) + a^y_{j,c}
\end{aligned}
\tag{A-11}
$$

here, $q^y_{j,c}$ is the percentage change in the production of output *y*, by farm type *j* in county *c*. Then, *i, l, n, k* are indexes for intermediate inputs, labor, land, and capital, respectively. While *q* shows the percentage change in the quantity of associated input or output, *θ* is the share parameter, and *α* is the percentage change in productivity.

The demand for agricultural products comes from four different sources including direct local sales (QD^{local}), non-local domestic sales ($QD^{national}$), exports (QD^{global}), and stocks (QD^{stocks}). The following equation shows major demand drivers of local production.

$$
QD_c = QD^{local}_c + QD^{global}_c + QD^{national}_c + QD^{stocks}_c
\tag{A-12}
$$

The total supply of agricultural products in each county c, QS_c, is the sum of production of different farm types j, $Q^y_{j,c}$. as shown in the following equation:

$$
QS_c = \sum_j Q^y_{j,c}
\tag{A-13}
$$

The consumer in each county *c*, chooses between local and non-local variety of foods. We assume these varieties are imperfect substitutes and thus change in their relative prices will affect their demand. Consumer demand for food is specified by solving the utility optimization problem for local and non-local agricultural commodities as shown in the following equations:

$$
QD^{loc}_c = \lambda \alpha^{loc}_c I_c \left(\frac{PC^{nloc}_c}{PC^{loc}_c}\right)^{\sigma_0}
\tag{A-14}
$$

where, *QC* is the consumer demand, *c* is the index for counties, *loc* is the abbreviation for local and *nloc* is the abbreviation for non-local, *α* is the CES utility parameter, *I* represents income, *PC* is the consumer price, and σ_0 is the substitution elasticity between local and non-local food varieties in the utility. Note that PC^{tot} shows the weighted average consumer price index for all the purchased food commodities. In this study, local income is exogenous to the model.

References

Bahalou Horeh, M., Haqiqi, I., 2020. Impacts of Economic Growth and Depression in the US, China, and India on Global Land and Water Resources.

Baldos, U.L.C., Haqiqi, I., Hertel, T., Horridge, M., Liu, J., 2020. SIMPLE-G: a multiscale framework for integration of economic and biophysical determinants of sustainability. Environ. Model. Softw. 104805.

Barrett, C.B., 2020. Actions now can curb food systems fallout from COVID-19. Nat. Food 1, 319–320. https://doi.org/10.1038/s43016-020-0085-y.

BLS, 2020. Labor Force Statistics from the Current Population Survey. Division of Labor Force Statistics, U.S. Bureau of Labor Statistics.

Calvin, K., Patel, P., Clarke, L., Asrar, G., Bond-Lamberty, B., Cui, R.Y., Di Vittorio, A., Dorheim, K., Edmonds, J., Hartin, C., Hejazi, M., Horowitz, R., Iyer, G., Kyle, P., Kim, S., Link, R., McJeon, H., Smith, S.J., Snyder, A., Waldhoff, S., Wise, M., 2019. GCAM v5.1: representing the linkages between energy, water, land, climate, and economic systems. Geosci. Model Dev. 12, 677–698. https://doi.org/10.5194/gmd-12-677-2019.

CDC, 2021a. Health Equity Considerations and Racial and Ethnic Minority Groups [WWW Document]. Centers for Disease Control, U.S. Department of Health & Human Services. URL. https://www.cdc.gov/coronavirus/2019-ncov/community/health-equity/race-ethnicity.html (accessed 2.28.21).

CDC, 2021b. Estimated Disease Burden of COVID-19 [WWW Document]. Centers for Disease Control. U.S. Department of Health & Human Services. URL. https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/burden.html (accessed 3.1.21).

Corong, E.L., Hertel, T.W., McDougall, R., Tsigas, M.E., van der Mensbrugghe, D., 2017. The standard GTAP model, version 7. J. Glob. Econ. Anal. 2, 1–119.

Cromartie, J., Dobis, E.A., Krumel, T., McGranahan, D., Pender, J., 2020. Rural America at a Glance: 2020 Edition (No. EIB-221). USDA, Economic Research Service.

Diffenbaugh, N.S., Field, C.B., Appel, E.A., Azevedo, I.L., Baldocchi, D.D., Burke, M., Burney, J.A., Ciais, P., Davis, S.J., Fiore, A.M., Fletcher, S.M., Hertel, T.W., Horton, D.E., Hsiang, S.M., Jackson, R.B., Jin, X., Levi, M, Lobell, D.B., McKinley, G.A., Moore, F.C., Montgomery, A., Nadeau, K.C., Pataki, D.E., Randerson, J.T., Reichstein, M., Schnell, J.L., Seneviratne, S.I., Singh, D., Steiner, A.L., Wong-Parodi, G., 2020. The COVID-19 lockdowns: a window into the earth system. Nat. Rev. Earth Environ. 1, 470–481. https://doi.org/10.1038/s43017-020-0079-1.

FAO, 1-4 September 2020. The impact of COVID-19 on food and agriculture in Asia and the Pacific and FAO's response. FAO Regional Conference for Asia And The Pacific. http://www.fao.org/3/nd476en/nd476en.pdf.

Fujimori, S., Masui, T., Matsuoka, Y., 2017. AIM/CGE V2. 0 model formula, in: Post-2020 climate action. Springer, pp. 201–303.

Hallegatte, S., Przyluski, V., 2010. The economics of natural disasters: Concepts and methods. In: Policy Research Working Papers. The World Bank. https://doi.org/10.1596/1813-9450-5507.

Hanna, R., Xu, Y., Victor, D.G., 2020. After COVID-19, green investment must deliver jobs to get political traction. Nature 582, 178–180. https://doi.org/10.1038/d41586-020-01682-1.

Hawkins, D., 2020. Differential occupational risk for COVID-19 and other infection exposure according to race and ethnicity. Am. J. Ind. Med. https://doi.org/10.1002/ajim.23145.

Hertel, T.W., Baldos, U.L.C., 2016. Global Change and the Challenges of Sustainably Feeding a Growing Planet. Springer.

Jacoby, H.D., Reilly, J.M., McFarland, J.R., Paltsev, S., 2006. Technology and technical change in the MIT EPPA model. Energy Econ. 28, 610–631.

Kenner, B., Jiang, H., 2021. Outlook for U.S. Agricultural Trade February 2021 (No. AES-115). U.S. Department of Agriculture, Economic Research Service and Foreign Agricultural Service Situation and Outlook Report.

Klump, R., McAdam, P., Willman, A., 2012. The normalized CES production function: theory and empirics. J. Econ. Surv. 26, 769–799.

Kmenta, J., 1967. On estimation of the CES production function. Int. Econ. Rev. 8, 180–189.

Le Quéré, C., Jackson, R.B., Jones, M.W., Smith, A.J.P., Abernethy, S., Andrew, R.M., De-Gol, A.J., Willis, D.R., Shan, Y., Canadell, J.G., Friedlingstein, P., Creutzig, F., Peters, G.P., 2020. Temporary reduction in daily global CO 2 emissions during the COVID-19 forced confinement. Nat. Clim. Chang. 10, 647–653. https://doi.org/10.1038/s41558-020-0797-x.

Leslie, I.S., Wypler, J., Bell, M.M., 2019. Relational agriculture: gender, sexuality, and sustainability in U.S. farming. Soc. Nat. Resour. 32, 853–874. https://doi.org/10.1080/08941920.2019.1610626.

Lu, Y., Fletcher, L.B., 1968. A generalization of the CES production function. Rev. Econ. Stat. 449–452.

Lusk, J., 2020. Purdue Food and Agriculture Vulnerability Index. Department of Agricultural Economics, Purdue University.

Miller, E., 2008. An Assessment of CES and Cobb-Douglas Production Functions. Congressional Budget Office, Washington, DC.

Perroni, C., Rutherford, T.F., 1995. Regular flexibility of nested CES functions. Eur. Econ. Rev. 39, 335–343.

Prywes, M., 1986. A nested CES approach to capital-energy substitution. Energy Econ. 8, 22–28.

Rosegrant, M.W., Msangi, S., Ringler, C., Sulser, T.B., Zhu, T., Cline, S.A., 2012. International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT): Model Description. International Food Policy Research Institute (IFPRI), Washington, DC.

Schnepf, R., 2020. U.S. Farm Income Outlook: February 2020 Forecast. U.S. Department of Agriculture, Economic Research Service.

Taylor, D.E., 2018. Black farmers in the USA and Michigan: longevity, empowerment, and food sovereignty. J. Afr. Am. St 22, 49–76. https://doi.org/10.1007/s12111-018-9394-8.

Torpey, E., 2020. Essential Work: Employment and Outlook in Occupations that Protect and Provide. Career Outlook. U.S. Bureau of Labor Statistics.

USDA-ERS, 2021a. Farms and Farm Households during the COVID-19 Pandemic. Economic Research Service, United States Department of Agriculture.

USDA-ERS, 2021b. U.S. Farm Sector Financial Indicators, 2014-21F. U.S. Department of Agriculture, Economic Research Service.

USDA-ERS, 2021c. Food Price Outlook, February 2021. U.S. Department of Agriculture, Economic Research Service.

USDA-ERS, 2021d. Farm Income and Wealth Statistics. U.S. Department of Agriculture, Economic Research Service.

USDA-NASS, 2019. 2017 Census of Agriculture. National Agricultural Statistics Service, United States Department of Agriculture.

USDA-NASS, 2021. Crop Production 2020 Summary. National Agricultural Statistics Service, United States Department of Agriculture.

Van Der Mensbrugghe, D., 2018. The Environmental Impact and Sustainability Applied General Equilibrium (ENVISAGE) Model, Version 9.0. The Center for Global Trade Analysis, Purdue University.

van Meijl, H., Van Rheenen, T., Tabeau, A., Eickhout, B., 2006. The impact of different policy environments on agricultural land use in Europe. Agric. Ecosyst. Environ. 114, 21–38.

Venter, Z.S., Aunan, K., Chowdhury, S., Lelieveld, J., 2020. COVID-19 lockdowns cause global air pollution declines. PNAS 117, 18984–18990. https://doi.org/10.1073/pnas.2006853117.

World Bank, 2020. Global Economic Prospects. Available at: http://pubdocs.worldbank.org/en/592561591977658545/Global-Economic-Prospects-June-2020-Foreward.pdf. Last accessed: September 2020.