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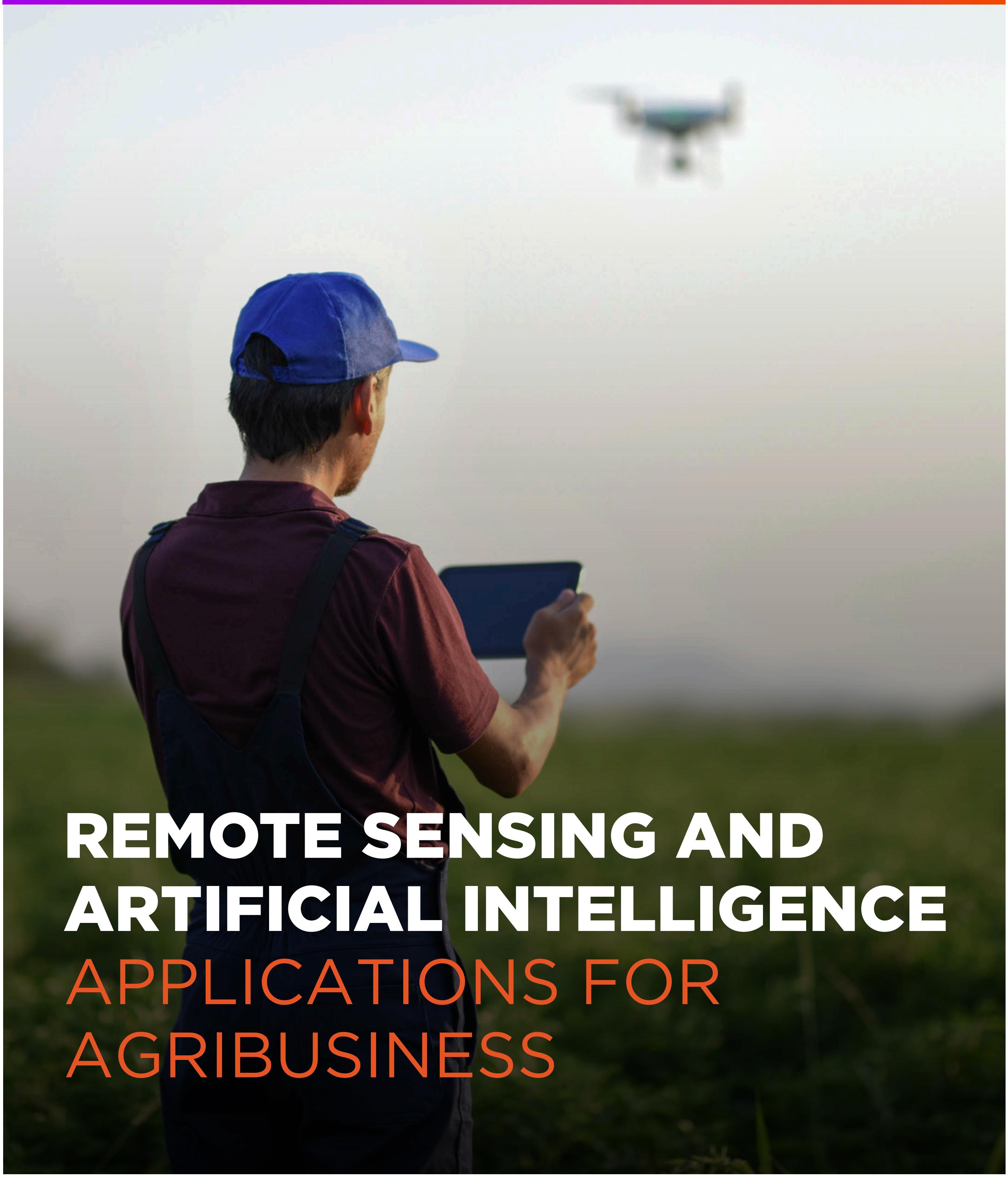

REMOTE SENSING AND ARTIFICIAL INTELLIGENCE APPLICATIONS FOR AGRIBUSINESS

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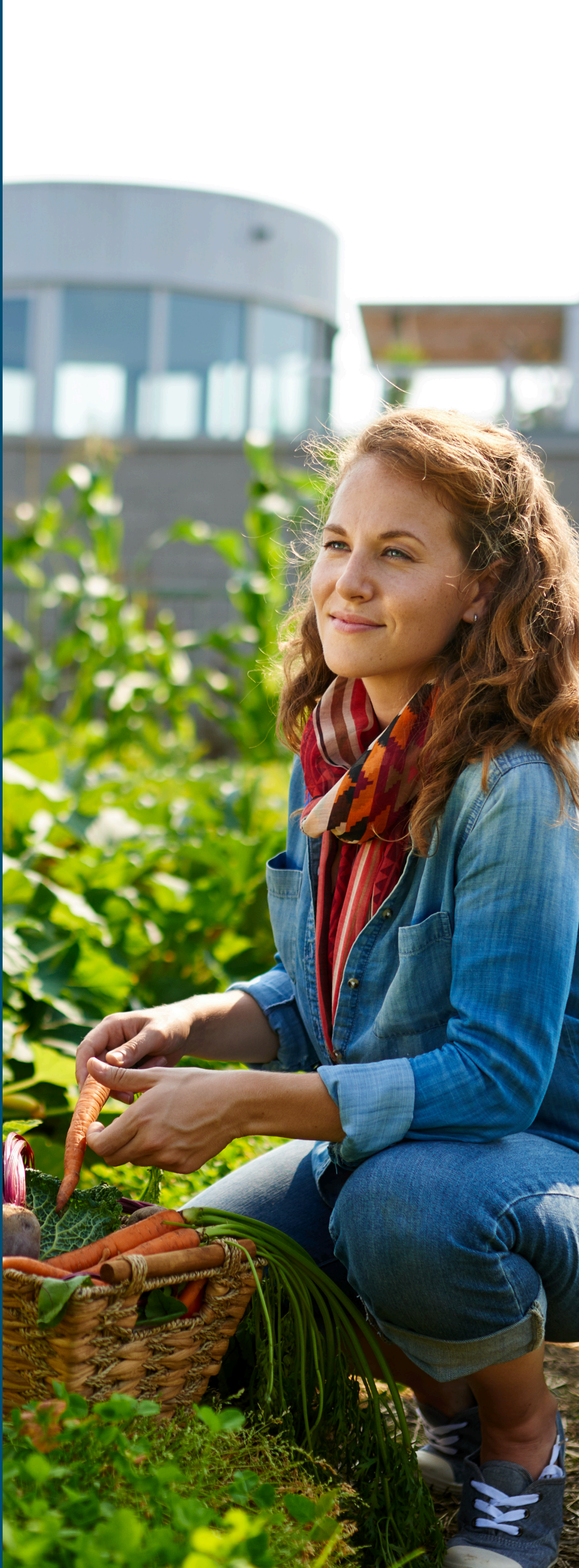

FORWARD

Over the past few years, the global economy has faced an extraordinary combination of Environmental, Social, and Governance (ESG) related disruptions as well as pressure from investors and customers to show tangible results on the sustainability agenda. These forces have set an irreversible new path, re-evaluating how companies do business and contribute to long-term value creation.

The growing alignment to the 2030 Agenda and the bold pledges made by government and business leaders at COP26 on accelerating towards a low-carbon society and one that contributes to our biodiversity and natural capital will need to be met by decisive action. This presents important implications for the adoption of impact-driven and ESG-focused sustainability solutions by corporations, and how they attract and direct capital on a path where profit and purpose are inter-twined.

Innovative technologies provide unprecedented opportunities to put data-driven decision-making at the core of how businesses operate and support the acceleration of sustainability-linked solutions at an unprecedented scale. For example, Artificial Intelligence (AI) is being employed to detect energy emissions, develop greener transport, monitor deforestation, predict extreme weather events and is being used by investors to bring greater transparency and accountability on ESG and impact investing. In other words, technology can help manage long-term risks and rewards, acting as the catalyst for sustainable investing at scale.

Unleashing the power of data, technology and ESG good practice holds great promise in the agribusiness sector. This paper, developed in partnership between Accenture and IDB Invest, aims to help map the current landscape of the adoption of remote sensing and AI technologies to strengthen ESG monitoring and business performance in the agribusiness sector with a focus on opportunities for Latin America and the Caribbean region.
The paper offers insights into current applications of remote sensing technologies adopted by leading organizations and aims to create awareness among industry practitioners and investors of the benefits these technologies in a range of applications including resource optimization, improving farm productivity and yield, and enabling robust monitoring and management of ESG outcomes in agribusiness investments. We also highlight the need to continue investing in building the capacity of companies in the agribusiness sector, overcome hurdles to effectively adopt and adapt these technologies and build long term competitiveness and resilience.

A significant window of opportunity has been presented to tie in the adoption of new technologies and sustainability solutions to meet the Sustainable Development Goals. We trust that this paper will contribute to the conversation on enabling AI-powered solutions to create roadmaps for sustainable investing and the application of ESG good practices in the agribusiness sector.

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Sustainable and efficient agribusiness is essential for food security, sustainable management of natural resources, and mitigating the impact of climate change to and from agricultural activities. These two conditions are particularly salient in Latin America and the Caribbean (LAC). The region is the cornerstone of the world's ecosystems regarding breadth of both land cover and biodiversity. In parallel, LAC countries are collectively the largest exporter of agricultural products.[i] The environmental, social, and governance (ESG) impacts of LAC agriculture and food systems are far-reaching with significant effect on the sustainability of the global food supply. Furthermore, agribusiness is crucial to economic growth and employment in the region, constituting over 14% of the total labor force and 5% of overall GDP in 2019.[ii]

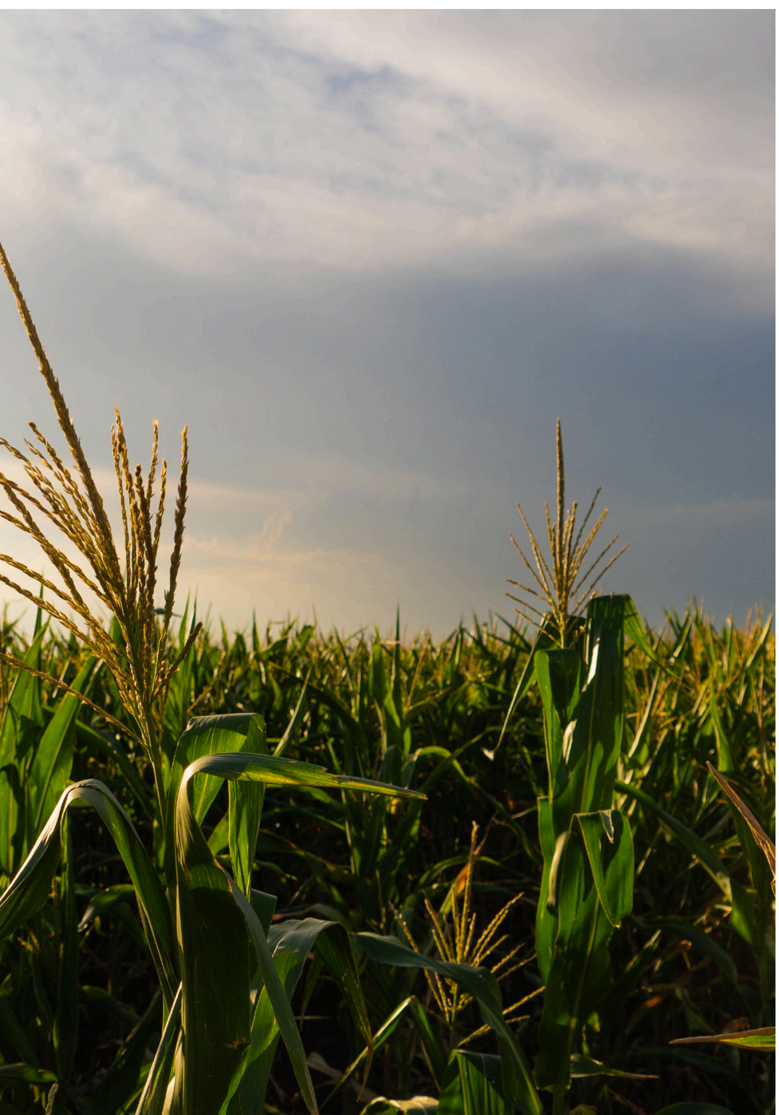
Improving monitoring across ESG impacts and production efficiency are both requirements for a sustainable global food supply. Remote sensing powered by artificial intelligence (AI) has significant potential to deliver the scientific and technological innovations required to realize these goals. This report details novel use cases of remote sensing technologies to enable sustainable agribusiness, particularly highlighting applications in LAC. While best practices for these applications are still being established, these use cases exemplify the potential for remote sensing to support environmentally and economically sustainable food supply systems.

We articulate key operational and cooperative objectives that should be prioritized to unlock this potential. This roadmap identifies current barriers to technology adoption that would enable sustainable agribusiness in LAC if addressed. These efforts will require action from practitioners across development finance, sustainability, and both commercial and open-source remote sensing. In parallel with continued technological and scientific innovation, stakeholders must improve the accessibility and interpretability of open-source remotely sensed information. Remote sensing is also positioned to power next generation management of ESG agribusiness impact if prioritized in monitoring and evaluation practices.

SECTION 1:

AGRICULTURAL REMOTE SENSING AT-A-GLANCE

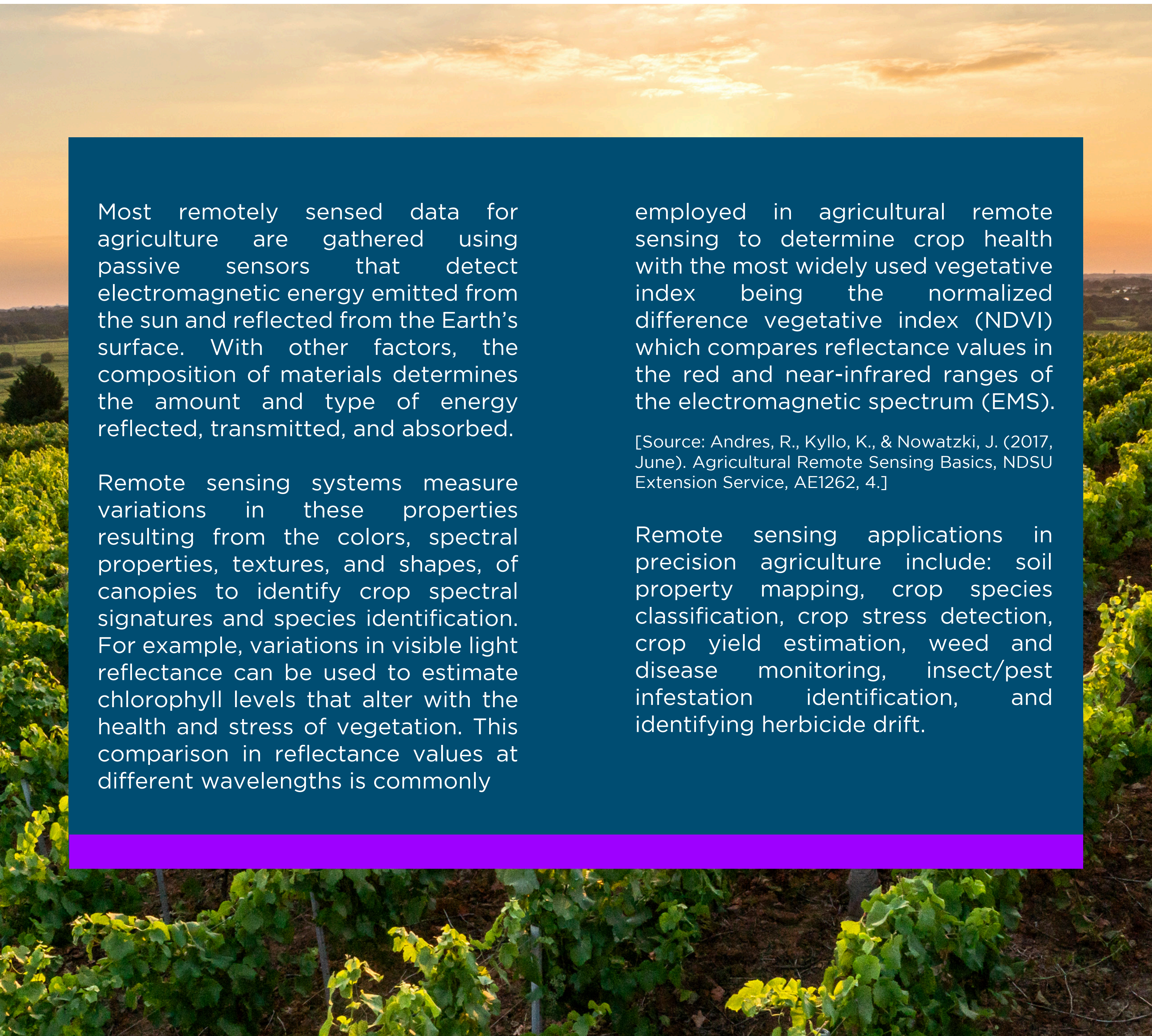
While remote sensing combines efforts from spectroscopy, optics, photography, computer science and artificial intelligence, electronics, and communications,[iii] insights derived from remotely sensed data are increasingly zfoundational across disciplines. Analytical findings from remotely sensed data now inform a variety of research and policy – particularly those related to ecology, environmental protection, and land management – and are integral to modern agribusiness.[iv, v, vi]



Adoption and the technical maturation of agricultural remote sensing have grown since the 1950s,[vii] with many key applications empowering practitioners with timely analyses that inform site-specific management of crops referred to as precision agriculture. Similarly, remote sensing is used to guide grazing and pasture management, enabling ranchers to identify quality grazing areas, as well as reduce impact to overgrazed lands. Remote sensing applications extend across the agribusiness ecosystem also informing lender decisions by leveraging remotely derived insights to measure crop histories of sites and manage risk in agriculture credit lending.[viii]

Analyses of remotely sensed data can map the location and extent of key crop and soil characteristics such as pest and weed infestations, nutrient deficiencies, disease, water deficiency and surplus, hail and wind damage, and herbicide damage. These insights enable agricultural producers to more precisely project crop yield, as well as more efficiently monitor and manage site inputs by directing manual inspection of crops and informing site-specific treatment plans. Timely and readily actionable insights through remote sensing can enable producers to more accurately estimate cost per unit of production and achieve greater operational efficiency, decreasing input costs and increasing yields. These data can also support producers in managing profit margins, mitigating operational risk, and making more informed decisions pertaining to debt and capital management.

Crucially, these technologies also empower producers to mitigate the environmental impacts of inputs through more targeted applications – for example, surveying weed location and chlorophyll content enables better variable rate applications of herbicide and fertilizer, respectively.[ix] Crop stress due to due to drought can be detected through remote sensing allowing for more precise irrigation practices.[x] These practices simultaneously reduce environmental damage and input costs to producers without negatively impacting crop performance. Additional key applications for remote sensing include monitoring of land use and cover to inform land management policies and growing efforts to monitor changes in biodiversity. When employed in conjunction with biodiversity and environmental monitoring, these applications can support environmentally and economically sustainable food supply systems.[xi]



Most remotely sensed data for agriculture are gathered using passive sensors that detect electromagnetic energy emitted from the sun and reflected from the Earth's surface. With other factors, the composition of materials determines the amount and type of energy reflected, transmitted, and absorbed.

Remote sensing systems measure variations in these properties resulting from the colors, spectral properties, textures, and shapes, of canopies to identify crop spectral signatures and species identification. For example, variations in visible light reflectance can be used to estimate chlorophyll levels that alter with the health and stress of vegetation. This comparison in reflectance values at different wavelengths is commonly employed in agricultural remote sensing to determine crop health with the most widely used vegetative index being the normalized difference vegetative index (NDVI) which compares reflectance values in the red and near-infrared ranges of the electromagnetic spectrum (EMS).

[Source: Andres, R., Kyllo, K., & Nowatzki, J. (2017, June). Agricultural Remote Sensing Basics, NDSU Extension Service, AE1262, 4.]

Remote sensing applications in precision agriculture include: soil property mapping, crop species classification, crop stress detection, crop yield estimation, weed and disease monitoring, insect/pest infestation identification, and identifying herbicide drift.

Producers in LAC countries are employing precision agriculture with evidence to-date identifying technology penetration in Brazil and Argentina and adoption by large-scale commercial farmers. Surveys among Brazilian producers in 2012 and 2013 report 45% of respondents employing some precision agriculture techniques[xii] and 22% specifically using remote sensing imagery.[xiii] Respondents among producers in Argentina reported 60% and 80% using remote sensing imagery in 2013 and 2018, respectively.[xiv] These surveys leveraged existing industry networks, including those that explicitly prioritized adoption of precision agriculture techniques, to identify potential respondents. These findings, therefore, strictly reflect adoption by larger agricultural producers. Yet, they do highlight how the benefits of remote sensing and precision agriculture are primarily captured by large-scale commercial farmers. While small-scale producers constitute greater than 85% of U.S. farms, few farms at this scale employ precision agriculture or remote sensing technologies.[xv]

REMOTE SENSING CONCEPTS

Remote sensing is the science of detecting and characterizing entities from a distance. The term also encompasses a suite of technologies through which information is remotely captured using sensors mounted on platforms such as satellites or aircraft. These systems measure electromagnetic energy, reflected or emitted by objects on the ground or the Earth's surface, that fall within a wavelength region of the EMS. Remote sensing measures and processes electromagnetic properties to derive insights on the physical, spectral, and chemical properties of entities at a distance.[xvi]

The field has evolved from interpreting visible light photographs captured from aircraft to modern remote sensing technologies that enable practitioners to derive complex information from the entire EMS, including the non-visible spectrum (e.g., infra-red). In turn, we can apply these insights across academic disciplines, policies, and commercial ventures.[xvii, xviii, xix]

REMOTE SENSING PROCESS

1. Emission of electromagnetic radiation (EMR)
2. Transmission of energy from the source (sun or active satellite sensor) to the surface of the earth
3. Interaction of EMR with the earth's surface (reflection and absorption)
4. Transmission of EMR from surface (back) to the sensor
5. Processing and analysis of data

The quality and value of information that can be derived through remote sensing is largely determined by two aspects of a system: sensor and carrier types.[xx, xxi,xxii] Sensors may be passive or active, depending on whether the instrument only detects external stimuli or itself generates signals for measurement.[xxiii,xxiv] **Passive sensors**[xxv] detect naturally occurring radiation reflected off the Earth's surface (e.g., reflected sunlight) while **active sensors**[xxvi] transmit energy and then measure the returned signal.[xxvii] While passive and active sensors can be used to capture similar information (e.g., systems across sensor types are used to monitor soil moisture), there are practical distinctions such as active sensors being better enabled to capture data regardless of time of day (or night) and cloud coverage.[xxviii] Cloud coverage can be a major hindrance in remotely gathering data, blocking aerial view of a target area and altering the characteristics of reflected energy.

Spectral and radiometric resolutions of a sensor also determine the types of information that can be derived. As energy strikes the Earth's surface, the transmission, absorption, and reflectance, of the electromagnetic radiation (EMR) is in part determined by the composition of the surface materials. **Spectral resolution** characterizes the EMR detectable by a sensor according to number and wavelength of EMS bands, i.e., the degree to which wavelengths are distinct.[xxix] Remote sensing systems are often identified by their spectral resolution. For example, light detection and ranging (LiDAR) are active sensors that employ laser emitted energy and measure ranges of returned energies. We can derive high-resolution 3D models of the Earth's surface from these data, ranging from elevation to surveys of vegetation. Other spectral resolution classes include multispectral, hyperspectral, thermal, electro-optical, and panchromatic. The **radiometric resolution** of a sensor determines its ability to precisely measure a given portion of the EMS based on its sensitivity to differences in reflectance values.[xxx]

The platform type on which a sensor is mounted directly affects the geographic coverage and temporal resolution of data that can be remotely gathered. Sensors can be mounted on satellites, allowing for regional and global coverage, as well as on manned aircraft or unmanned aerial vehicles (UAVs) for more targeted coverage.[xxxi, xxxii, xxxiii]

Temporal resolution describes the frequency with which a remote sensing system revisits the same geography. While geostationary satellites can allow for continuous monitoring of target area, most remote sensing systems mounted on spacecraft travel by orbiting satellites. The coverage of these systems are constrained by their orbit path, velocity, and imaging swath. [xxxiv]

Remote sensing is most powerful when systems repeatedly revisit and monitor sites, allowing for detection of changes in surface over time while also helping to mitigate interference in monitoring by cloud coverage. Conversely, poor weather can diminish the quality and usability of gathered data, effectively reducing the temporal resolution of a remote sensing system.

Finally, **spatial resolution** describes the ground physical area represented by a single pixel. This is often referred to as ground sampling distance (GSD) and is usually expressed in meters. For example, one-meter spatial resolution indicates that every (square) pixel in the captured image represents an area of one square meter. Higher spatial resolution systems return images of smaller areas on the ground and more geospatially precise images.[xxxv]

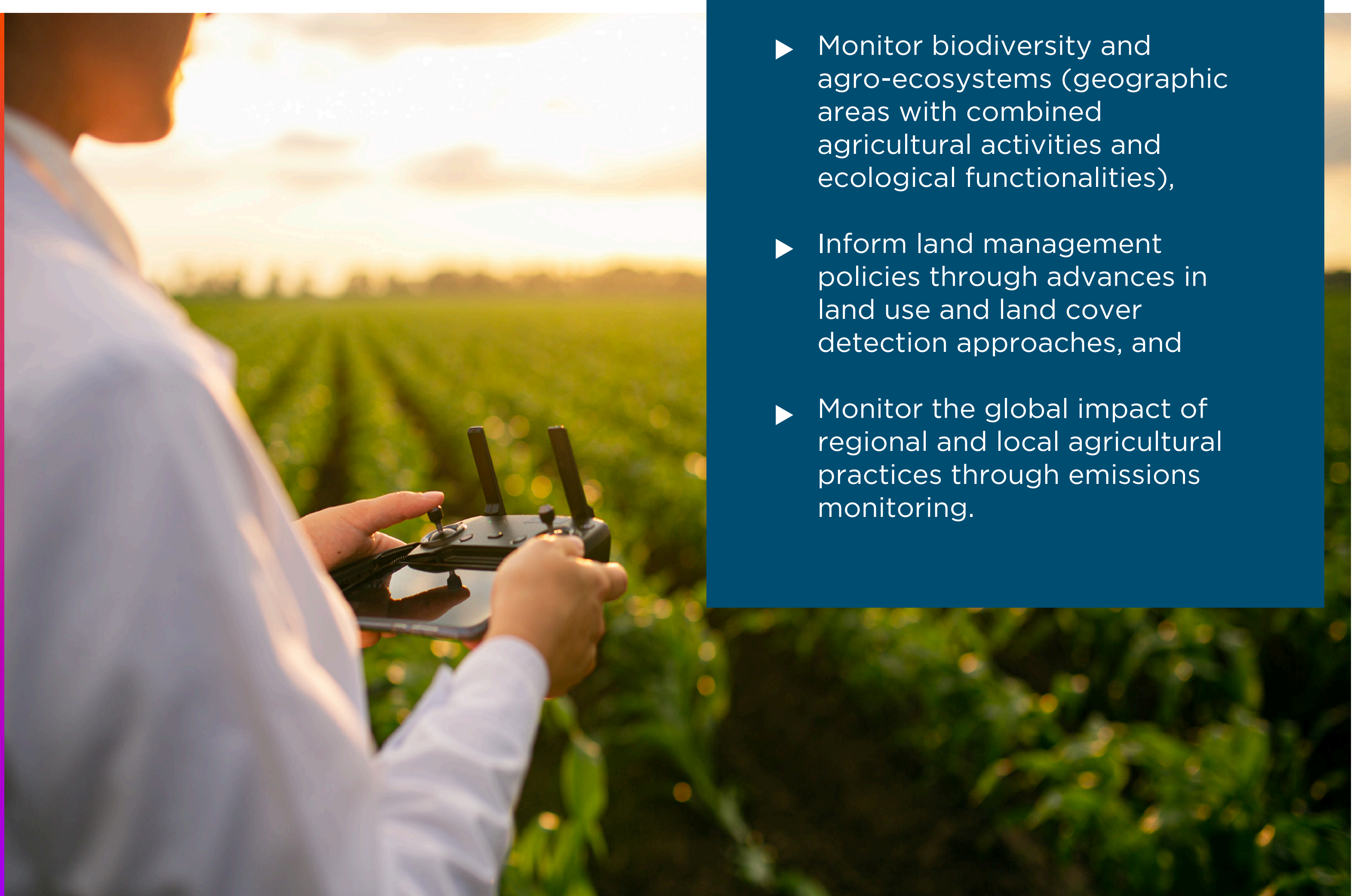
SECTION 2:

NEXT GENERATION APPLICATIONS OF REMOTE SENSING IN SUSTAINABLE AGRIBUSINESS

Recent advances in remote sensing, artificial intelligence, and computer vision techniques, are poised to enable next generation applications of remote sensing in agriculture. These advances deliver refinements in current precision agriculture applications as well as vastly expand the accessibility of remote sensing applications across the agribusiness ecosystem. Given the cost of remote sensing and technical expertise required if data processing and analyses are conducted in-house, use of remote has historically been limited to larger producers. Through greater investment in commercial and open-source offerings – along with novel, relatively low-cost monitoring frameworks – remote sensing practices are becoming increasingly more accessible to producers regardless of scale.

These innovations are also enabling a wide catalogue of agribusiness use cases with researchers developing and evaluating frontier remote sensing applications for monitoring and managing the impact of agribusiness on environmental and human health. In addition to further improving site management, advancements in remote sensing are increasingly leveraged to:

- Monitor biodiversity and agro-ecosystems (geographic areas with combined agricultural activities and ecological functionalities),
- Inform land management policies through advances in land use and land cover detection approaches, and
- Monitor the global impact of regional and local agricultural practices through emissions monitoring.



While best practices for these applications are still being established, these use cases exemplify the potential for remote sensing to support environmentally and economically sustainable food supply systems. We primarily highlight remote sensing implementations and studies in LAC countries.

POTENTIAL TO INCREASE ADOPTION OF REMOTE SENSING BY SMALLER AGRICULTURAL OPERATORS THROUGH LOW-COST ALTERNATIVES

Remote sensing technologies are integral to delivering timely and reliable information for optimization of crop inputs and management of farming practices in modern agriculture. Remote sensing applications for precision agriculture yield a wide variety of insights that enable practitioners to maximize crop yield and food security while conserving resources and minimizing environmental impacts.[xxxvi, xxxvii, xxxviii, xxxix, xl]

Innovations in near-surface and aerial remote sensing can potentially deliver lower-cost alternatives to satellite-based remote sensing. While these approaches return data with more limited geographic coverage, they could potentially make participation in the collection of and access to remotely sensed data more immediately accessible to smaller agribusiness entities.[xli] Crucially, use of low-cost UAVs and red, green, and blue (RGB) wavelength cameras can provide smaller agribusiness entities with a relatively affordable and accessible alternative to information generated by commercial, satellite-based systems.

PRECISION FARMING WITH UNMANNED AERIAL VEHICLES (UAVS) IN BRAZIL:

For example, agricultural and remote sensing scientists in Brazil and Italy recently evaluated the potential for employing UAVs and RGB digital cameras to optimize coffee farming in Brazil. The developed approach for monitoring of coffee crops using RGB vegetation indices enabled researchers to identify the introduction and spread of weeds and better inform farm management.

In parallel, researchers are developing frameworks for mapping weed distribution using low-cost UAVs along with open-source GIS software and AI libraries (e.g., OpenDroneMap, TensorFlow, PyTorch and OpenCV classification algorithms).[xlii, xliii, xliv] Weed management is crucial to ensuring crop yield and quality. Employing remote sensing to develop precise, site-specific management of herbicide applications can help to increase the sustainability of weed management practices. These relatively low-cost implementations are promising initial frameworks for adoption of these practices by small and medium agribusinesses.

Researchers are also evaluating the potential for near-surface remote sensing employing smartphones that can be used to monitor crop phenology and damage events.[xlv, xlvi] These studies illustrate the potential for remote sensing frameworks to deliver high-resolution, plot-specific data relying on near-surface monitoring and UAVs. While further work is required for these approaches to be adopted at scale, they hold significant potential for supporting crop growth and health modeling. Furthermore, these data can inform agribusiness insurance programs that are crucial to mitigating production risk among smaller producers.

NEAR-SURFACE REMOTE SENSING IN NORTHWEST INDIA:

Researchers developed a framework accomplishing this leveraging crowdsourced photograph streams of small size agribusiness entities taken with widely available, relatively inexpensive smartphones. Researchers were able to reliably quantify phenological stages and growth disturbances of winter wheat that cannot be detected by most vegetation indices or crop cut surveys derived from satellite-based remote sensing.

POTENTIAL FOR NEXT GENERATION LAND MANAGEMENT PRACTICES SAFEGUARDING BIOLOGICAL DIVERSITY

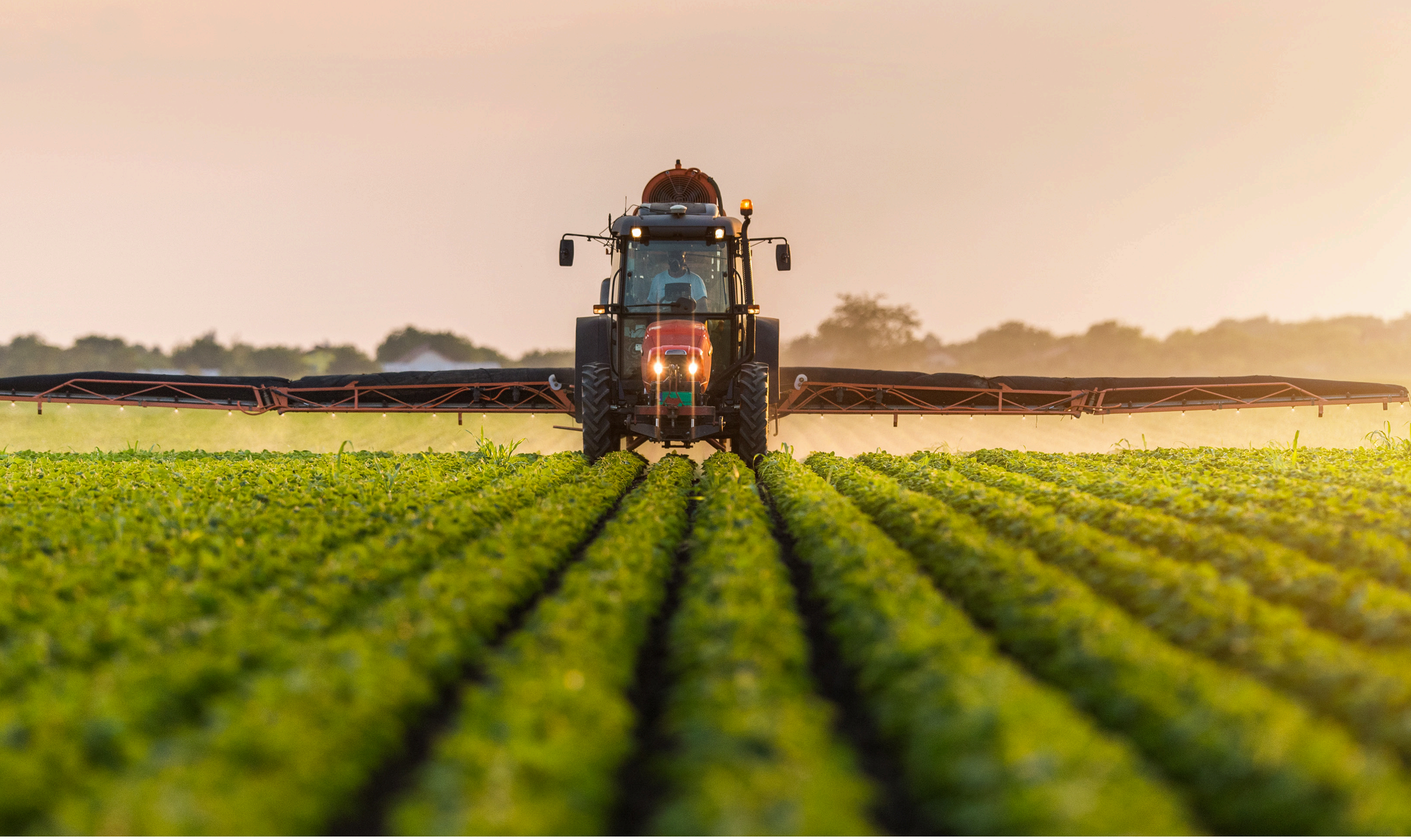
Remote sensing technologies are widely used to document land use and land cover (LULC) mapping which serves as foundational information for policies that shape agribusiness at national and regional levels and directly impact the sustainability of crop production and efficiency of land management. Advances in remote sensing technologies are not only addressing challenges in modeling land use change over time but are allowing researchers to evaluate the environmental impacts of land use and management policies through biodiversity monitoring.[xlvii, xlviii]

Advancement of these applications are essential managing the ESG impacts of agribusiness in LAC. Agriculture activities require approximately one-third of the region's land area and three-quarters of its freshwater resources.[xlix] Agribusiness is also a significant contributor to LULC

change in the region – for example, forest cover loss in Brazil between 2000 and 2016 is estimated to be over 45 million hectares.[l] With growing interest in employing remotely sensed data to protect biodiversity and agro-ecosystems, researchers are actively building out baseline measures and frameworks for monitoring changes in these areas over time. These efforts employ novel artificial intelligence and computer vision techniques as well as establish comprehensive baseline data. These data captures are the groundwork for time series monitoring of ecosystems.[li] Significant contribution in this area has been in service of mapping essential natural habitats in South America with the majority of LULC mapping efforts being concentrated in Brazil.

In 2017, Peruvian and Brazilian researchers reviewed 23 regional and global mapping initiatives and concluded that only three LULC maps exist nationwide for Brazil and Chile. Furthermore, there exist no LULC maps derived from remotely sensed data for Argentina, Bolivia, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela. Maps that do exist are built with Landsat (incl. 4-5 Thematic Mapper and 7 Enhanced Thematic Mapper Plus), Advanced Very High-Resolution Radiometers (AVHRR), and Moderate Spatial Resolution (MODIS), data. Relying on these medium-to-coarse spatial resolution data prove challenging in identifying vegetation. Greater access to high-resolution geospatial data products, such as Landsat 8, Landsat 9 or Sentinel-2 is necessary for more comprehensive mapping of these ecosystems. Building more robust and finer resolution data catalogs are crucial for understanding the vulnerability of and how agricultural activities impact agro-ecosystems.[lii]

Brazilian researchers have since employed historical Landsat 5 and Landsat 8 data to measure spatiotemporal patterns in Brazilian pasturelands, quantifying the health of the ecosystem using remote sensing. Brazilian pastures make up 20% of the country's ecosystem and help sustain livestock – a central pillar of agribusiness in the country.[liii] Researchers find that greater than 50% of pasturelands exhibit some level of degradation linked to deforestation and biodiversity loss.[liv] This can reduce the count of livestock that can be sustained within a single pasture, leading to not only environmental damage but food supply and economic insecurity. Additional recent work, also by Brazilian researchers, has generated LULC information across Brazilian biomes using



higher spatial resolution time series data to better measure the LULC dynamics and changes. These researchers leverage 33 years of historical data reconstructed using a multi-disciplinary network, MapBiomas, and artificial intelligence techniques to classify LULC across the country with 30m2 resolution. They estimate a significant loss in natural vegetation primarily due to cattle ranching and agricultural activities with pastures and farmlands expanding by 46% and 172%, respectively.[lv]

These are essential developments in monitoring the interaction between agricultural activities and biodiversity within LAC. Reliable and precise evidence documenting changes in agro-ecosystems enables industry to identify the consequences of agricultural practices and the public to hold agribusiness accountable. With greater precision and timeliness, these data could also enable firm- and sit-level ESG monitoring. Furthermore, advancements in LULC data will better inform land management policies that shape further agribusiness.

[1] Similar efforts have been completed by Argentinean remote sensing scientists assessing the completeness of LULC maps for South American wetlands, specifically focusing on the wetland macrosystems of South American mega-rivers: the Amazon River, Paraná River, and the Pantanal at the headwaters of Paraguay River.
Kandus, P., Gonzalez, E.B., Grimson, R., Minotti, P.G., Moranderira, N.S., Trilla, G.G. (2017, Oct 30). Remote sensing of wetlands in South America: Status and challenges, International Journal of Remote Sensing, 39(4), 993-1016.

DEEP LEARNING FOR LULC MAPPING:

Finally, Brazilian researchers are establishing novel machine learning and cloud computing frameworks for mapping the country's pasturelands. Researchers employed long short-term memory (LSTM) neural network and U-Net, a type of convolutional neural network (CNN), deep learning algorithms to process and evaluate thousands of PlanetScope images of Central Brazil over a 12-month period. This effort highlights the potential for deep learning and neural network architectures to employ a range of satellite data (e.g., PlanetScope, Sentinel-2, Landsat-8) in LULC mapping.

[Ferreira, L., Parente, L., Silva, A.P., Souza, C., Taquary, E. (2019, Dec. 3). Next Generation Mapping: Combining Deep Learning, Cloud Computing, and Big Remote Sensing Data. Remote Sensing, 11(23), 18.]

Similar work has been completed using CNNs to identify areas suitable for and aquaculture and salt-culture activities, as well as the presence of aqua and salt-culture infrastructure in the Brazilian Coastal Zone (BCZ). The BCZ is approximately 9000km long and extends over 17 coastal states. Most of the local water sources such as lakes and rivers have large amounts of aquaculture, but economic, geological, and climatic changes have significantly reduced the ability to sustain large-scale aqua-salt-culture in the Northern coast of Brazil. Researchers employed a U-Net classifier and CNN to distinguish between aqua/salt-culture and other surfaces of water like rivers, lakes, and coastal waters.

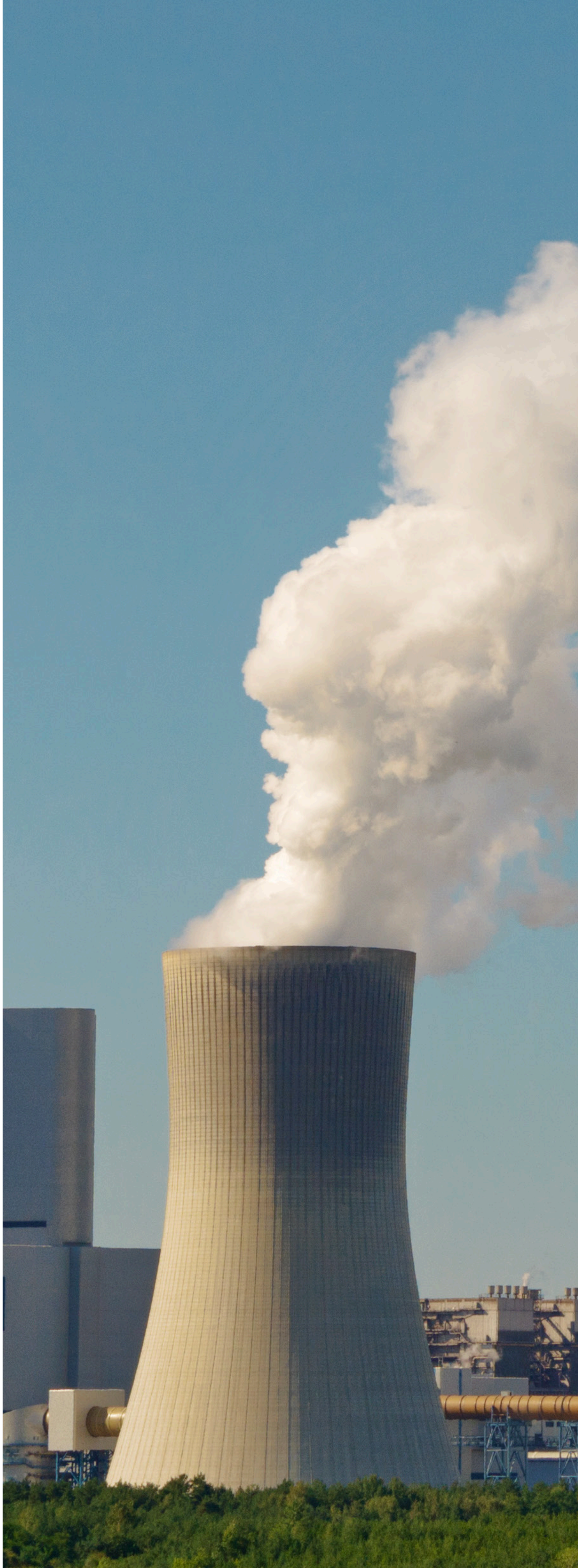
[Adami, M., Baumann, L.R.F., Cortinhas, L., Diniz, C., Filo, A.F., Souza-Filho, P.W.M, Pinheiro, M.L., Sadeck, L. (2021, April 7). A Large-Scale Deep-Learning Approach for Multi-Temporal Aqua and Salt-Culture Mapping, State-of-the-Art Remote Sensing in South America, 13(8), 16.]

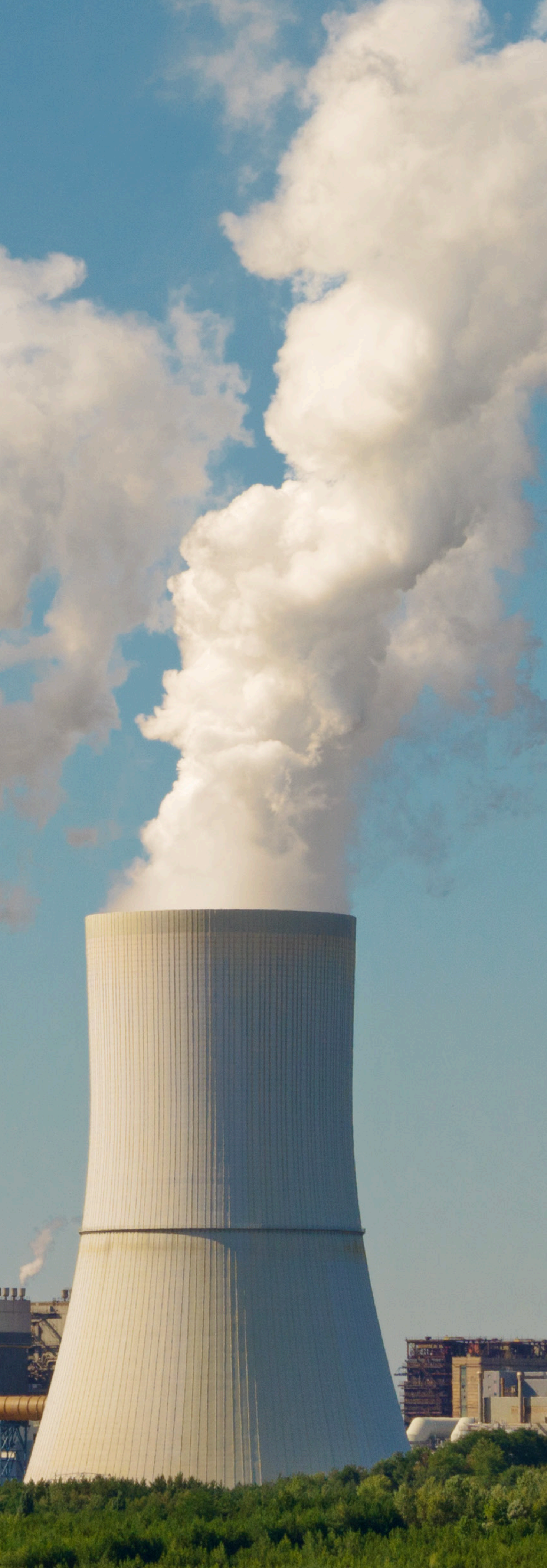
BEYOND EMISSIONS INVENTORIES – USING REMOTE SENSING TO TRACE EMISSION SOURCES

Agribusiness is a significant source of greenhouse gases (GHGs), including methane which is 84 times more potent than carbon dioxide over a 20-year horizon.[lvi] Furthermore, agricultural activities in LAC are recognized as core contributors. According to the UN Global Livestock Environmental Assessment Model (GLEAM), the livestock industry in the region is ranked highest according to emissions with an estimated 1.9 gigatonnes of carbon dioxide. This holds while regional production levels are comparable to those originating in Western Europe, North America, and South Asia. This is primarily generated through beef production and pasture expansion with associated deforestation.[lvii]

National emissions inventories for GHGs are built primarily using engineering estimates for stationary and nonstationary sources that are supplemented with remote sensing data and known emissions events reported by sub-national agencies.[lviii] These efforts significantly vary in methodology (e.g., top-down versus bottom-up calculation approaches) and therefore in reliability, limiting comparability. Furthermore, the coarseness in resolution for these estimates, as well as the temporal dynamics of GHG plumes, do not allow users to robustly attribute emissions to any specific asset or company.

Recent advances in commercial and open remote sensing technologies to identify and measure GHGs aim to address this challenge. High-resolution, satellite-based





systems operated by Canadian company, GHGSat, detected and measured methane emissions ranging in size from 361 to 668kg/h across distinct feedlots in California's Joaquin Valley. This constitutes the first time that emissions have been detected from space and then attributed to livestock activities.[lix] This highlights one use case achieved by recent launches of commercial and open remote sensing systems specifically aimed at methane detection. Other launches include MethaneSAT (a collaboration between the Environmental Defense Fund, Harvard University, and the Smithsonian Astrophysical Observatory), the European Space Agency's Sentinel 5-P, and the Italian Space Agency's PRISMA.[lx]

These technological advances and expansion of the remote sensing ecosystem will play a central role in empowering stakeholders to trace methane and other GHG plumes to the source. Specifically, finer spatial resolution and lower detection thresholds enable asset-level monitoring for GHG emissions. With this technology, industry and researchers alike are enabled to better monitor environmental outcomes of agricultural activities. Furthermore, these highly localized estimates could improve the accuracy and comparability of national emissions inventories, as well as attributing emissions to specific agribusiness activities and sectors. Both would serve as foundational information for holding governments and industries, including agribusiness, accountable for meeting emission reduction targets.

SECTION 3:

REALIZING THE POTENTIAL OF REMOTE SENSING IN LATIN AMERICA AND THE CARIBBEAN: BARRIERS AND PATHS TO ADOPTION AT-SCALE

We articulate below how remote sensing can enable next generation monitoring that is necessary for effective management of agribusiness ESG impacts in LAC, as well as the key roadblocks that must be addressed to unlock this potential. These are operational and cooperative objectives that should be prioritized in parallel with continued technological and scientific innovation:

1. Improve accessibility and interpretability of remotely sensed information, and
2. Establish high-quality, standardized frameworks for evaluating ESG outcomes using remote sensing.

Addressing these constraints can allow for adoption of remotely sensed analytics by producers and stakeholders across the agribusiness ecosystem, including financing institutions that drive investment and growth.

Next generation ESG monitoring through remote sensing

Through the recent expansion of commercial satellite offerings and technological and analytical advances, remote sensing offers novel data streams that have the potential to improve the scale, accuracy, and comparability, of ESG measurements.[lxi, lxii] Remote sensing technologies can deliver insights that are not only reliable and timely, but also at the scale required to evaluate impacts of agribusiness across LAC. When combined with artificial intelligence techniques and industry subject matter expertise, further returns can be realized as our ability to extract insights from a single observation and develop predictive frameworks advances.

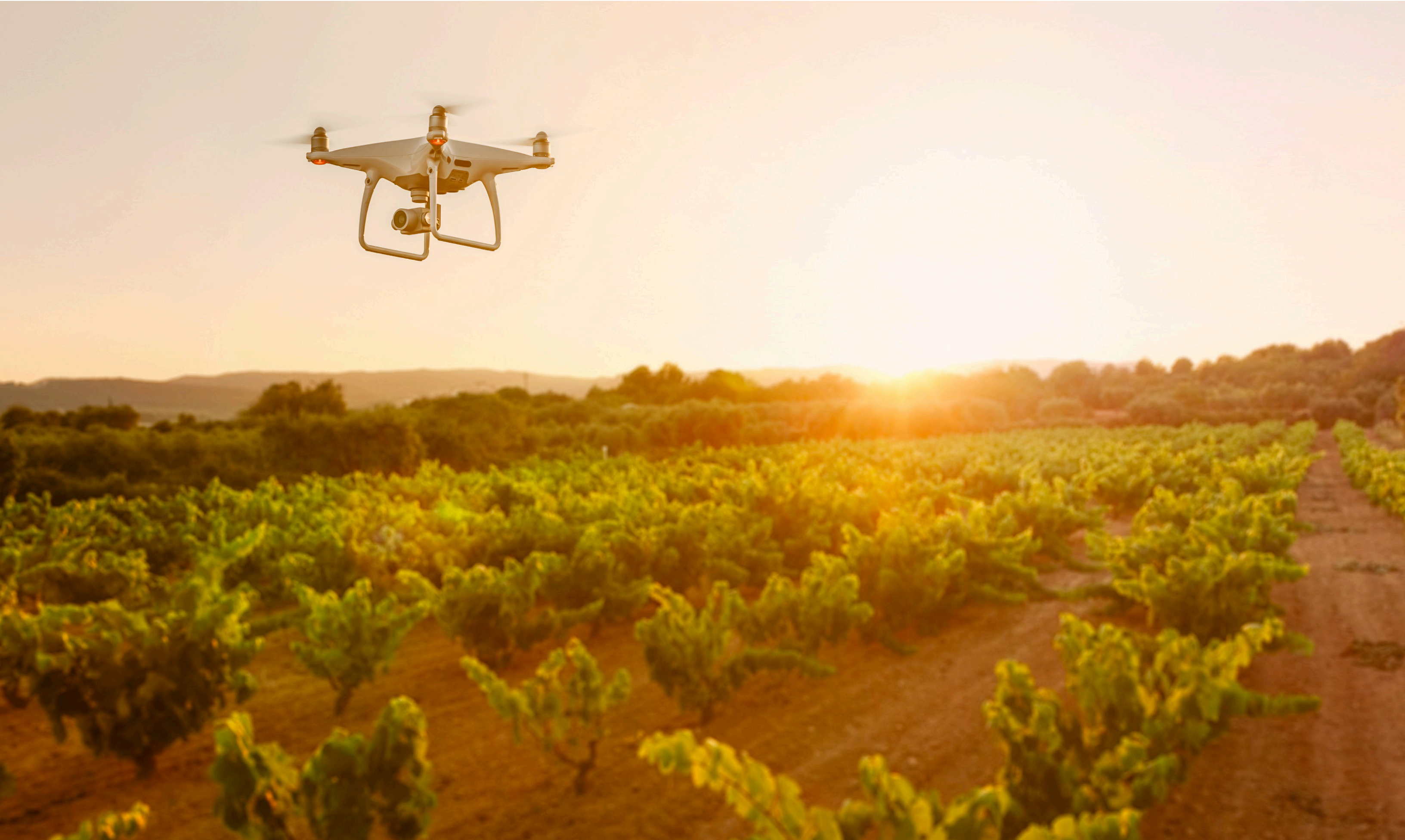
Satellite-based remote sensing systems, in particular, enable data collection with global or regional coverage, constrained only by orbit path, velocity, and imaging swath. These systems can efficiently gather data across relatively large geographies and cover remote areas in which data capture can be difficult and costly. This can help stakeholders to circumvent data scarcity and collection constraints frequently raised in ESG monitoring.[lxiii]

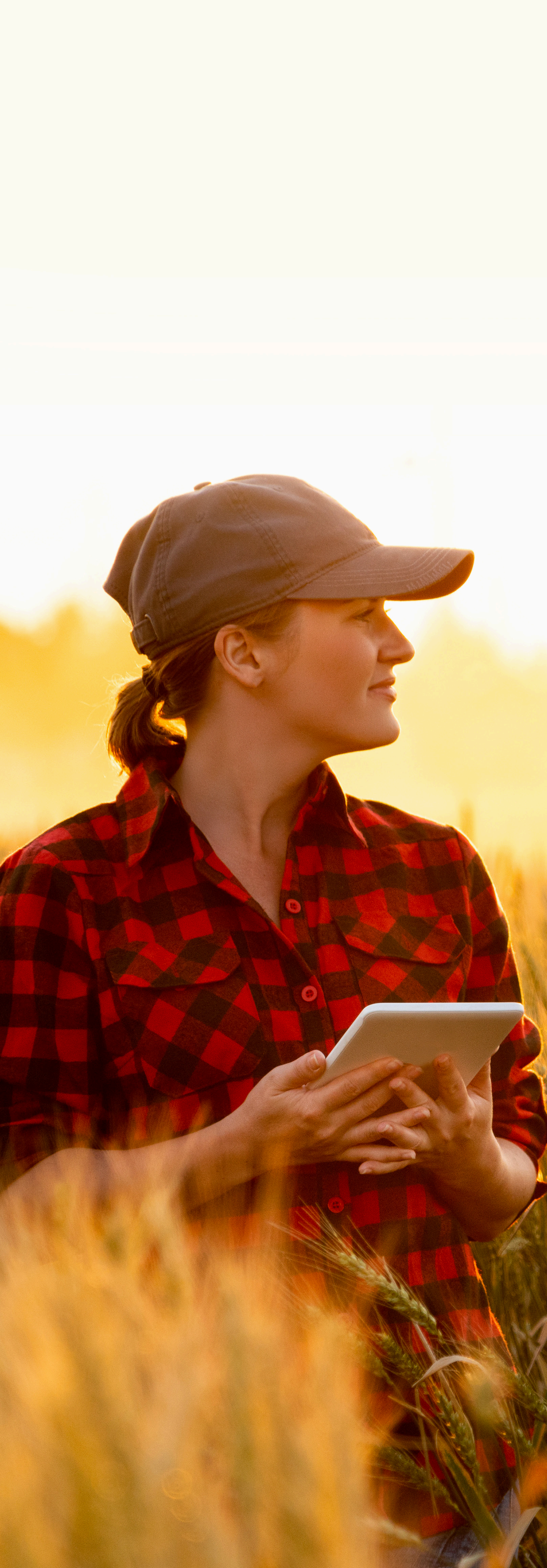
These systems also increase temporal coverage according to their revisit frequencies. Remote sensing greatly increases our capacity to repeatedly capture observations for the same area or entity, allowing for more robust detection of changes over time. Employing time series methodologies and observations consistently captured by the same remote sensing instrument, analysts can conduct historical analyses as well as detect recent changes. These data and techniques are key in determining how agribusiness activities impact natural characteristics over time. More frequent data captures inform more precise mappings of how agricultural activities impact biodiversity and climate, enabling more robust evaluations of land management policies.

Crucially, more timely insights can also empower stakeholders and policymakers to identify and mitigate damage to ecosystems that, if not addressed, can be impossible to remediate.

Remote sensing is also poised to improve the accuracy of ESG monitoring by delivering independent, observational information determined by the physiochemical properties of the observed surface or entity. While estimates inherently carry measurement errors, information derived from remotely sensed data provides a relatively reliable and cost-effective substitute for ground-truth observations. These data streams can help mitigate potential biases of self-reported data that often populate corporate sustainability reports and self-disclosed ESG performance metrics. With commercial offerings becoming increasingly specialized, remote sensing is allowing practitioners to identify specific activities at a distance (e.g., methane plumes[lxiv]). Sensor refinements such as spatial resolution are also increasing across the space and, in combination, these advances now allow for detection, quantification, and highly accurate geolocation of activities. These measurements would be costly and difficult to falsify further bolstering the reliability of remotely sensed ESG outcomes. By extension, the objectivity of remote sensing observations also enables greater standardization and, therefore, comparability of ESG metrics.

We detail below the operational and cooperative objectives that should be prioritized to realize this potential, specifically focusing on ESG performance measurement in agribusiness. Addressing these roadblocks is required for large-scale adoption of remote sensing to develop robust, timely, and reliable frameworks for monitoring ESG performance.





REQUIREMENT 1 –

IMPROVE ACCESSIBILITY AND INTERPRETABILITY OF REMOTELY SENSED INFORMATION:

While the past decade has seen a significant increase in the availability of open-source remote sensing data, significant barriers to large-scale adoption of remote sensing in agribusiness remain. This is primarily due to technological and financial barriers in access and expertise required to extract insights from remotely sensed data.

The open-source data marketplace for remote sensing is well established through offerings by government agencies.[lxv] These are primarily data portals that allow users to download raw remote sensing data. Agencies that capture and maintain these data have made significant strides in improving the accessibility, offering integrated visualization tools to support users in navigating Earth observation data. However, these platforms are often most valuable in their efficiency allowing users to extract data through robust application programming interfaces (APIs) and then conduct analyses and modeling independent of the platform.

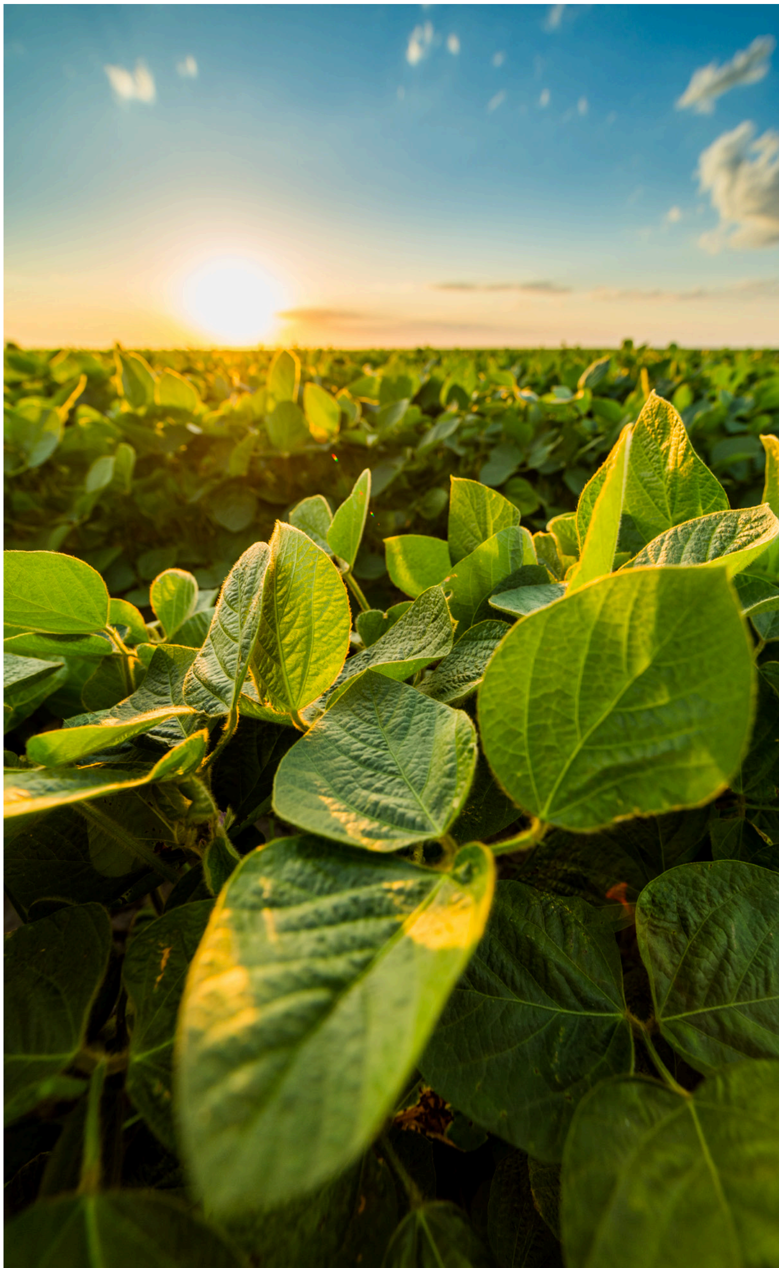
Commercial actors offering analytical products based on remotely sensed data are incentivized to develop solutions that offer digestible and actionable insights most valuable to their clients. To this end, commercial remote sensing entities are more willing and better equipped to take on the financial risks required to enable the computational and technical costs of acquiring, storing, processing, and analyzing, remotely sensed data. Building high-performing, robust models based on artificial intelligence algorithms requires massive amounts of data – this only becomes more salient given the size and computational requirements for processing remotely sensed data. Commercial entities also have greater flexibility in soliciting and retaining remote sensing and geospatial analytical expertise required to gather and fully leverage these data.

While the commercial ecosystem of remote sensing and geospatial data and analytics providers is rapidly growing, the demand for geospatial insights continues to outpace market offerings. Furthermore, the accessibility of these offerings across agribusiness is largely determined by operator scale and resources. We propose the following objectives to ensure more equitable access that is necessary for usez of remote sensing at-scale:

- Prioritize the development and delivery of analysis-ready, open-source data products; and
- Enable efficient and impactful use of these tools through capacity building and training users.

Insights from remotely sensed data must be made more accessible regarding both interpretability and computational and technological capacity. Open-source, web-based platforms that deliver analytical insights through intelligent visualization tools are best positioned to offer stakeholders actionable information regardless of resources. We highlight several intelligence visualization platforms that offer users readily available insights that can drive more productive and sustainable agricultural activities.

However, these portals are only impactful when prospective users are both aware of and empowered to leverage their findings. Crucially, this also assumes access to these resources – the World Bank estimated the median share of households with Internet access in 2015 to be less than 30% across LAC.[lxvi] Most areas with Internet access are concentrated in urban areas with relatively dense populations and, inherently, most agricultural activities and the workforces that support them exist in more rural areas. Without significant expansion in Internet infrastructure and accessibility, the benefits of remote sensing to agribusiness will remain concentrated to a disproportionately small share of producers.



OPEN-SOURCE INTELLIGENT VISUALIZATION PLATFORMS:

Climate TRACE:

- Aggregates data from a variety of sources, including remote sensing systems, to characterize GHG release activities
- Provides user-friendly, dynamic data visualizations representing emissions estimates by sector and country

GeoGlam Crop Monitor:

- International crop conditions map and information center
- Provides an interactive map of crop conditions worldwide, with a choice between Agricultural Market Information System (AMIS) Crop Monitoring, or Early Warning Crop Monitoring, and filtering by crop type
- Also provides monthly reports on AMIS, Early Warning, Special Repots, Conflict reports, and Climate Forecast

Global Fishing Watch:

- Interactive world map of fishing specific ocean monitoring
- Provides information on daily fishing activity, cumulative hours, and type/tools of apparent fishing
- Data portals with access to carrier vessel data and marine health data,

Global Forest Watch:

- International forest cover and deforestation information center
- Provides interactive, global map of forest change, land cover, land use, climate, and biodiversity. Optional aggregate stats by country
- Also has dashboard interface with land cover, forest change, fire, and climate information by country or globally

Global Surface Water Explorer:

- International surface water information center
- Provides interactive, global map of spatiotemporal surface water history
- Data available for download

SoilGrids (International Soil Reference and Information Centre):

- International Soil Reference and Information Centre
- Provides interactive, global map of soil properties

Resource Watch:

- An international climate/sociology data center
- Downloadable dataset repository with variety of datasets spanning from specific natural hazards to air quality, to global hunger index
- Interactive map interface that visualizes any chosen dataset

Brazil Data Cube:

- National Institute for Space Research, Brazil
- Analysis-ready time series data for medium-resolution remote sensing images across Brazil
- Web-hosted computational platform enabling users to readily process and analyze data

REQUIREMENT 2 –

ESTABLISH HIGH-QUALITY, STANDARDIZED FRAMEWORKS FOR EVALUATING ESG OUTCOMES USING REMOTE SENSING:

While the ESG impacts of agribusiness are becoming increasingly central to investor and consumer choices alike, standardized frameworks for measuring these outcomes remain elusive. Organizations such as the Global Reporting Initiative (GRI), Sustainability Accounting Standards Board (SASB), and the International Financial Reporting Standards (IFRS), have led the effort to establish consistent accounting and reporting standards. These efforts enabled a meaningful shift in reporting across ESG measures over the past decade and most third-party data vendors offer companies metrics in service of these standards.

Demand persists, however, for greater reliability in evaluating the impact of agriculture activities and comparability of these measures across the industry. Remote sensing offers significant potential to accelerate the harmonizing of reporting frameworks as well as power robust program evaluation.

The most essential roadblock to robust and standardized ESG frameworks is the development of best practices for linking information derived from remotely sensed data to specific companies and sectors. The traditional ESG monitoring framework begins with an asset of interest and then quantifies sustainability based on activities tracked and reported by the owner company. Conversely, ESG measures driven by remote sensing inherently begin with unstructured, observational data.

We are now required to process and analyze these data, as well as geospatially attribute measurements to an asset.

The complexities and variations in agricultural operations within industry and across LAC are nontrivial. Identifying and quantifying how these site-specific activities interact with and impact different populations and ecosystems has proven to be extremely challenging. Remote sensing offers a path for more efficiently and reliably capturing this information by delivering time series, often highly localized data. Standards for measuring these outcomes primarily with remote sensing technologies are nascent but in development. We describe several frontier techniques for accomplishing this in the Section "Next generation applications of remote sensing in sustainable agribusiness." Additional work is being done to translate these types of remote sensing studies to aggregated metrics, [lxvii, lxviii] including recommendations for integrating approaches that rely remotely sensed data and that are gathered in the field.[lxix]

As standards for asset-level measurements using remote sensing are established, this work can be extended, yielding high returns to ESG performance measures. Frameworks for aggregating asset-level measures to corporate- and industry-level can be developed. Additionally, outcomes can be tied to specific agricultural activities assuming there exist data detailing on-site agricultural infrastructure and practices. Leveraging remotely sensed data to trace outcomes across agricultural supply chains is of significant interest. While establishing best practices for deriving asset-level measurements will advance this effort, conventional data scarcity challenges for agricultural supply chains will persist realizing this approach such as tracking upstream suppliers. Remote sensing systems and computer vision techniques can support building out foundational data necessary for ESG monitoring across supply chains. These technologies can be used to detect and classify assets and production sites along with their location. This could support build asset networks, including smaller producers, that can be associated with specific sectors and companies when partnered with subject matter and regional expertise.

One path that both yields immediate returns and accelerates this standardization of ESG metrics is researchers, investors, and project owners, adopting remotely sensed time series data as a cornerstone of program evaluation. Remote sensing delivers repeated, objective observations of an entity that are essential in change detection and, with appropriate evaluation methodologies,

enable causal inference. Evaluators can also leverage these technologies to augment traditional data sources, circumventing data quality and collection issues inherent to self-reported and survey data.[lxx] The resulting monitoring and evaluation findings are both reliable and potentially comparable across projects, offering insights that can prove critical in investment decisions.

Accomplishing this, however, requires access to data captured by remote sensing systems with characteristics that meet the evaluation requirements.[2] Each point in the selection of a remote sensing system, including data processing and analyses, must be considered prior to implementation. At minimum, spatial resolution of the data must be sufficiently fine to enable geospatial attribution of measurements (i.e., generate site-specific measurements with confidence). Critically, evaluators should consider the temporal frequency and seasonality of activities they hope to detect and quantify. Private and public remote sensing systems alike face constraints that shape orbital paths – evaluators must carefully consider the realities of site revisit frequencies when attempting to detect intermittent or seasonal practices (e.g., burning of crop residue).

Effectively integrating remote sensing in program evaluation efforts requires significant resources, ranging from the cost of data acquisition to analytical expertise. Yet, remote sensing is still observed as a significantly underutilized tool in program evaluation.[lxxi] Increased adoption should result in lower barriers to entry over time through maturation of the remote sensing product ecosystem and growth in open-source data and tools. Furthermore, increased use of remotely sensed data in targeted program evaluations should in turn inform how these data are integrated into standardized ESG reporting frameworks.

SECTION 4:

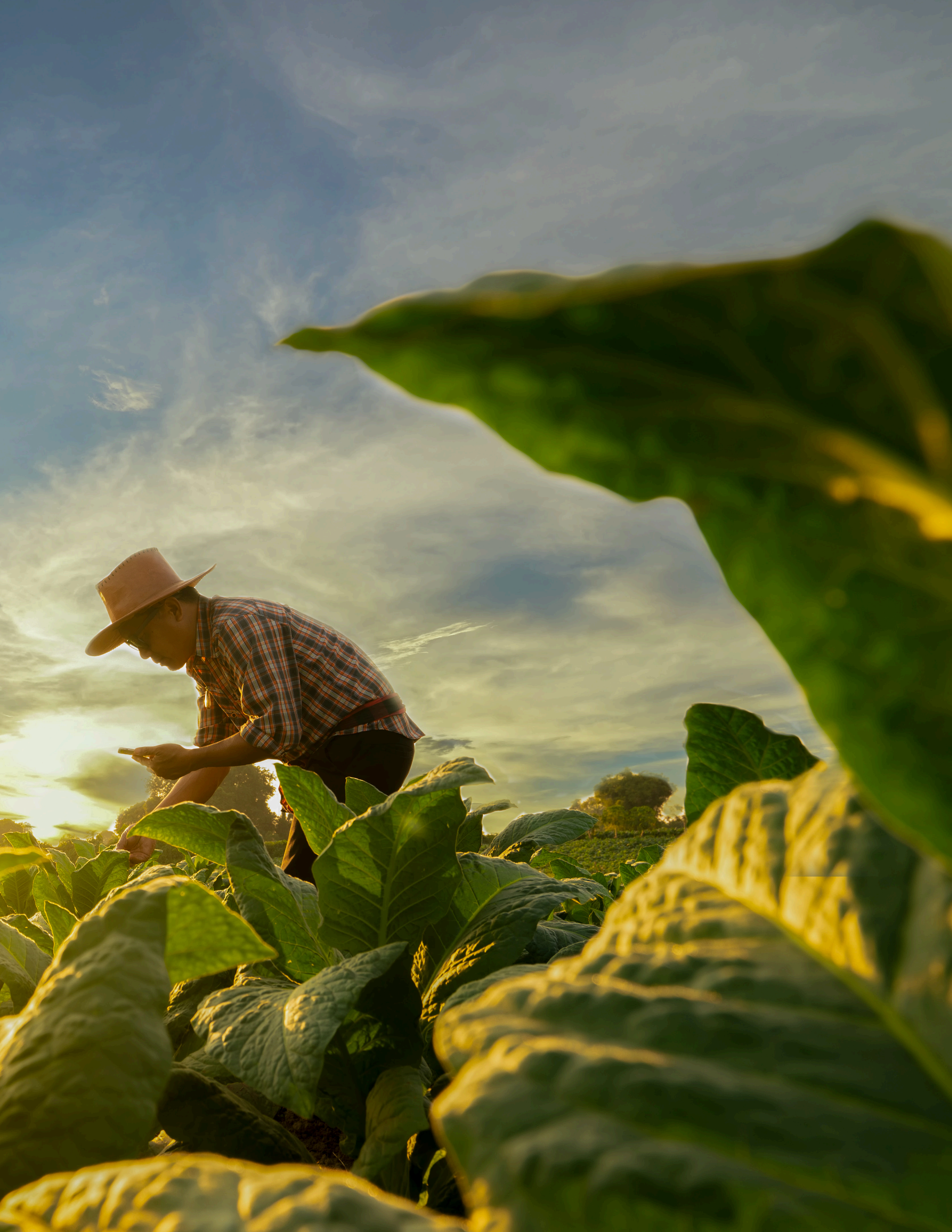
CONCLUSIONS

Advances in remote sensing technologies and AI techniques are delivering significant refinements precision agriculture while improving capacity for monitoring the impacts of agribusiness on biodiversity and GHG levels. While best practices for these applications are still being established, the use cases highlighted exemplify the potential for remote sensing to support environmentally and economically sustainable food supply systems. Yet there remain significant barriers to large-scale adoption of remote sensing in LAC agribusiness. The accessibility of remote sensing offerings is largely determined by operator scale and stakeholder resources, including the technological and methodological expertise required to extract insights through AI and computer vision techniques.

Realizing the full potential of remote sensing in sustainable agriculture requires action from practitioners across development finance, sustainability, and both commercial and open-source remote sensing. Stakeholders must enable equitable access to remote sensing products and information. This can be achieved by prioritizing the development and delivery of analysis-ready, open-source data products. Crucially, end users must have access and capacity to leverage these tools.

Remote sensing systems offer the foundation for robust and efficient monitoring and evaluation of ESG outcomes in agribusiness. These technologies can deliver insights that are not only reliable and timely, but also at the scale required to evaluate impacts of agribusiness across LAC. These findings are both well founded and potentially comparable across projects, offering insights that can prove critical in investment decisions. Furthermore, increased use of remote sensing in program evaluation can help to accelerate the standardization of industry ESG reporting driven by remote sensing.

Section 1 details the characteristics of a remote sensing system that determine what information the technology can capture.



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