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Indigo Agriculture, GeoInnovation Data Science



Executive Summary

Indigo's GeoInnovation team used satellite imagery and in-field identification to map regenerative farming practices and evaluate potential resilience against environmental stressors across the continental United States. With algorithms for detecting regenerative practices and for quantifying crop health and extreme weather, the team's data scientists looked across 3.4 million fields in 1,498 counties to generate insights into the use of cover crops, crop rotations, and no-till management. The study – which is the most expansive field-scale regenerative practice analysis to date – covered more than 304 million acres, 10 terabytes of data, and was supported by the collection of 4,300 field level observations.

On average between 2017-2019, Indigo observed 17 million acres of cover crops (5.6% of total harvested areas) and 104 million acres of no-till (34.3% of total harvested acres) across the US. We also identified fields with multiple regenerative practices, a result not available in the public domain at this time. This allowed Indigo to profile different types of regenerative fields, including those that combined planting cover crops and practicing no-till, fields that used at least one regenerative practices, and fields that planted cover crops but continued conventional tilling. Additionally, by linking field-level practices to measures of plant greenness, our work demonstrated that regeneratively farmed fields performed as well as conventional fields under normal and stressed conditions.

Regenerative farming practices are connected to long-term benefits in soil health, increased carbon sequestration, and improved resilience to extreme weather events. Understanding how and where these practices are undertaken is essential for greater practice adoption and benefit documentation.

Tracking regenerative practices, however, is under-developed, especially when contrasted with the suite of information available on planting and production from conventional agricultural reporting. Today's accounting of regenerative farming is limited to an infrequent USDA Census of Agriculture (taking place every five years), survey work provided at coarse spatial scales. The OpTIS product, developed by Dagan Inc. and supported by CTIC, TNC, and others, is also based on remote sensing data, and that team has performed a similar analysis focused on the Corn Belt. There is a clear need for methodologies that enable more timely, frequent, and detailed estimates of regenerative practice adoption and we welcome these complementary approaches, and believe that an intercomparison of results could lead to enhancing the accuracy and positive benefits of large scale satellite based approaches.

Indigo's approach provides information at the field, county, state, region and national scales, while providing insights into how farmer practices compare across geographies and time. The company will update its inventory and resilience estimates on at least an annual basis to provide the most current view of regenerative practice use, based on improvements in algorithms and additional field data inputs.

Methodology

General

Our study region included 1,498 counties across 40 states, which contain roughly 90% of the total cropland area of the US (96% of corn and soy). We created auto-delineated field boundaries across all the counties in the domain, based on historical sequences of predicted crop types from the USDA Cropland Data Layer (CDL), and used these field boundaries to generate daily time series of satellite-derived vegetation indices, which were used to identify annual cover crop and tillage practices for each field, along with other important covariates such as crop health, extreme weather, flooding, and soils. In all there were over 100 attributes generated for each field and for each season from 2013-2019.



To support our model development and assessment of results, a field campaign was conducted in early 2020 that leveraged Indigo capabilities in field agronomy and technology-assisted data collection, which utilized a customized mobile application to collect field level data. Collected samples were roughly balanced in regard to tillage and cover crop practices, and the resulting data supported algorithm development, testing, and map assessment. This campaign provided data for over 300,000 acres across the continental US, encompassing about 4,300 fields allowing us to better train our models and interpret the results.

Algorithms

Detection of cover crops

Our study region included 1,498 counties across 40 states, which contain roughly 90% of the total cropland area of the US (96% of corn and soy). We created auto-delineated field boundaries across all the counties in the domain, based on historical sequences of predicted crop types from the USDA Cropland Data Layer (CDL), and used these field boundaries to generate daily time series of satellite-derived vegetation indices, which were used to identify annual cover crop and tillage practices for each field, along with other important covariates such as crop health, extreme weather, flooding, and soils. In all there were over 100 attributes generated for each field and for each season from 2013-2019.

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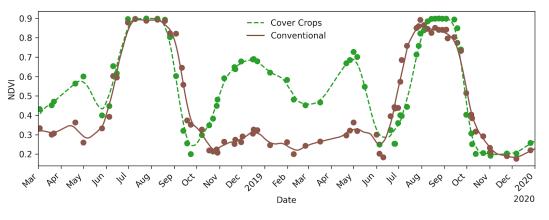


Figure 1: Time-series of NDVI derived from HLS imagery for two fields in Clark County, IL. One field was conventionally farmed, while the other was likely planted with cover crops in both 2018 and 2019, resulting in additional peaks in vegetation greenness.

Detection of tillage events

Detecting tillage events with remote sensing relies on an ability to observe residue cover on fields. Fields with residue cover absorb more shortwave infrared (SWIR) radiation than bare soil, with greater absorption at longer SWIR wavelengths. The Normalized Difference Tillage Index (NDTI), which can be calculated with Landsat, Sentinel-2, and MODIS data, among others, is able to characterize this absorption feature of residue, allowing fields with residue (high NDTI) to be separated from fields with bare soil (low NDTI) (Figure 2).



Using the HLS time-series, two features were calculated and used in a decision tree to classify fields as tilled or not filled on an annual basis: The minimum NDTI between Sept 1 and Aug 31, and the difference between the minimum NDTI and the 90th percentile of NDTI from 2013-2020 for each field. In order to focus the analysis between harvest and planting, when tillage occurs, only NDTI observations occurring when NDVI is low (e.g., less than 0.3) were used to calculate minimum NDTI and the 90th percentile of NDTI. Thresholds for the two model features were chosen which maximized accuracy against the field dataset while maintaining high correspondence with USDA state-level adoption rates in 2017. Specifically, fields with minimum NDTI < 0.05 or a difference of greater than 0.09 between the minimum and 90th percentile of NDTI were flagged as tilled. As NDTI is also sensitive to surface wetness, data from the Soil Moisture Active Passive (SMAP) mission was used to screen observations during periods of high soil moisture.

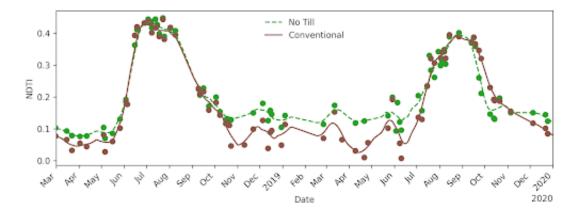


Figure 2: Time-series of NDTI derived from HLS imagery for two fields in Bureau County, IL. One field is conventionally tilled, resulting in dips in NDTI in the fall of 2018 and the spring of 2019. The second field, which was likely not tilled, has consistently higher winter time NDTI.

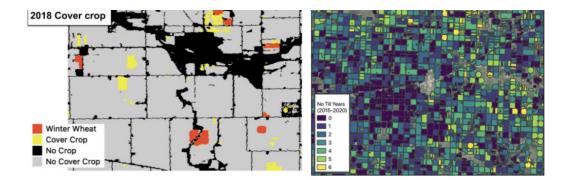


Figure 3: a) 2018 field-scale classification of cover crops for a subset of fields in Iowa, and b) The number of years detected as no-till for fields in Kearney County, Nebraska between 2015-2020.



Inventory Scaling

In order to derive estimates of cover crop and no-till adoption, a scheme was developed to scale estimates from field-level predictions to county, ag district, production region, and national levels. To begin, adoption rates were derived at the county-level by determining the fraction of acres in each practice to the total area mapped within each county for six crop classes: corn, soy, cotton, small grains (e.g., wheat, oats, barley), other grains (e.g., rice, peas, dry beans) and other crops (e.g., vegetables). Next, these adoption rates were multiplied by the total area of each crop class in the county according to the previous year's CDL map, providing an estimate of the number of acres in each practice at the county-level. We used the CDL to determine crop areas because our satellite-derived field boundaries do not explicitly match true field boundaries (Figure 4a), resulting in a potential underestimation of crop area. The same process was repeated to calculate areas at the ag district level, with production region and national estimates derived through summations of the ag district level estimates.



Figure 4: a) Example of field boundaries generated through segmentation of CDL crop histories. b) Counties included in the study

Resilience and Adoption

In order to assess the benefits of regenerative practices, we compared the health of approximately 24,000 fields that planted cover crops against their conventional neighbors across the US. Fields that planted cover crops in at least two of four years between 2016-2019 were selected, and matched to their nearest conventionally farmed neighbor of the same crop type, with conventional defined as zero years of cover crops between 2016-2019. If no conventional neighbor could be identified within 5 km, that regenerative field was dropped from the analysis. Once matches were determined, crop health was compared between each field pair using a time-series of the Enhanced Vegetation Index 2 (EVI2) derived from the HLS dataset. The difference between the season peak of EVI2, a demonstrated indicator of crop yield, was calculated for each field pair, providing an indication of the relative benefit of regenerative practices. In addition to assessing peak EVI2, average EVI2 time-series were generated across the regenerative fields at county and ag district levels, and compared against time-series from neighboring conventional fields, allowing for a full season assessment of crop progression.



Results and Implications

Inventory

Our analysis generated predictions for cover crop and no-till acres for nearly every state and ag district in the county (Figure 5). We estimate that roughly 34.3% of acres used no-till management across the US (104.3M acres) and 5.6% used cover crops (17.0M acres) between 2017 and 2019. These estimates were similar to 2017 USDA Census of Agriculture estimates (37% for no-till, 5.6% for cover crops). While cover crop adoption rate was the same for our dataset and USDA Ag Census (5.6%), our estimate of total cover crop acreage (17.0M acres) was higher than the acreage reported by the Ag Census (15.1M acres). This difference is caused by discrepancies between our estimate of total crop area (estimated from CDL maps) and the USDA surveyed area. Alternatively, for no-till, while the adoption rates differ slightly, the estimated total acreage of no-till adoption is very similar (104.3M vs 104.5M for Indigo and USDA Ag Census, respectively).

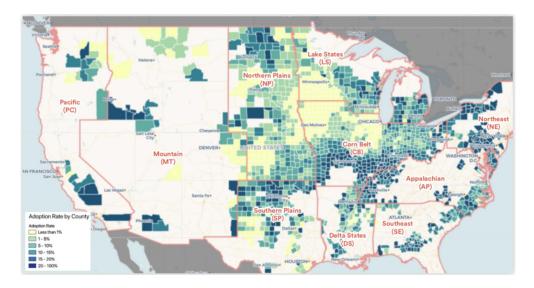


Figure 5: National map of 2017-2019 average county-level cover crop adoption rates

Table 1: National adoption rates and acreage estimates for Indigo [2017-2019 average] and NASS Ag Census [2017]. Total crop area estimates differ between the datasets, resulting in discrepancies between adoption rates and adoption areas.

Practice	Indigo	NASS Ag Census*	
No-Till	34.3% (104.3 M acres)	37.0% (104.5 M acres)	
Cover crop	5.6% (17.0 M acres)	5.6% (15.4 M acres)	

*https://soilhealthinstitute.org/wp-content/uploads/2019/07/Soil-Health-Census-Report.pdf



In order to assess how our estimates compare to existing remote sensing derived products, we compared our results to CTIC OpTIS, which provides estimates of cover crop and tillage across the major Corn Belt states (Table 2). Results were compared for 2017, as USDA census data was also available for this year. Across the region where OpTIS data is available, we estimated that 5.3% of acres used cover crops (6.7M acres) in 2017 while the estimate from OpTIS was slightly lower (5.0%, 6.0M acres). Both cover crop estimates matched fairly well with USDA census data (6.2M acres). We predicted a higher no-till rate across the region (31%, 39.3M acres) than OpTIS (25.3%, 31.3M acres), both of which were lower than the estimated area from the USDA (43M acres). An adoption rate could not be calculated for USDA, as we did not have an estimate for the total area surveyed for this study region.

		Acres	Adoption Rate			
Practice Indigo		OpTIS	USDA	Indigo	OpTIS	
Cover crops	6,694,998	6,021,886	6,193,772	5.3%	5.0%	
Tillage	39,303,588	31,250,104	42,999,897	31.1%	25.3%	

Table 2: Comparison of Indigo, Optis, and USDA acres and adoption rates for the OpTIS study region (major Corn Belt states) in 2017.

Note: An adoption rate could not be calculated for USDA, as we did not have an estimate for the total surveyed area for this study region.

The comparison and contrast of adoption rates across production regions in a systematic and repeatable way provides critical insights into where practices are well established, and where opportunities for expanding these practices exist (Table 3). We found that adoption of regenerative farming practices was most prevalent in the Southeast, Northeast and Northern Plains production regions with 38%, 37%, and 35% of acres in those regions, respectively, using at least one regenerative practice. Notably, in the Northern Plains which represents 24.7% of all acreage planted to crop land in the US, 33% of all acreage (25M acres) in the region used no-till only and 1.7% (1.3M acres) of all acres planted cover crops and used no-till practices. The Corn Belt, which represents the largest amount of cropland in the country (25%), showed slightly more acreage utilizing both cover crops and no-till practices than the Northern Plains at 1.8% (1.4M acres). In the same region, 26% (20M acres) employed at least one regenerative practice. These estimates will set a baseline for us to explore the factors that lead to unequal adoption regionally, which can inform future efforts to expand adoption nationally.



Table 3: Indigo adoption rates for crop production regions. Crop rotation is defined here as planting more than two crop types between 2013-2018.

USDA Production Regions	Total Planted Acres (millions)	Field Count (millions)	Cover Crops Planted (%)	No-Till (%)	Rotations (%)	Applied One Practice (%)	Applied Two Practices (%)	Applied Three Practices (%)
Appalachian	13.9	0.14	10.1	63.6	37.8	68.6	26.6	2.4
Corn Belt	76.2	1.04	3.7	35.3	11.2	38.8	6.5	0.5
Delta States	14.0	0.16	7	32.1	24.9	46.1	10	0.8
Lake States	36.0	0.46	6.8	24	24.7	39.9	8.5	0.7
Mountain	28.1	0.19	5.2	32.1	35.3	58.4	10.8	0.3
Northeast	8.9	0.08	17.7	66.3	30.9	69.8	25.2	3
Northern Plains	76.5	0.94	2.9	36.5	31.2	52.6	12.9	0.6
Pacific	14.8	0.08	7.6	24.2	25.6	41.7	6.2	0.4
Southeast	8.8	0.06	14.2	41.2	37.9	64.6	21.2	2.5
Southern Plains	27.1	0.24	7.6	22.6	21.7	42	8.3	0.5
US Total	304.3	3.4	5.6	34.3	24.8	47.8	10.8	0.7

Accuracy Assessment

The accuracies of the tillage and cover crops algorithms were assessed using amassed field data in early 2020 (see methods section for details). For tillage, fields were divided into two categories: (1) Conventional tillage fields with less than 25% residue cover, and (2) No-till fields with greater than 50% residue cover. To provide a balanced assessment of the conventional till and no-till categories, an equal number of conventional till and no-till fields were sampled per crop type, resulting in a reduced validation set. Overall, the tillage algorithm accuracy was higher than 70% accuracy for all assessed crop types (Figure 6). The model correctly predicted tillage practice status on 319 of 364 corn fields (88%), 152 of 194 soy fields (78%), 46 of 64 winter wheat fields (72%), and 24 of 26 sorghum fields (92%), for an overall accuracy rate of 83%.

In order to assess cover crop accuracy, the training dataset was also split into two categories: (1) fields with no vegetation cover at the time of visit (2560 fields), and (2) fields labeled as cover crops with greater than 50% surface cover (295 fields). The cover crop algorithm correctly identified presence or absence of cover crops in 2,696 (94.4%) of the fields (Figure 8). However, of the 295 fields identified as having cover crops in the field campaign, only 176 were correctly identified by the algorithm (60% producer's accuracy).

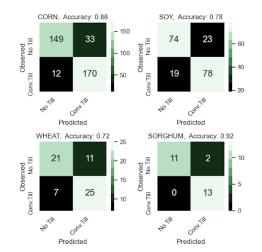
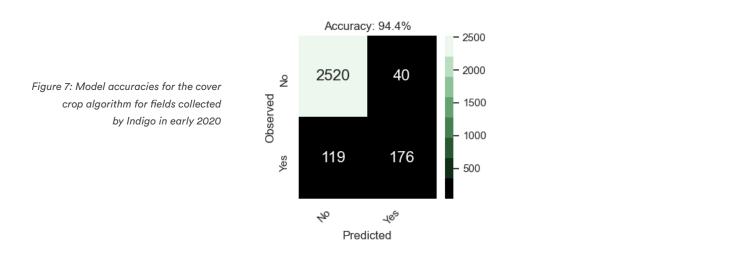


Figure 6: Model accuracies for the tillage algorithm against various crop types for fields collected by Indigo in early 2020





Resiliency

Nation-wide comparison of crop health between regenerative fields and their neighbors

The time-series in Figure 8 show the seasonal progression of crop health in 2018 for fields planted with cover crops in at least 2 years (2016-2019) versus their conventional counterparts for corn and soybeans in the Corn Belt production region. EVI2 is displayed, which is a strong remote sensing indicator of crop health and crop yield. These figures reveal that using cover crops will not lead to a lag in crop development for either corn and soybeans, and similar EVI2 peak values are reached. There appears to be a small seasonal shift in the crop health curve for soybeans, with slightly delayed emergence, but this is accompanied by a slightly greener period in the fall. The higher EVI2 values outside of the growing season for the cover crop group capture the signal of cover crops.

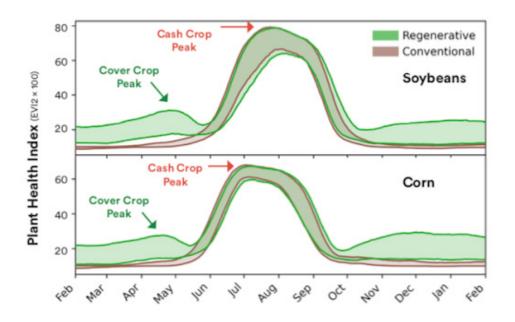


Figure 8: Health of regenerative fields relative to conventional fields across the Corn Belt Production Region in 2018 for Soybeans and Corn. Regenerative fields are defined as greater than or equal to 2 years cover crops. These plots show that using regenerative practices does not negatively impact the progression or health of corn and soy. The time-series captures the center 50% of all fields (~5K fields in each group, 20K total fields displayed).



By calculating the difference in EVI2 peak between each regenerative field and their closest conventional neighbor, we were able to demonstrate the similarity in peak crop health between regenerative and conventional fields across approximately 24K fields in 10 production regions (Figure 9). In certain areas, particularly in the Pacific and Mountain production regions, fields with regenerative practices tended to slightly outperform their conventional neighbors. In certain cases, such as soybeans in the Delta States and Lake States region, show slightly poorer performance for regenerative fields (distribution skewed slightly to the left), which may suggest that farmers tend to transition poorer quality fields to regen practices prior to transitioning their most productive fields in these areas. If poorer quality fields were only recently transitioned to regenerative practices in these areas, it may be too soon to see any positive benefits from these practices.

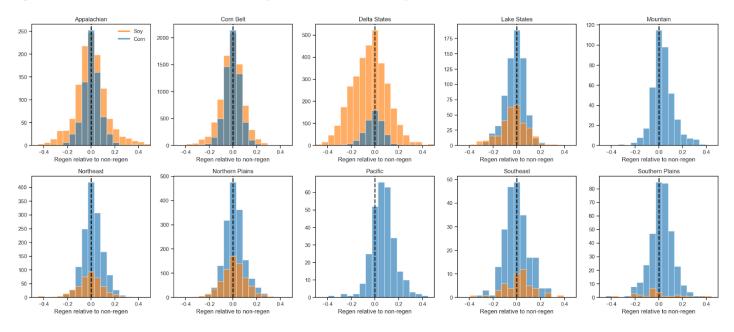


Figure 9: Histograms of the difference in 2018 peak EVI2 between cover cropped fields and non-regen fields of corn (blue) and soybeans (yellow). Values greater than zero represent cases when peak EVI2 was higher for the cover cropped field compared to non-regen neighbors. In general, these results reveal that peak EVI2 is quite similar between regen and non-regen fields, with the majority of fields close to zero.

Local stories of improved resilience to extreme events

While regenerative fields typically showed similar crop health progression as their conventional neighbors, some localized stories of improved resilience to stress emerged. For example, in Livingston County, Missouri, which experienced a drought in 2018. Both cover cropped fields and conventional fields had lower crop health in 2018 relative to 2017 (Figure 10a). However, while conventional fields showed a marked decrease in health in August of 2018, cover cropped fields stayed healthy longer, suggesting that these fields were less impacted by water stress.

In a second case, Hancock County, OH was hard hit by excessive rains in the spring of 2019, preventing field access for planting across many fields. This resulted in lower crop health across many fields in the county for the 2019 growing season. When compared to their conventional neighbors, fields that had planted cover crops in 2+ years tended to have a higher crop health curve in 2019, suggesting an improved ability to plant. While we attempted to control for field location by pairing neighboring farms, exact field position in the landscape may strongly influence this finding, and a deeper investigation is required.



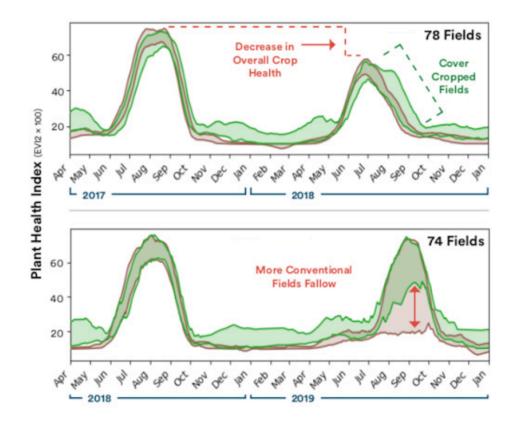


Figure 10: a) Health of regenerative fields (2+ years cover crops) relative to conventional fields in Livingston, County Missouri during the 2018 and 2019 growing seasons for corn. This area experienced a drought in 2018, resulting in an overall decrease in crop health in 2018 relative to 2017. b) Health of regenerative fields (2+ years cover crops) relative to conventional fields in Hancock, County Ohio during the 2018 and 2019 growing seasons for all crops besides winter wheat. These plots show the center 50% of the time-series data for each group.

Impact of field location in the landscape

In addition to county-level analyses, we are currently investigating whether results at county scale hold true under close inspection at field scale. For example, in a number of counties that were hard hit by flooding events in 2019, conventional fields were more likely to be impacted by flooding events relative to regenerative fields in those counties. A close investigation of these findings revealed that field position in the landscape was the main driver of these trends. Specifically, in counties like Monroe County, IL, regenerative practices tended to be practiced on lower quality land further from the floodplain of the Mississippi river, while the majority of high quality land on the floodplain remained in conventional agriculture practices (Figure 11). Therefore, the 2019 floods disproportionately affected conventional fields given their proximity to the river. This suggests that fields most prone to flooding are the least likely to adopt regenerative practices, as these fields are typically the most productive and farmers may be hesitant to change practices on highly productive land. To avoid spurious results, our resilience analysis used a strict requirement of only comparing regenerative fields to their closest conventional neighbors.



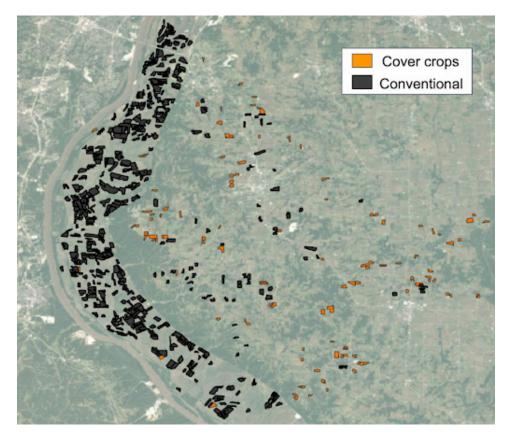


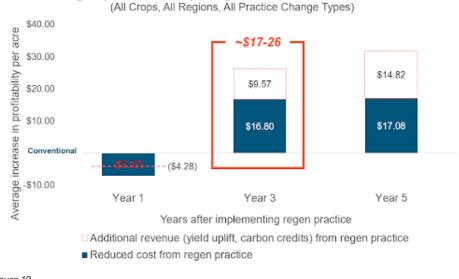
Figure 11: Distribution of regenerative fields within Monroe County, IL, revealing that the majority of fields practicing regenerative agriculture are located on less productive lands away from the floodplains of the Mississippi River. Because of this, fields practicing regenerative agriculture were less affected by the 2019 floods in this county. Here, cover crop fields practices 2+ years of cover crops (2016-2019)

Economics and Financial Benefits

Per-Acre Economic Impact

The adoption of regenerative practices can have a significant impact on profitability. While impact of adoption varies by region and operation, Indigo analysis shows adoption of no till and cover crops has, on average, a \$17-26 per acre impact by the third year (Figure 12). Of this impact, cost savings (reduced inputs) comprises ~\$17 per acre, while potential revenue from yield uplift and carbon credits comprise an additional ~\$9. The impact builds over time, increasing substantially from years 1 to 5. We found impact in years 3 and 5 depend heavily on whether or not we incorporate cover crop yield uplift and carbon credit assumptions into our models - the potential for added profit is substantially higher if both are included.





Average Impact on Profitability of Regenerative Over Conventional Practices

Figure 12 To explore the per-acre economic impact associated with transitioning to regenerative farming, we looked at the impact on profit as compared with 'baseline' across 5 adoption scenarios. These scenarios included conventional to cover crops, conventional to no-till, conventional to both, no-till to both and cover crops to both. For each scenario, crop, and state combination, we included the (1) cost savings from reduced inputs (fertilizer, pesticides, and direct tillage impact) as well as (2) additional revenue from carbon credits and yield uplift potential. We chose to focus on the third year of transition because it provided enough time to see the potential benefits without the transition effects felt in year 1, or uncertainty

associated with forecasting out to year 5.

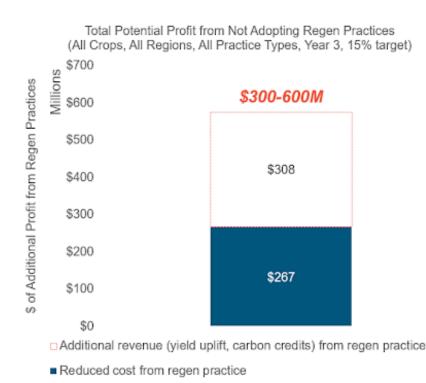


Figure 13: Per Acre Profit from Adopting Regenerative Practices by State



National Economic Impact

This economic impact is significant if scaled up to the national level. If all states increased adoption of both no till and cover crops to 15% (close to the adoption rate of the highest adopting state of Maryland) - the United States would generate an additional \$300-600 Million annually in farm profit (Figure 13). ~50% of this increase in profit comprises cost savings, while the other ~50% comprises additional revenue from potential yield uplift and carbon credits. We calculated this by looking at the acreage distribution of 'baselines' (conventional, no till only, or cover crops only) in each state, and analyzing the impact of converting growers to 'both' in proportion to baseline, up to a total adoption rate of 15%.



Looking Ahead

In this publication, we have looked at the average effect of regenerative practice adoption on growers. To achieve this level of national impact, however, it is imperative that we take into account variation in profit impact across locations, crop types, soil types, and current management practices of each operation. In future publications, Indigo will continue to explore the intricacies of these factors, and show the variation in effects, including levels of carbon sequestration and financial data collected as part of the broader Terraton Experiment.



Conclusions

Why is this study important?

This study presents a first estimate of 2017-2019 regen practices at a national-level, as well as a more granular view of how growers combine or use these practices independently. This has allowed our team to identify two major categories of farms; ones that are slowly adapting regen practices to their farm, and others who see these practices as integral to their farms success. We hypothesize that these behaviors are being driven by three main outcomes. First, the need for growers to develop more robust risk-abatement strategies to combat extreme weather and large climatic events including droughts and floods. Second, there is an opportunity to leverage regenerative practices in order to improve soil quality and increase yield potential while reducing the need for chemical inputs like fertilizers which in-turn increases grower profitability. Finally, there is enormous potential for growers to add another revenue stream to their business by getting paid to sequester carbon in their soil. Not only is this an economic incentive but one that will lead to a more resilient food system.

We have developed a complementary dataset (in addition to the Ag Census and OPTIS) upon which we are able to investigate trends in regen ag practices from field to national scales, however there are some improvements that have made us unique in this space. First, we are able to identify the combined adoption of both cover crops and tillage practices to assess how these practices intersect at the field-scale, which has not previously been reported nationally. Secondly, unlike USDA data sets, our estimates of the adoption of regenerative farming practices are based on detected outcomes of seasonal plant greenness, rather than a large-scale self-reported survey. This has allowed us to observe the actual presence of established cover crops while eliminating regional reporting biases that stem from self reporting.

Additionally, because these USDA surveys are only conducted every five years and take months to develop, implement, and assess, our approach allows for a more frequent in-season analysis of regenerative metrics without the resource devotion that a large scale survey of this nature would require. Finally, the scale of our study area is larger than any other of its kind allowing our team deeper insight into the adoption of these practices then any other leaders in this space. Coupled with our proprietary in-season yield forecasts these improvements will allow Indigo to better track the adoption of these consequential practices at a scale and accuracy level no other organization can match.

Further, Indigo is unique in that we can observe large scale changes to agriculture from space, while also having in-house tools in place allowing us to verify our work with on-the-ground observations. Indigo works closely with thousands of growers across the country allowing us to build novel data sets of grower decisions that are made throughout the year. We strive to use our field scale planting, emergence and harvest data to better calibrate our models and refine our algorithms. In doing so we aim to improve our understanding of the adoption of regenerative practices across the United States.

Where does Indigo's technology go from here?

Applications

By creating a spatially comprehensive inventory of US regenerative practices and corresponding measures of crop health, the datasets provide us statistical power to further investigate the impact of regen across crop types, soil types, climate, and other environmental factors that were not previously possible. By having regen practices measured over multiple years, we can begin to tease out how regen intensity over time impacts resilience in ways that single survey years cannot. Further, by being spatially comprehensive, we will be able to look at specific extreme events and not limited to specific geographic regions. Improving our accuracy for cover crop and tillage is key to better understanding regenerative resilience. By adding additional field data, especially over multiple years, trying to get at tillage intensity, building models that tie field level yield directly to our vegetation indices, we will be able to continue building on this work and better understanding the impact of regenerative farming across the country.



Opportunities for improving the algorithms, results, and understanding

This effort is just the beginning of a program to establish an accurate and complete assessment of regenerative practices for individual fields and over large areas. Our work going forward will benefit from:

- Historical grower inputs on practices for thousands of fields, covering the past five years, through the Indigo Carbon program
- Large volumes of field-scale machine data inputs on management events including planting and tillage
- Continued field survey campaigns, applying what we've learned about optimal times for sampling cover crop and tillage
- Direct observation from a growing network of on-field webcams
- More in-depth exploration of hypotheses and observed patterns with Indigo agronomy staff, focused on both spatial and temporal patterns and at local to national scales
- Inclusion of more and potentially complementary sources of remote sensing data, e.g. from Landsat 7 and Sentinel-1
- A complete 2020 season of remote sensing data to enable better comparison with 2020 field campaign observations

How others can use these data

Our estimates of the combined impact of regenerative practices on grower profitability are preliminary and will be refined in the near future. These results are all conceptual and are based solely on the state of public information we've aggregated into a profitability tool. It is important to note that our estimates do not reflect any single farm or field, but are the result of larger state level aggregations. We call on the scientific and business communities to help us continue pushing the bounds in this space as we recognize the shared potential that this information can provide to the wider community. We are also committed to working internally and engaging with scientists externally to build upon these tools and follow this report with more detailed, peer-reviewed publications. Additionally, we are committed to updating our inventory estimate for the 2019/2020 growing season when we are able to gather more data and provide a more accurate estimate.

For questions regarding the study or access to the underlying data, please write to progressreport@indigoag.com.



