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Inducing the adoption of emerging technologies for sustainable intensification of food and renewable energy production: insights from applied economics*

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Emerging advances in sustainable intensification technologies have the potential to transform land use and crop management approaches in ways that can increase resource productivity and reduce adverse environmental impacts of agricultural production. This paper describes emerging technologies that can sustainably intensify food and renewable energy production. We apply the findings from studies examining the adoption of technologies with similar stylized features to provide insights about the incentives and barriers for the adoption of these emerging technologies. We also present a landscape-based systems approach, based on welfare economics, to go beyond relying on a positive approach to explain observed adoption decisions to examining normative questions about the optimal mix, level, and location of adoption of these technologies to achieve desired societal outcomes. We conclude with a discussion of the insights from applied economics for the design of policy incentives to achieve these outcomes.

Key words: advanced biofuels, agricultural systems, agrivoltaics, input-use efficiency, policy design, precision agriculture, technology.

JEL classifications: Q01 Q55

1. Introduction

The agricultural sector faces significant challenges in the coming decades of meeting the demands for food with a growing population, the looming threat of a changing climate and increasing concerns about protecting open spaces, air and water quality and biodiversity. While yields of food crops have increased dramatically in the last five decades (FAOSTAT, 2020;

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Pretty, 2018), this increase in the intensity of agricultural production per unit land has been accompanied by an increase in total nitrogen use and nitrogen use per unit of land, growth in area under irrigation and in total energy use in agriculture (FAOSTAT, 2020; Foley et al., 2011; Pretty, 2018). As a result, this intensification is not sustainable because it is worsening water quality and hypoxic zones and leading to growth in greenhouse gas (GHG) emissions and loss of aquatic ecosystems and biodiversity (Foley et al., 2011).

The incentives for intensification of land use are being further exacerbated by growing demands for renewable energy production from biofuels for transportation and utility-scale solar energy for electricity. Both biofuels from food crops (as currently produced) and utility scale solar energy (supplying electricity directly to the grid) are land intensive. In the US, currently about 40 per cent of corn is diverted from use for food/feed to produce ethanol. With declining costs of photovoltaic (PV) technology and rising market and policy incentives, utility-scale solar is now the largest growing source of solar energy in the US. Expanding production of these sources of renewable energy can reduce GHG emissions but raises concern about diversion of cropland to energy production, rising crop prices and expansion of cropland (Khanna et al., 2021; Ong et al., 2013). Corn ethanol and utility scale solar also have other adverse impacts on the environment with corn contributing to water quality degradation (Ferin et al., 2021) while PV panels on land adversely affect soil ecological and hydrological functions and other ecosystem services compared to land with vegetation (Choi et al., 2020).

The need to meet the increasing demands for land while reducing environmental impacts has led to a call for "sustainable intensification" which refers to technologies/practices that increase the productivity of cropland while reducing environmental externalities. The concept of sustainable intensification was first proposed in 1983 but began to gain attention in the late-1990s after its characteristics were defined more precisely by Pretty (1997) (see review in Xie et al., 2019). Sustainable intensification has gained popularity in the academic and policy literature as a strategy to produce more valued products while improving environmental outcomes (see Pretty, 2018); the U.S. Department of Agriculture has embraced it as a core strategy for feeding a growing population sustainably while coping with a changing climate (Clayton, 2019).

A key cause of the environmental degradation caused by agricultural production is due to inefficiency in the way that variable inputs, such as fertilizer and water, are converted to usable outputs. The effectiveness with which these inputs are used for crop production (the proportion of applied input that is converted to final output) is inversely related to the proportion of inputs that are wasted and become pollution (Khanna & Zilberman, 1997). Zhang et al. (2015) estimate that only 68 per cent of the applied nitrogen, in the United States, is absorbed by crops and the rest is released to the environment as surplus. Similarly, about 40 per cent of irrigation water applied using flood and furrow methods is not taken up by plants and is drained away from the field (Brouwer et al., 1989). Additionally, technologies differ in the productivity with which they use land. Inefficiency in input-use combined with inefficiency in the use of land (productivity of land) exacerbates the detrimental effects of agriculture on the environment.

Sustainable intensification has the potential to reduce the amount of environmental degradation from cropland in two ways. First is by switching to technologies that increase input-use efficiency of on-farm inputs and increasing yield per unit input and reducing the wasted portion of input (Caswell & Zilberman, 1986; Khanna et al., 2002). The second approach is by switching to new crops and technologies that have the same functionality but are higher yielding and more environmentally friendly than existing technologies. This could lead to an increase in productivity (yield per unit land) while reducing the amount of land under agricultural production to meet given demands.

We focus here on emerging technological advances that can enable sustainable intensification of food crop and renewable energy production using these two approaches.[1] For example, digital technologies and autonomous technologies offer the potential to increase the efficiency with which inputs such as fertilizers, irrigation water, and pesticides are applied. Renewable energy production technologies (e.g. advanced biofuels from cellulosic feedstocks) and agrivoltaics (producing crops and solar energy on the same land) can substitute for existing technologies (food crop–based biofuels and solar energy alone, respectively), increase yield per unit land and provide more ecosystem services. The emerging availability of these technologies for sustainable intensification leads to several key questions. What factors are likely to influence the adoption of these technologies by landowners? What is the socially optimal level of adoption of these technologies to achieve desired environmental outcomes? What type of policy incentives would be most effective in inducing adoption to achieve these desired outcomes?

In the absence of observed large-scale adoption, we turn to the existing literature in applied economics to obtain insights about key factors likely to

[1] Sustainable intensification involves a wide range of technologies and practices that have been available for many decades. These include soil and water conserving tillage, drip irrigation, integrated pest management, diversified crop production, genetic improvement of crops to resist pests and diseases, as well as precision farming to use nutrients more efficiently (see Pretty, 2018 for a description of existing technologies). There is a considerable literature examining the incentives and barriers to the adoption of these technologies (Piñeiro et al., 2020) as well as other conservation technologies (Knowler and Bradshaw, 2007). For a comprehensive review of sustainable intensification technologies see Weltin et al. (2018).

influence the adoption of these technologies.[2] To develop these insights we first discuss the stylized features of these technologies. The existing literature has examined the determinants of observed adoption of similar or earlier versions of these technologies (e.g. Khanna, 2001), used surveys to analyze ex-ante decisions to adopt these technologies (such as Khanna et al., 2017; Pascaris et al., 2020), and used simulation models to analyze the potential drivers of adoption behavior for these technologies (Miao & Khanna, 2017a, b). We discuss the effects of technology characteristics, site-specific characteristics of the soil and growing conditions, behavioral and attitudinal characteristics of farmers and institutional context for the adoption of these types of technologies.

Although these technologies appear to promise 'win-win' outcomes for agriculture and the environment because they potentially increase farm profitability and improve environmental outcomes, win-win situations are scarce (Khanna & Zilberman, 2012; Struik et al., 2014). Adoption of these technologies is not costless, and there is heterogeneity in site-specific costs and benefits (private and public) from adoption. Voluntary adoption of sustainable intensification technologies may not be sufficient to achieve desired social outcomes. We discuss the effectiveness and design of policies for inducing adoption of these technologies.

A key question in policy design is the extent to which it is socially optimal to induce sustainable intensification. Universal adoption of these technologies may be neither achievable nor desirable because its costs may exceed benefits. It is, therefore, important to determine how much, where, and what mix of technology should be induced to achieve a sustainable agricultural system that achieves optimal economic and environmental outcomes at a landscape, local, or regional level. We describe a framework for embedding information about these technologies in a regional systems approach to examine the optimal extent, mix and location of adoption to maximize net social benefits. This framework allows considerations of the effects of sustainable intensification not only on environmental outcome but also on production levels, market prices for food, fuel and fiber, and consequently the returns to all landowners (whether they adopt the technology or not) as well as consumers of agricultural products. We discuss key components of a landscape-based systems approach to achieve desired environmental outcomes and identify optimal land use decisions after considering all these costs and benefits. Lastly, we discuss some insights from studies applying this landscape-based approach to the technologies described here for the socially optimal patterns of adoption and the corresponding design of policies.

[2] We focus here on the literature examining the adoption of sustainable intensification technologies in developed countries. We refer readers to other studies that have examined the adoption of these technologies in a developing country context (e.g. Lee et al., 2006).

2. Three emerging sustainable intensification technologies

We now describe three types of emerging technologies and their stylized features.

2.1 Precision farming technologies

Precision farming includes an array of technologies that can discern and address the heterogeneity in growing conditions at the sub-field level or even at the plant-level. Earlier forms of precision farming technologies, such as variable rate technology and global navigation satellite systems, have been available for a few decades (see Lowenberg-DeBoer and Erickson (2019) for the early timeline of the development of precision farming). Recent development in low-cost sensors, wireless internet, mobile technologies, machine learning, big data, and farm machinery automation is leading precision farming technologies into a new era (Rose & Chilvers, 2018). By collecting large amounts of geo-referenced information about the heterogeneous growing conditions within the field and coupling that with field-based precision agricultural technologies, it is becoming increasingly possible to have automated implementation of spatially varying input applications and an increase in the precision with which inputs are applied. Combined with developments in Internet-of-Things technology that facilitates data transfer among people, devices, and machines (see Ibarra-Esquer et al., 2017 for an introduction), precision technologies can enable farmers to manage crop production autonomously with real-time information and limited need for labor. The adoption of the technologies is expected to increase production efficiency, crop yields and perhaps profits as well as to reduce over-application of inputs and nutrient run-off.

2.2 Second-generation biofuels from high-yielding dedicated energy crops

Unlike first-generation biofuels that are derived from food crops (e.g. corn and soybeans), second-generation biofuels can be produced from corn residues and high-yielding dedicated energy crops, such as miscanthus and switchgrass. These energy crops have substantially higher fuel yield per unit of land and lower requirement for inputs per unit of land than food crops (see Debnath et al., 2019). They can be grown productively on low quality land and therefore reduce the competition for land with food crops (Khanna et al., 2021). They also provide several environmental benefits such as reducing nitrogen run-off, increasing soil carbon sequestration relative to food crops and lower GHG intensity than food crop–based biofuels (Dwivedi et al., 2015; Ferin et al., 2021).

2.3 Agrivoltaics

Agrivoltaics is an emerging technology that co-locates agricultural crop production and solar energy production on the same land. While shading crops might be expected to lower yields, there is now evidence that low-density panels may increase yield (due to reduced exposure to extreme heat, excessive solar irradiance, wind and greater water conservation) compared to conventional crop production (Miskin et al., 2019; Weselek et al., 2019). Several studies report that moderate reductions in daily irradiance caused by PVs can provide multiple synergistic benefits, including reduced plant water stress, higher and more stable yields, reduced solar panel heat stress on the land and an increase in water use efficiency by reducing evapotranspiration from crops (Barron-Gafford et al., 2019; Sekiyama and Nagashima, 2019). Agrivoltaics can increase the utilization of solar radiation compared to conventional monocrop production and, therefore, have the potential to increase the combined food and energy calorie output per unit of land (Dupraz et al., 2011). It is also a climate-smart technology that enables adaptation to climate change while enhancing ecosystems services from the land as compared to crops alone or solar alone (Choi et al., 2020; Proctor et al., 2021).

2.4 Stylized features of these technologies

Although quite different in their technological nature, these three types of technologies share some common attributes that can affect their adoption by farmers. First, these technologies increase the efficiency of input use (e.g. water use efficiency and fertilizer efficiency) and the productivity of land (yield per unit land). Second, they reduce environmental damages per unit of land (such as nitrate run-off) and may even increase ecosystem services from the land (e.g. soil carbon and pollinator habitat). Conditions under which these features can lead to a reduction in input use and in pollution are expected to vary spatially and temporally (see Caswell & Zilberman, 1986; Khanna & Zilberman, 2012). Third, adoption of most of these technologies requires upfront investment in capital equipment and can involve lags between incurring those upfront costs and revenue-generating output. These new technologies also likely require technology-specific investment in learning and implementation. Fourth, there is uncertainty about the extent to which these investment costs and learning costs may decline in the future as these technologies become more widely adopted. There is also a risk of obsolescence as improvements in the technology may make current versions outdated. These technologies may increase or decrease the risk of crop production relative to conventional practices (see Isik and Khanna (2003) for the effects of precision technologies on production risks and Miao and Khanna (2014) for the effects of energy crops on the riskiness of income for a farmer). Bioenergy crops and agrivoltaics can also reduce the riskiness of crop production by diversifying the sources of income (from crops and solar energy). Lastly, these emerging technologies can be adopted gradually on some portion of the field/farm or one component at a time; some technologies such as precision farming and agrivoltaics have many different components and configurations that can be adopted sequentially; thus adoption decisions may be partial and gradual (see Isik et al. (2001) and Khanna (2001) for precision technology adoption and Khanna et al. (2017) for energy crop adoption).

3. Economic theories explaining adoption by heterogeneous farmers

Early literature (Rogers, 1962) noted that technology diffusion follows an S-shaped curve as a function of time. However, it did not identify the economic drivers to explain diffusion. Economists have developed various theories to explain technology adoption decisions that consider the profitability of the technology as well as the riskiness and uncertainty of returns relative to conventional technologies to explain adoption behavior. These theories also consider the heterogeneity in these returns and risks across locations, farmers, and time to explain why adoption of these technologies may not be universal. Additionally, recent advances in behavioral economics are showing how behavioral preferences and non-economic factors may affect adoption decisions. Based on this literature, we briefly describe the economic drivers of adoption in the context of these emerging technologies.

3.1 Profit maximization

According to models that explain adoption decisions by farmers motivated by the objective of profit maximization, adoption of a new technology occurs if it leads to higher profits than the status quo. A new technology with high capital costs is likely to be adopted if it raises annual crop yields and/or lowers input costs by more than the increase in annualized capital costs. The extent to which a technology will increase yields and lower input costs is expected to vary across characteristics that are heterogeneous across farmers, such as soil quality and farm size. The reliance on profitability of new technologies as a metric for adoption decisions has been extended, using real option models, to incorporate the stochastic and dynamic nature of technology adoption decision when there is uncertainty about returns and/or costs of investment in a technology (Dixit & Pindyck, 1994). The real option approach has been used to address not only whether to adopt a technology but also when to adopt it. Khanna et al. (2000) apply this approach to examine the effects of sunk costs and uncertainty about returns on the decision of when to adopt precision technologies, such as variable rate technology for fertilizer application. Dumortier et al. (2017), Miao et al. (2012), and Song et al. (2011) have applied the real option approach to studying decisions about investments in a cellulosic biorefinery and in bioenergy crop establishment while Pascaris et al. (2020) examine the effects of uncertainty about returns and of concerns about the irreversibility of the establishment investments on adoption of agrivoltaics.

3.2 Utility maximization

The threshold model and the real option approach are designed to explain the adoption decision by farmers that care only about net returns; they ignore farmers' attitude toward risk, loss, and ambiguity, and cannot be used to model "how much to adopt on a farm" without further qualifications. The emerging technologies discussed here often involve decisions on the extent to which the technology is adopted (e.g. the portion of land on a farm to be devoted to a new crop variety or agrivoltaics) and the sequence of technology components or configurations to be adopted (e.g. upgrading a manual-steering tractor to an auto-steering tractor). Therefore, various utility maximization models have been widely used to explain continuous adoption behavior when technologies differ in their risk and return profile. Several studies have applied expected utility maximization models to explain incentives and barriers to adoption of precision technologies (Isik & Khanna, 2003) and energy crops (Miao & Khanna, 2017a,b). Moreover, Khanna et al. (2017) have conducted a survey to examine the role of risk aversion and the discount rate in explaining motivations to adopt energy crops. A few studies have applied prospect theory to predict adoption behavior by loss-averse farmers who care more about down-side risks than about up-side gains from adoption (Anand et al., 2019; Bocquého et al., 2015).

3.3 Behavioral economic analysis

There has been growing recognition of the need to allow for departures from neo-classical economic behavior that assumes that adoption decisions are based on profit or utility maximization (Weersink & Fulton, 2020). Behavioral economic models incorporate insights from psychology to examine the role of non-economic factors, such as inertia, status quo bias, cognitive factors, peer effects, social networks and social preferences in influencing technology adoption decisions (see reviews by Dessart et al., 2019 and Streletskaya et al., 2020).

4. Insights on factors affecting adoption from economic models

We now review findings from the economics literature on the factors that influence adoption decisions and apply them to the three types of emerging sustainable intensification technologies. We group the factors that have been shown to influence adoption in the following categories: characteristics of the new technology, characteristics of farms and farmers, as well as social and economic environments where the adoption may occur.

4.1 Technology characteristics

Montes de Oca Munguia and Llewellyn (2020) show that technology characteristics are critical determinants of technology adoption decisions.

The effects of a given characteristic of a technology on adoption behavior will depend on market conditions, location, as well as farm and farmer characteristics. Yield-increasing or input-conserving technologies are more likely to be adopted when output price or input prices are high while the capital and learning costs of adoption are low (Khanna & Zilberman, 2012). Technologies such as energy crops and precision technologies with high upfront capital costs are less likely to be adopted when output price uncertainty is high or when farmers have higher discount rates or are more risk averse (Isik & Khanna, 2003). High sunk costs and irreversibility of these costs create incentive to delay adoption even if the net present value of returns from adoption is positive. Higher-yielding energy crops are likely to be adopted at a lower biomass price by risk-averse farmers if these crops are also less risky (Miao & Khanna, 2014) and by loss-averse farmers if they have lower probability of leading to a loss in income relative to the status quo (Anand et al., 2019; Khanna et al., 2017). Song et al. (2011) show that the adoption of switchgrass is sensitive to the underlying stochastic nature of crop returns. Dumortier et al. (2017) find that when the option value of delaying switching from conventional crops to bioenergy crops is considered, then the biomass price required for such a switch is significantly increased. Technological complexity can dis-incentivize and delay adoption. Technology components that are simpler to adopt and can lead to learning that improves the efficacy of more complex components are also likely to be adopted earlier and to lead to sequential adoption of other components (Khanna, 2001).

4.2 Farm and location characteristics

Because heterogeneity across farms in soil quality, sub-field variability in soil quality, water availability, size, access to terminal markets, and environmental sensitivity implies that the same technology or crop diversification portfolio may generate different profits and environment impacts on different farms, studies have shown that technology adoption is influenced by farm and location characteristics. For instance, Khanna (2001) finds that the adoption of soil testing technology is determined by soil quality whereas the adoption of variable rate technology is more likely to be influenced by farm size. Miao and Khanna (2017a) find that high-yielding energy crops can be risk-reducing and are more likely to be adopted in locations where conventional crop production is riskier.

4.3 Characteristics of farmers

Farmers' attitudes toward risk, loss, ambiguity, and time have received much attention in the agricultural technology adoption literature. Standard expected utility theory predicts that risk-averse farmers are less likely to adopt new technologies that involve risky returns (Chavas & Nauges, 2020). Recent studies based on prospect theory show that farmers who are more loss-averse are less likely to adopt perennial bioenergy crops (Anand et al., 2019; Bocquého et al., 2015). This literature shows that loss aversion and overweighting of small probability events can explain lower than expected adoption of profitable technologies with a small likelihood of loss. Since adoption of the emerging technologies generally involve upfront costs and have a long lifespan, a key factor shown to influence technology adoption decisions is farmers' discount rate. Studies have found that impatient farmers tend to be less likely to adopt new technologies that require up-front investment (e.g. Duquette et al., 2014), which is particularly the case for perennial bioenergy crops. These crops require large establishment costs and offer little returns during their establishment period (Miao & Khanna, 2017a, b). Because precision farming technologies and agrivoltaics also involve significant upfront investment in physical and human capital, similar to bioenergy crops, we expect that these findings would apply to the adoption of these technologies as well.

Credit constraint is another factor influencing adoption. Not only do farmers in many developing countries face credit constraints, but also some farmers, particularly new start-up farmers, in the developed countries such as the United States are in a similar situation (Kirwan, 2014). Studies have documented that credit constraints are correlated with low adoption of capital-intensive technologies in developing countries (e.g. Gine & Klonner, 2005). The same conclusion holds for farmers in developed countries. Miao and Khanna (2017a,b) show that establishment cost-share subsidies have considerable impact on increasing perennial bioenergy crop adoption, with the magnitude of the impact depending on farmers' risk and time preferences.

Moreover, studies have shown that many other behavioral factors such as dispositional factors (e.g. farmers' personality, values, farming objective, attitude toward changes) and social factors (e.g. willingness to abide to social norms, pursuit of higher social status, and involvement in social comparison) also affect farmers' adoption decisions (see Dessart et al. (2019) for a comprehensive review).

4.4 Social preferences and enabling environment

Social and economic environment is also expected to shape technology adoption decisions in various ways. First, the viability of a new technology in a region is influenced by the infrastructure and market development in the region. For instance, to harness the benefit of advanced precision farming technologies coupled with big data and machine learning, high-speed internet connectivity and access to computers are indispensable. The availability of biorefineries in proximity to biomass production areas is an important determinant of the returns from energy crop production. Moreover, access to the electric grid is a basic premise for adopting agrivoltaic systems. Legal protection for ensuring privacy and security of farm data is required to adopt precision technologies that require data sharing (Miao & Khanna, 2020;

Weersink et al., 2018). In addition, the success of a new technology often requires complementary supply chains of inputs and technology service providers, extension agents, and other trusted information sources (Duflo et al., 2011; Emerick et al., 2016).

Second, social norms, social acceptance, and peer effects have been shown to affect the diffusion of new technologies. Non-pecuniary features of a new technology, such as the effects of a new crop on the amenity value of the land or the aesthetics of the landscape can affect adoption (Skevas et al., 2016; Villamil et al., 2008). Schelly et al., (2021) emphasize that community priorities, values, and concerns can be potential barriers for solar energy adoption.

Third, existing policies such as crop insurance for conventional crops can disincentivize adoption of new crops not covered by such policies (Khanna et al., 2017); offering insurance for bioenergy crops may incentivize the adoption of these crops (Anand et al., 2019; Miao & Khanna, 2017). Policies that reward farmers for internalizing the environmental benefits of adoption or the positive externality generated by enabling learning by doing and lowering learning costs of these technologies for other farmers can also incentivize adoption. Foster and Rosenzweig (2010) show that subsidies for early adoption can enhance adoption while Khanna et al. (2002) show that penalties for generating run-off can incentivize adoption of more efficient irrigation technologies. Since the emerging technologies in this article can reduce environmental damages, their adoption is likely to be incentivized by imposing a price on those damages (Khanna et al., 2002). Khanna et al. (2002) find that high output prices, high input prices, and a tax for pollution can incentivize the adoption of water-efficient irrigation technologies that increase yield, lower input use, and reduce pollution. In the case of second-generation biofuels, studies have shown that policy uncertainty reduces the incentive to invest in cellulosic biorefieneries and innovation (Clancy and Moschini, 2018; Miao et al., 2012).

5. Optimal sustainable intensification of food and energy production

Sustainable intensification calls for a shift to new technologies that increase the productivity of agricultural inputs with the potential to lower input costs and environmental damages. While there is some potential for win-win outcomes with their adoption, voluntary incentives for adoption are likely to be limited for various reasons, including high fixed costs of adoption, large learning costs and behavioral preferences, and the absence of any monetary rewards (policy incentives) for providing environmental services. Existing studies on incentives for adopting precision farming technologies indicate this to be the case (Khanna, 2020). Moreover, voluntary adoption may not occur in the right locations or to the extent needed to achieve desired environmental outcomes.

We define the socially optimal level of adoption of sustainable intensification technologies in a region or economy as the level that maximizes aggregate social welfare that considers the net benefits to food and fuel consumers and producers net of the value of environmental damages. In determining the socially optimal level of adoption it is important to note that inducing adoption of technologies for sustainable intensification is not the end goal; rather it is a means to achieving desired social outcomes, such as obtaining the benefits from food and renewable energy production from land while improving environmental quality. It requires balancing the economic costs to consumers and producers of switching from the status quo to new technologies with the value of the environmental benefits obtained. In doing this analysis it is important to recognize that improved environmental outcomes can also be achieved by two other approaches: (i) reducing the use of polluting inputs with existing technologies (referred to as an intensive margin effect) and (ii) reducing land under crop production (extensive margin effect) (see Khanna et al., 2002). The optimal mix of these three approaches will depend on their relative costs and effectiveness in achieving desired environmental outcomes. A normative approach is needed to examine the optimal mix, extent, and spatial location of these three approaches to maximize social net benefits.

To determine the socially optimal mix of these three approaches (i.e. technology adoption, intensive margin effect, and extensive margin effect) to reducing the environmental impact of agriculture, economists have developed a social benefit–cost framework based on welfare-economic theory. This framework aggregates the effect of individual decisions by heterogeneous decision makers, in a region, about technology choice, input applications and land use, and then examines their implications for input and output markets, prices, consumer and producer net benefits and the environment. It incorporates the trade-offs between the value of improvements in ecosystem services and the costs of achieving them as well as the consequences of technology adoption on input and output markets and land use. This framework can be applied at a regional level to determine socially optimal strategies for improving environmental quality. It can also be used to design policy incentives that lead to the socially optimal level of sustainable intensification and land use decisions by making them compatible with privately optimal decisions of producers and consumers.

This framework consists of four key components: (i) ecosystem modeling of the impacts of conventional and sustainable intensification technologies on the ecosystem, (ii) site-specific monetary value of the benefits/damages from these multiple environmental impacts, (iii) integrated economic-ecosystem modeling of the effects of large scale adoption of sustainable agricultural practices, and (iv) design of policy incentives to induce producers to internalize the multiple externalities caused by their agricultural production activities. This framework determines the optimal approach to maximize net social benefits subject to various constraints on land availability, heterogeneous land quality and behavioral preferences in the region. A regional approach incorporates the feedback effects of a large-scale switch to sustainable intensification technologies in a region on crop prices, land rents and other market variables as well as their welfare implications for food and energy consumers and producers. We briefly discuss each of these components:

5.1 Ecosystem modeling

Ecosystem models are key to quantifying the site-specific impacts of specific technologies on crop yields, input requirements and the environment. This information is critical to determine the potential economic incentives for adopting them and for the system-wide impacts of adoption. For technologies that are being adopted widely, this information could be obtained from observed data, but for emerging technologies that are still at an experimental stage, crop models provide a mechanism for extrapolating data from a few fields to a larger regional scale. Quantifying environmental impacts, such as those on water quality and soil carbon stocks, is difficult for both existing and emerging technologies because they cannot be observed and monitored due to their diffuse nature. These impacts are also difficult to directly relate to observed information about input use and practices adoption due to the spatial heterogeneity in the links between input use and polluting discharges and the effects of stochastic climatic and biophysical factors on these links. Spatially explicit biophysical models are, therefore, needed to predict the multi-dimensional environmental outcomes of agricultural production in a region with existing and new technologies.

There are many crop models that simulate crop yield responses to climate, soil, plant species characteristics and management practices (see review in Jones et al., 2017). These models can also simulate crop water use, nitrogen uptake, nitrate leaching, soil erosion, soil carbon, greenhouse gas and nitrous oxide emissions and residual soil nutrients at a point in time as well as carry-over changes in soil nutrients and organic matter over time. Scenario analyses can be conducted using these models to predict responses to various climate and soil conditions, management practices and to analyze their implications for economic and environmental trade-offs. Most models are designed to model a single "point" in space that could be a field or a county, although some models do simulate the transport of nutrients over space, from fields to the water bodies (Cibin et al., 2016; VanLoocke et al., 2010). These models are typically calibrated using field data which makes their accuracy reliant on the availability of data under various management practices; this is likely to be data from experimental fields in the case of technologies that are not yet commercially viable. To couple these models with economic analysis, they need to simulate the outcomes of interest under the full range of alternative technologies or management practices that economic decision makers are expected to choose from and at a fine spatial resolution in order to incorporate spatial heterogeneity in climate and soil conditions.[3] In some cases researchers have used comprehensive crop models to create reduced form relationships between yield (or pollution) and a range of site-specific conditions and management practices. These can be interpreted as "production functions" and "pollution functions" and embedded in economic models (see an example in Larson et al., 1996).

5.2 Non-market benefits of sustainable intensification

Sustainable intensification can lead to multiple environmental benefits that range from local to global, including those to air and water quality, soil health and carbon sequestration, and displacement of fossil fuels. These benefits can be synergistic or involve trade-offs. Non-market valuation of the multi-dimensional environmental consequences of these technologies is critical to quantifying the net social benefits of sustainable intensification and the optimal level that balances these net benefits with its economic costs. Conducting primary non-market valuation studies at diverse sites in a watershed or region for differing levels of environmental improvements with the adoption of sustainable intensification technologies will be time-consuming and expensive. Benefit transfer methods that apply monetary value of environmental benefits from primary studies at one or more study sites to predict willingness to pay at other (policy) sites is a promising and pragmatic approach to determining the overall benefits of adoption and their variation across spatial locations so that policies can be targeted to regions where the net benefits are maximized. Benefit transfer methods for ecosystem service valuation range from taking simple unit values or single-site benefit functions and applying them to other sites to more complex meta-analysis and Bayesian methods that can accommodate site and preference heterogeneity. Although the evidence to support the claim that sophisticated methods for benefit transfer are more accurate than simpler methods is mixed and context specific (Johnston et al., 2018), there is emerging consensus over the advantages of using meta-regression models (Johnston & Bauer, 2020). Chen, Debnath, et al. (2021) apply the unit value approach to quantify the non-market benefits, in the form of greenhouse gas reduction and nitrogen leakage reduction, of advanced biofuels using energy crops and crop residues. Chen, Blanc-Betes, et al. (2021) apply the same approach to examine the

[3] Examples of this approach can be found in Hudiburg et al. (2016) where the authors couple the biogeochemical model DayCent with the economic model Biofuel and Environmental Policy Analysis Model (BEPAM) to simulate spatially heterogeneous yields and soil carbon effects of high yielding perennial energy crops and conventional crops to examine the spatially varying incentives for switching from conventional crops to energy crops for cellulosic biofuels. Another example is Ferin et al. (2021) where the Agro-IBIS-THMB model is coupled with BEPAM to examine the effects of substituting energy crops on water quality to meet a cellulosic biofuel mandate.

value of economic and GHG savings from growing energy crops on Conservation Reserve Program land in the US.

In the absence of monetary values of ecosystem services from sustainable intensification, economists have conducted cost-effectiveness analysis of the least cost approach to sustainable intensification that would achieve desired environmental quality objectives at least cost. Khanna et al. (2002) analyze the optimal level of adoption of more efficient irrigation technologies as well as changes in water use at the intensive and extensive margins to achieve targets for reducing polluting drainage at least cost. Housh, Khanna, et al. (2015) analyze the optimal mix of high-yielding energy crops to displace conventional crops to meet biofuel and water quality goals in a watershed. Cost-effectiveness analysis is typically conducted to achieve a single environmental goal at least cost. There are a few examples that analyze the implications of cost-effectively achieving multiple environmental targets for the design of environmental policy incentives (Egbendewe-Mondzozoet et al., 2015; Housh, Yaeger, et al., 2015).

5.3 Economic modeling

Economic models that integrate biophysical information about outcomes of alternative technologies with economic information about the costs and benefits of various choices and the non-market impacts of these choices can be applied to examine the optimal mix of intensive, extensive, and technology switching choices. Examples of these integrated models applied to the technologies being considered here range in scale from a small region (see Isik & Khanna, 2003; Khanna et al., 2002) to national and global scales (see review in Hudiburg et al., 2016; Khanna et al., 2014; Moore et al., 2020). These models can vary in the preferences of the decision makers they analyze (such as their risk and time preferences), their inclusion of various uncertainties about technology performance and location specific characteristics (e.g. Khanna et al., 2000; Miao & Khanna, 2017a,b).

While the socially optimal technology and land use decisions will vary across spatially heterogeneous units, large-scale adoption in a region is expected to impact total agricultural production which in turn could affect crop prices, input prices, and land rents. This could affect the extent of diffusion of these technologies, positively or negatively. It will also impact consumer and producer benefits from agricultural production, the socially optimal level of sustainable intensification and other changes at the intensive and extensive margins. Some large-scale models examine these feedback effects on the socially optimal choices (e.g. Hudiburg et al., 2016). These models assume that land use decisions are being made by decentralized micro-units (that may be grids, counties, aggregates of counties, or agro-ecological zones) based on net economic returns taking input and output prices as given. The aggregate production decisions of these micro-units determine aggregate supply of various agricultural commodities that together with aggregate demand for these commodities affects prices at national and global levels. Thus, these models simultaneously determine land use and technology choices at the micro-level and the economic consequences of those choices on commodity prices, exports and imports, and the environment at the macro-level. These models explicitly incorporate key technology features and their effects on inputs and outputs from biophysical models as well as the spatial heterogeneity in the effects of alternative technologies depending on local production conditions across these micro-units (e.g. Ferin et al., 2021; Hudiburg et al., 2016).

The systems-based framework described above can improve understanding about the economy-wide impacts of various agri-environmental policies and their implications for environmental quality. It can be used to determine optimal policy parameters, either as shadow prices of constraints on environmental outcomes by conducting a cost-effectiveness analysis or based on the monetary value of ecosystem services. This framework is useful for designing and analyzing the need for policy incentives to achieve a more sustainable agricultural system and the design of policy incentives to induce internalization of externalities of agricultural production.

A systems approach can be applied to examine the incentives that these agri-environmental policies provide for sustainable intensification technology adoption and other land use choices and their social welfare benefits. A recent example of this can be seen in Chen, Debnath, et al. (2021) that apply this approach to examine the mix of energy crops that will be incentivized by biofuel policies in the US and compare their economic costs with the monetary value of effects on GHG emissions and nitrogen leakage.

5.4 Key insights from systems models for inducing optimal sustainable intensification

We now briefly discuss several insights about the optimal level, mix, and location of sustainable intensification technologies from the landscape or regional systems models. First, they show that spatial heterogeneity in the costs and benefits of adopting sustainable intensification technologies implies that it is not likely to be privately optimal to adopt these technologies at all locations. The environmental benefits from adopting these technologies also vary across a region based on a variety of location-specific characteristics; the social optimality of adoption decision will be site-specific. More specifically, Khanna et al. (2002) show that adoption of input-efficiency–enhancing technologies, like drip irrigation, is more optimal in areas with lower quality land and on high-valued crops. Similarly, studies examining the most profitable locations for producing energy crops in the rainfed region of the US show that these crops are more likely to be profitable in the southern region of the US where the yields of these crops are high and the opportunity cost of converting land from food crops to energy crops are low (Hudiburg et al., 2016). Energy crops can be a source of risk diversification and Miao and Khanna (2017a,b) show that risk-averse farmers are more likely to adopt them in regions where alternative conventional crops are riskier even though the returns from adopting these energy crops in those regions may be relatively lower than those with conventional crops. Anand et al. (2019) show that if farmers are loss-averse then the type of energy crop they adopt and the regions where it is optimal to grow these crops are substantially different compared to the case where farmers are loss-neutral. High establishment cost of adopting these crops also makes it profitable to adopt in regions that have larger farms.

Second, the social benefits from adopting these technologies are likely to be higher in areas that are more likely to experience adverse environmental consequence from crop production, including areas where soils are more erodible, prone to nutrient loss, and have high within-field spatial variability in growing conditions. By valuing the environmental damages that can be avoided by adopting sustainable intensification technologies and rewarding (penalizing) landowners for the value of ecosystem services (disservices) they provide.

Third, economic models also show that first-best approaches to achieving sustainable outcomes in agriculture should be targeted to the source of the externality (for example, a tax on nitrate run-off or a tax on carbon emissions). A pollution tax is socially efficient because it achieves abatement through a cost-effective mix of the three mechanisms discussed above: a negative extensive margin effect (retirement of polluting and less productive land from crop production), a negative intensive margin effect (a reduction in input use with the existing technology) and a technology switching effect. In contrast, cost-share subsidies and input-reduction subsidies are more restrictive in the types of incentives they provide. For example, a cost-share subsidy has no intensive margin effect and may induce entry of land that is highly polluting while input reduction subsidies may induce changes at the intensive margin but not induce a switch to a high-cost sustainable intensification technology.

Fourth, economic models also show that, to be efficient, cost-share subsidies should be related to the environmental performance outcomes it leads to and not be uniform across space and time. This is because the environmental outcomes from the same technology can vary across locations due to their biophysical features and over time due to climatic conditions. Requiring all areas in a watershed to adopt the same practices would not be the most efficient strategy because not all areas contribute equally to the environmental outcome or have the same cost of abatement and because the incentives needed may differ with farmer-specific behavioral characteristics (Ancev et al., 2006). These efforts are likely to be inefficient and costly because they do not recognize the differences in environmental impacts of the same set of practices due to differences in location, topography, weather, and soil conditions.

Lastly, adoption of these technologies alone may increase input use or pollution rather than decreasing it due to unintended effects. Khanna et al.

(2002) show conditions under which such technologies can increase input-use and lead to adverse environmental outcomes. Large scale adoption of renewable energy technologies can have unintended consequences because they divert some land from food crops and affect their market prices. For example, food-crop-based biofuels can lead to an increase in food crop prices and indirectly cause expansion of cropland and loss of carbon stored in soils and vegetation that can offset some of the GHG savings from using biofuels to displace fossil fuels (see Khanna & Crago, 2012). These incentives are much smaller with advanced biofuels from energy crops because they can be grown on less productive marginal lands; additionally, the amount of land needed to meet biofuel mandates is smaller because these crops are high yielding compared to food crops (Hudiburg et al., 2016). Sustainable intensification technologies, like drip irrigation, can make low-quality marginal land more profitable and create incentives for expanding cropland which would not have occurred otherwise. Policies to promote sustainable intensification should consider these market-mediated effects and design safeguards to prevent them.

6. Conclusions

Sustainable intensification of agriculture is appealing because of its emphasis on increasing agricultural productivity while reducing environmental harm. This article describes several promising technologies that can sustainably intensify food and renewable energy production and have the potential to provide private benefits to landowners and to the environment. It applies the insights from the economic literature analyzing technology adoption decisions to discuss the key factors likely to influence the adoption of these technologies. We also argue for the need to go beyond a focus on examining the incentives for adoption to a systems-based approach to understand the extent to which adoption of these technologies is socially optimal. We describe a landscape-based systems approach that links decisions at a micro-scale with outcomes at a regional/global scale and vice-versa that can be applied for a normative analysis of the extent, mix, and location of adoption of these technologies to achieve sustainability goals.

We summarize key insights obtained from the economic research on these issues. First, it shows that the characteristics of sustainable intensification technologies will interact with the spatially heterogeneous soil quality, climate factors, farm and farmer behavioral preferences, as well as other determinants of agricultural productivity to lead to heterogeneity in technology adoption decisions. Second, this research shows that a combination of approaches is likely to be needed to achieve sustainable agricultural production, including changes in input use at the intensive margin and changes in land use at the extensive margin, in addition to the adoption of sustainable intensification technologies. Third, while bringing out the role for economics in promoting sustainability of agriculture, we also highlight the need for integrating economic and ecosystem modeling to determine the optimal mix of these approaches as well as systems-level feedback effects of these approaches. Lastly, economic analysis shows that optimal policies to induce these approaches in a market-based agricultural sector should be performance-based and not provide uniform practice-based incentives to farmers. Overall, we conclude that the availability of sustainable intensification technologies does not ensure their widespread adoption or that socially optimal environmental outcomes will be achieved; policy incentives and farmer behavioral preferences will play a key role in ensuring the optimal level, mix, and location of adoption of these technologies to achieve agricultural sustainability.

Data availability statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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